Fractal Neural Vector - Machines, Tomography and Inheritance of Behaviour

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Abstract: Results of intensive studies of neural systems could not fully explain the astonishing performance of biological nervous systems in complex situations. Therefore alternative models of neural nets and their ways of pattern-processing might be of interest. Fractal neural nets offer interesting rich and flexible connectivity and biomorph aspects as hemispheres, lobes, gyri, sulci, decussatio of fibres, ventricular systems, thalamic structures and a high dynamism of processed patterns. Combining these fractal features with intracellular memory-strings to encode sequences of activities as engrams or vectors, to store, compare and reconstruct patterns of activities, a new tomographic form of information-processing seems to be achievable for such fractal neural vector-machines. Those memory-strings could, though completely hypothetically concerning their biological relevance, at least in principle allow the inheritance of behaviour. Though very preliminary, the results of a first small simulation may shed a light on the interplay of innate talents and learning experiences as well as on hypothetical mechanisms of genetic adjustments of organisms to the environment during evolution.

Key-Words: three-dimensional fractal neural nets, vector-machines, memory-strings, engrams, tomography, inheritance of behaviour

1 Introduction

The function of biological neural networks remains enigmatic in various aspects. Whereas main hypotheses of the functioning of neurons like changing synapses as base of learning [1] have proven their validity in many studies, full understanding is still lacking. Long term potentiation of synapses is found by non-physiological protocols of activation [2]. Artificial neural networks are used in a great variety of areas: They are used, as examples, in fields of image compressing [3, 4], of pattern detection and classification in medicine [5] or to predict temperature in tanks in models of energy plants [6]. Open questions remain: amongst others, the inheritance of innate behaviour cannot be explained by determining the strength of single synapses by genetic means. But very complex behaviours are inherited, as we may find e.g. in many species of insects, so there have to be additional mechanisms to explain the function of biological neural nets.

Fractal neural nets, their connectivity being completely determined by fractal functions [7] show interesting features, resembling to those of biological neural nets concerning morphology, structure and dynamical aspects as their ability to flexibly connect distant neurons and the occurrence of con- and divergence in different regions of the net as well [8].

Some examples of such neural nets shall be presented. The connectivity of the three-dimensional nets is determined by using algorithms analogue to the Mandelbrot- and the Julia-algorithm, the squaring of quaternions and related functions combined with the addition of a constant vector to calculate the target-region, to which each neuron will project its activity. The trajectories of the projections from one point of the complex plane or in case of three-dimensional fractal nets of the three-dimensional space are logarithmic spirals or their three-dimensional pendants as loxodromes. Those are modified by the addition of a constant vector by the fractal formula. Combining these two different motions, along the spiral trajectory and the straight vector, we get resulting trajectories of modified spirals, as well in 2D as 3D- structures as well. These trajectories may be interpreted as axons of neurons, projecting their activity from one location

of the net to its target-region. Thus, within the Mandelbrot set, we find a central structure, with certain 'nuclei' and efferent and afferent connections as well, resembling to a thalamus and analogue structures in three-dimensional 'Mandelbrot-sets' too (fig. 1).
In those networks, caused by the iterative nature of the process, at each neuron, a sequence of activity will occur, completely determined by and reflecting aspects of the starting pattern. Recording these sequences in form of intracellular memory-strings, strictly hypothetical in the biological hypothesis, in form of chains of triplets of RNA or DNA, allows a very efficient way to store, process and reconstruct information by these networks and at least principally the inheritance of behaviour by passing sets of memory-strings from one generation to the other, allowing evolutionary mechanisms to optimize these sets of memory-strings.
The results of several preliminary studies with regard to these various aspects of those neural systems, shall be presented.

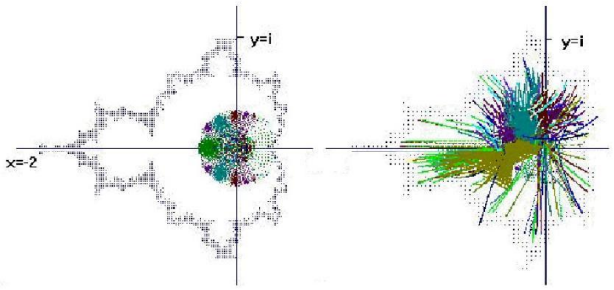

Fig. 1 Central 'thalamus' of the Mandelbrot-set, 'nuclei' (left) and 'efferent connections' to the periphery ('cortex') (right)

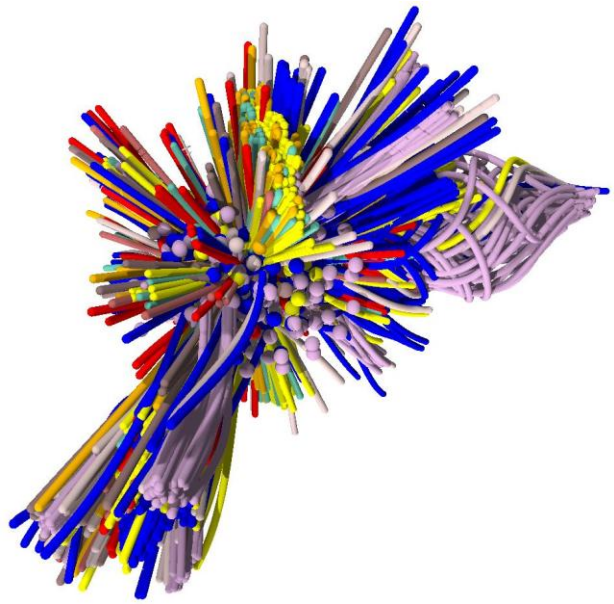

Fig. 2 A three-dimensional analogon ('thalamus' and efferent projections) to fig. 1

2 Methods and Material

Equation 1 shows the fundamental squaring of complex numbers, combined with an addition of a constant vector c, base of Mandelbrot- and Julia-sets:

$$f(z) = c + z^2 \quad (1)$$

c and z being complex numbers, the iteration of equation (1) leads to the well-known fractals of the Mandelbrot- and the Julia-sets. In case of the Mandelbrot-set, we start for each point z1 of the plane at zero, the vector c equalling z1, while in Julia-sets, the vector c is chosen before starting the iterations and remains the same for all starting points z1 of the complex plane. The iterations are performed n-times until the modulus of the resulting z(n) will exceed a chosen limit(often called bailout, usually 2.0) or n will exceed a certain limit of iterations(often called maxiter). The behaviour during the iterations might be analyzed and used to color each point z of the complex plane according to a distinct color-table, thus resulting in a pseudocolor-representation of the complex plane, which we know as the typical fractals. The same basic procedure may be performed for each point z1 of a three-dimensional space, whose coordinates x1, y1 and z1 may be used to calculate in an iterative manner the according point z2, to which a neuron at z1 is assumed to project its activity. Analogue to the two-dimensional fractals, we get according three-dimensional fractal structures. By equation (1) no certain trajectory is determined, which we should follow when starting at z1 to reach point z2. Very sensible continuous functions to represent the movement from z1 to z1 in case of two-dimensional fractals are logarithmic spirals, because z1 as well as z2 will lie on the same logarithmic spiral.

As a basic assumption, it is assumed, that the trajectories of the fractal functions shall represent axons of neurons, located at z1, projecting to ('innervating') neurons at z2, the same should apply to all neurons z(n) and z(n+1).
For most simulations of neural nets, based on memory-strings, it is, very simplifying, assumed, that each neuron may have two states: active or inactive. All neurons may act synchronously in a certain sequence of activations. The neurons will project their activity along the trajectory of the modified spirals to their target-neurons. All connections are assumed to be recurrent, which means, all neurons may activate the neurons, they get activity from, as well. 80 % of connections in brains are recurrent [9]. In fractals these recurrent

connections are determined by reversing the squaring of the complex number z by calculating the two square-roots of any z or performing by geometrical means analogue functions for all three-dimensional points z and subtracting c instead of adding it.
Squaring of a complex number z is equivalent to a rotation around zero until the argument of z is doubled and squaring the distance from zero. The squaring of quaternions will do the same in an oblique 'complex plane', which is rotated around the x-axis, until the point z will lie within this plane. Geometrically we can combine these movements with additional movements, for instance a rotation of the oblique plane through z around the x-axis until its angle to the positive y-axis will be doubled, to get a way to calculate analoga of 'squares' of three-dimensional points z.
In the simulations, all, or only certain, neurons are assumed to be able to record the sequence of activity, arriving at them, in form of 'intracellular engrams', short strings of numbers, representing the degree of activity at each activation cycle. These intracellular 'memory-strings' are used to compare them later to newly formed ones by comparing the encoded sequences of activity. The memory-string with the best fitting sequence, the most homologous one, will be chosen by the neuron, to send an associative answer to the net by recurrent activation of the adjacent chain or tree of neurons (fig. 3).
Figure 3 displays this very schematically: above: The activity of each neuron of a chain of 4 neurons is projected stepwise to the next neuron in direction towards neuron 4. Neuron 4 (blown up) encodes each state of activity arriving at it at each working-cycle by forming an intracellular engram, a chain of molecules (oligonucleotides or oligopeptides in the biological hypothesis), which reflects in its sequence of different components the sequence of activity. Thus two patterns are 'learned' by neuron 4 and stored in engrams as base of 'long-term-memory'. Below: A third presented pattern leads to the forming of a third 'memory-string'. The first learned string proves to be the most homologous. It will be chosen to be the string, with which the chain of neurons will be activated using its sequence (last in, first out) to reactivate the neuronal chain in reversed direction to reconstruct pattern 1 as an answer of the chain to pattern 3.

To investigate principal aspects of the inheritance of behaviour, in a very preliminary study, a little organism, a 'worm' is simulated, which will move in a cellular world with 'food' and 'enemies'.

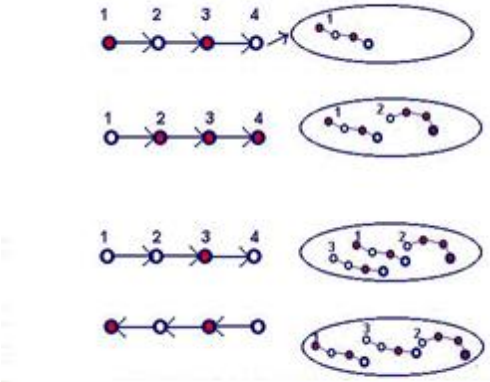

Fig. 3 Formation and using of memory-strings (schematic view)

It is assumed to have a small 'nervous-system', consisting of a grid with 16 neurons (their x- and y-coordinates ranging from 1 to 4), which will have two possible states of activity: on or off. The first 8 neurons (fig 23, 24) are 'sensory neurons', reflecting the existence of an obstacle in front of the worm by 'on', its absence by 'off'. The first 4 neurons 1-4 are 'on', if the obstacle will cover two cells of the environment, the neurons 5-8, if the obstacle will cover at least one cell. The basic information, the pattern within the sensory-neurons will be distributed over the whole net by a fractal algorithm. Each cell will activate its neighbour in vertical direction (e.g. neuron 5 will innervate neuron 9). Additionally, the x-coordinate of the neurons with x= 1 or 2 will be squared, and a constant vector vx, choosen to be 3, will be added. If the resulting value will be greater than 4, 4 will be subtracted. The resulting value will be the x-coordinate of the second innervated neuron. The y-coordinate will be treated as the x-coordinate, the constant vector vy was choosen to be 0. Thus we get the coordinates of the second neuron, which will be innervated. For the neurons with x-coordinates 3 or 4, the corresponding neurons will be determined to be symmetrical to the midline to the second- target-neurons of the neurons with x- coordinates 1 or 2. The resulting structures of connections will be symmetrical to the midline. Thus, in the course of 5 iterations, in all neuron will arise a sequence of 5 states of activity, which will distribute the starting information of the sensory-neurons over the whole net. The neurons 13 – 16 will work as motor-neurons. They will compare the sequence of activity, occuring at them within 5 iterations to the bsequences of a set of 50 memory-strings, which

they possess as genotype 'by birth'(in the simulation by a random sequencing or by mixing them from two formerly existing sets of memory-strings of two 'parents'), selecting the memory-string with the best fitting sequence. Each memory-string has at the sixth position one 'base triplet', a codon, encoding activity or no activity. According to this 6th position, the motoneuron will be, as a consequence of the starting pattern represented within the 'sensory neurons', active or inactive. The motoneurons are assumed to have a hierarchical order: If the second motoneuron (neuron 14) will be active, the worm will move one cell forward in the same direction as before. If the second motoneuron will be inactive, the first motoneuron (neuron 13) will be deterrmining the reaction of the worm, if it is active. Then the worm will move one cell to the left (in respect to the former direction). If the first motoneuron will be inactive too, the third motoneuron (neuron 15), if active, will cause one step to the right, if inactive as well, the 4th motoneuron (neuron 16) will cause a movement two cells backwards. In 20% a step of one cell in a random direction will be choosen (to avoid endless loops). The number of cells with 'food' or 'enemy', hit by the 'worm' will be counted as a base for evaluating. As a positive or negative reinforcement, an additional codon, 'base-triplet', will be added to the memory-string, causing the last action, encoding positive or negative evaluation, influencing the selection of strings in later moves. In the presented study, this part of simulating the individual learning history is performed in a preliminary form. Each 'worm' will get a set of 50 memory-strings at the beginning, simulating a set of 'genes'. There were three kinds of sets used: one with only 20% of the encoding positions encoding 'activity', the second with 80% encoding activity and the sets of the 'children', as a 'mixture' of two 'parental' sets.
Codes were written using Blitzbasic, Lazarus and Delphi, fractal programs PodMe and ChaosPro(freeware) and the Raytracer PovRay(freeware).

3 Results

3.1 Trajectories and connectivity

Starting at any point z1 we get a sequence of points as result of the iterations of equation 1. These might be shown as a series of single points as in figure 4a. We can show the connections of points z1, z2, ... zn by connecting them directly(fig. 4b), we may as well show the influence of the two terms of equation 1 to the results (segments of logarithmic spirals representing the squaring of the complex number, the straight lines the addition of the constant vector c)(fig. 4c) or we may (fig. 4d) show these two influences by both terms as a combined movement along modified spirals, leading from z1 to z2 and so on. This last concept is used throughout this paper to determine the course of the trajectories, or 'axons'.

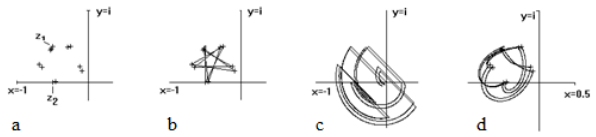

Fig. 4 Course of values, starting at z1, various forms of visualization

We get a basic trajectorial system of segments of logarithmic spirals, representing the squaring of complex numbers (fig.5).

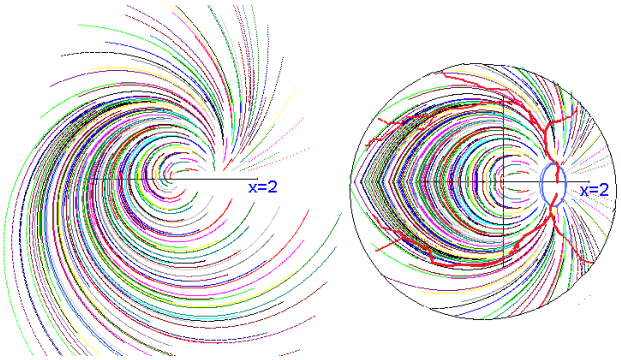

Fig. 5 Left: trajectorial system of segments of logarithmic spirals, upper half of the complex plane; to the right: The trajectorial system matches the course of the fibres of the optical nerve within the eye quite well (artistic-schematic view, according to [10])

The trajectorial system does fit the course of the fibres of the optic nerve (papillomacular and arcuate fibres) within the eye nearly perfectly, the blind spot representing point 1 on the x-axis. By convergence of the trajectories towards zero, a 'macula densa' will arise there (fig. 5 right).

In case of the Mandelbrot-set, a neuron, getting activity, would not necessarily 'know', where to project, because this will depend on the actual constant vector c, which differs from starting neuron to starting neuron. With additional layers, which project from respective points to different targets in the basic layer, a net would be able to perform this algorithm (fig. 6).

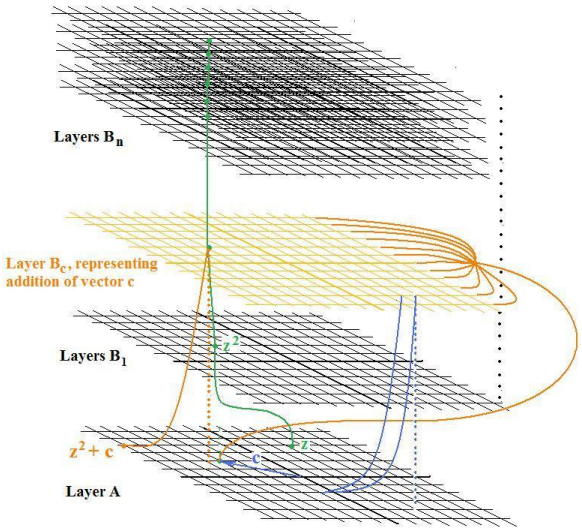

Fig. 6 Hypothetical circuitry, able to perform the Mandelbrot-algorithm

The starting point z1 has to activate the according layer B to determine, with which constant vector c the net should perform the projections. The structure with many parallel layers with two pathways innervating them resembles to the cerebellum with its mossy- and climbing-fibres. Such a net would have the option to compare and to process a much greater variety of patterns than a net based on the Julia-algorithm with fixed wiring only.

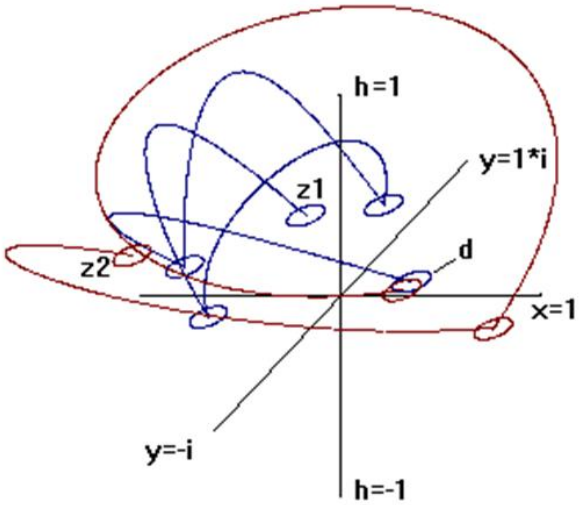

Fig. 7 Connections between distant neurons

Thus even very distant neurons may be connected directly or by only few interneurons. By the affine projections of the fractal algorithm, the neurons will, projecting their activities to the subsequent neurons, be organized in chains of neurons (fig.7). In three-dimensional nets the trajectories, examples shown in figures 2, 8, 23 and 24, the logarithmic spirals are replaced by their 3-D analogues, the squaring of quaternions, with fourth parameter set zero, or by loxodromes or variations of these functions.

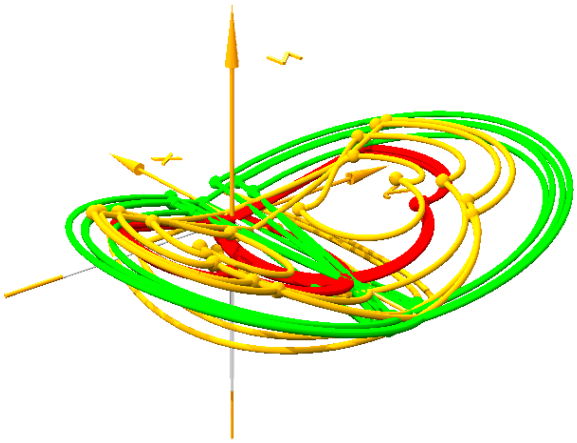

Fig. 8 Examples of three-dimensional trajectories

We can see some characteristics of biological connections within brains: strictly topographic projections, systematic crossing of the midline (decussatio), spiral 'biomorph' courses, circuits from the center to the periphery and backwards (figs. 8 and 24). We may identify neurons, belonging to circuits with various numbers of neurons within them, reflecting different frequencies, after which a circuit will begin to repeat its course. Thus we get the central structures (figs. 1, 2 and 23) resembling to a thalamus, contending distinct nuclei with different afferent and efferent projections to the periphery ('cortex').

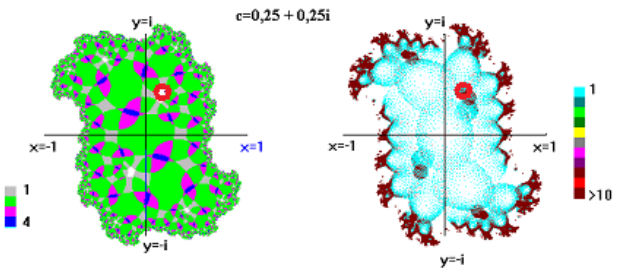

Fig. 9 Fractal neural net(Julia algorithm c=0.25 + 0.25*i), connections of the whole net to a circumscribed region(red circle) by applying the squaring(left)- and in reversed direction the square-root-function(right).

The rich connectivity will, by interneurons, allow the whole net or wider parts of it, to 'innervate' circumscribed regions and, by recurrent connections, in reversed direction, the activation of

these wide parts of the net by this circumscribed region (figs. 9 and 16).

3.2 Morphology and morphogenesis

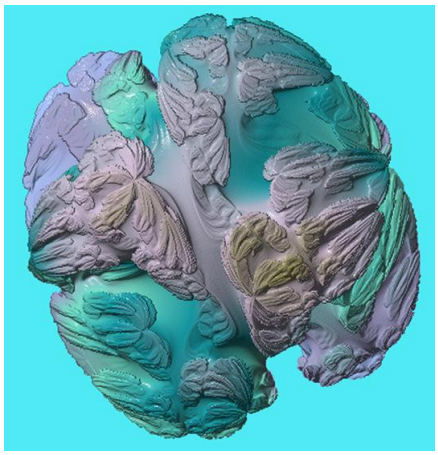

Fig.10 Three-dimensional fractal neural net

As a result we get three-dimensional fractal structures, which can be interpreted as neural nets (fig. 10). These are usually calculated by 'squaring' three-dimensional numbers (or related analogue functions) and adding a constant vector c, continuing the iterations, until a sphere around zero will be left or until a chosen number of iterations will be exceeded. But we may get these structures by reversing this procedure. We start with a sphere or bubble of points ('cells') and triplicate each 'cell' by projecting its two 'children-cells' to its positive and negative 'square root' combined with the subtraction of a constant vector. Imagining recurrent connections between each 'parent-cell' and each 'children-cell', we get 3-D neural nets with the same rich connectivity as in 2-D-nets (Fig. 11).

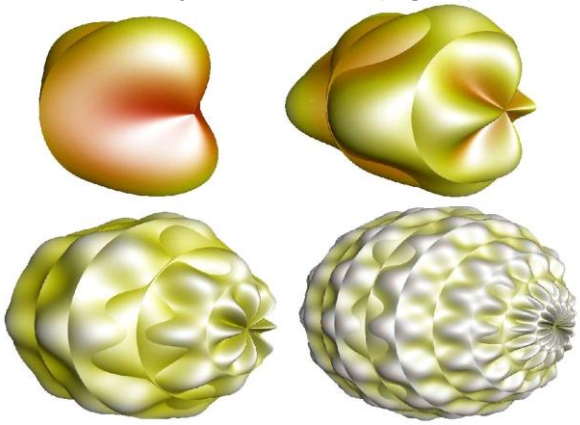

Fig. 11 Morphogenesis (iteration 2 to 5)

If we start with a solid sphere, the result will be a solid structure, if we start with a bubble, we will get a fractal structure (with wide variability depending on the location and size of the starting 'bubble', the basic trajectorial system and the constant vector as well) with 'lobes', 'gyri', 'sulci' as if starting with a solid sphere, but now with an additional 'ventricular system' (fig. 12).

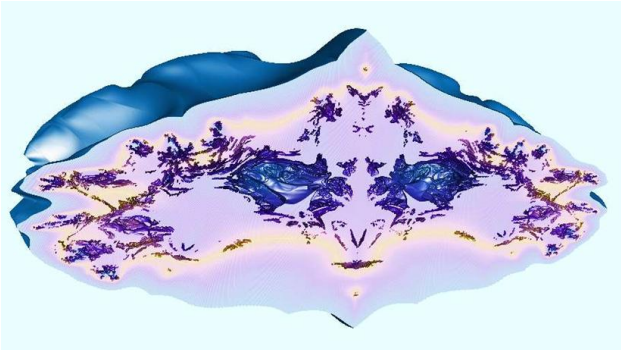

Fig. 12 Three-dimensional net with 'ventricular system'

As in two-dimensional fractals, distant cells will be connected by few interneurons, thus being able to synchronize their activity and to act as a neural ensemble (fig. 13).

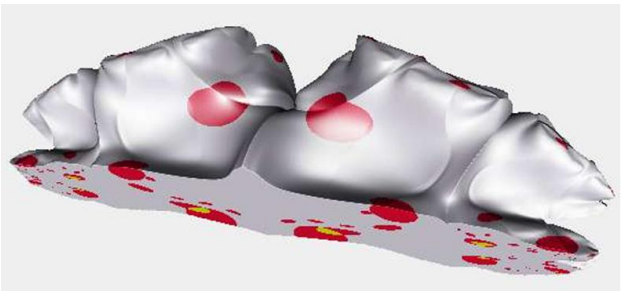

Fig. 13 Connected neurons, neural ensemble

3.3 Memory-strings and Tomography

Assuming each neuron will project its activity to its subsequent neurons, specific sequences of activity will arise in each neural chain, depending on the starting-pattern. Though very hypothetically, neurons might be able to record and store this sequence (using modulations of intracellular calcium-levels, reflecting the changes of the membrane-potential, which will transport information about the sequences of activity along the endoplasmatic reticulum to the nucleus of the neuron, to form respective molecules by calcium-dependent Kinases and related enzymes), by forming short molecular chains, for instance oligonucleotides (or according oligopeptides), each base-triplet encoding a distinct degree of activity. Very early, engrams [11] were thought to be the

base of long-term-memory, whose consolidation can be blocked by inhibitors of protein-synthesis.
In this model, these memory-strings might be used any time later to reactivate the neural ensemble with their specific sequence in recurrent direction, reconstructing the pattern completely or partially. In case of neural ensembles in form of binary (fig. 14) (or in three-dimensional fractal nets occasionally quaternary) trees, the reconstruction will reflect the way, by which structures are reconstructed in tomographic pictures. In those, straight rays are summing up specific information (degrees of absorption) of each voxel they pass. To reconstruct the pattern, the averaged degree of absorption is attached to each voxel, formerly passed by the ray. Overlapping of many rays enables us to reconstruct the original pattern sufficiently. In fractals, there are no straight rays, but neural ensembles in their most simple form as chains of neurons or, more complex and realistic, as binary (or, in three-dimensional nets even quaternary) trees.

The root of each tree might get the information about the average activity of all neurons. Reactivating the neural tree by reversing the procedure, using the stored information, the fractal neural net will be able to reconstruct the original pattern by overlapping the information of many neural trees. Because the information might not only

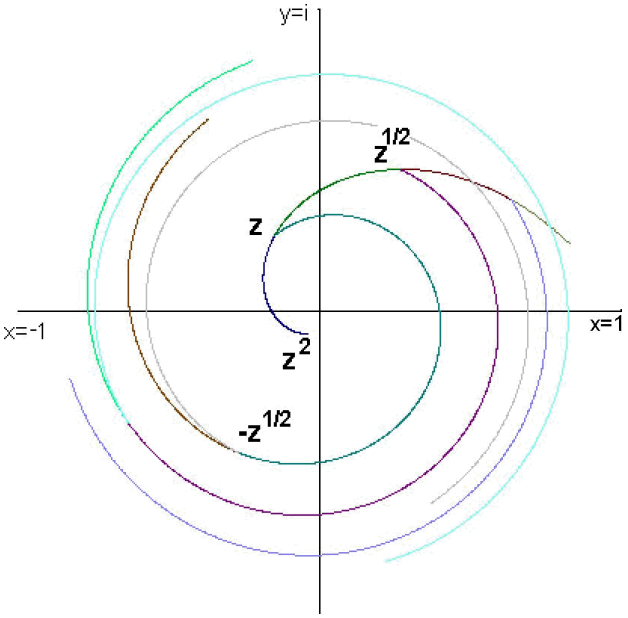

Fig. 14 Binary tree of neurons connected with z

be averaged to all neurons of the tree, but might be attributed to the different levels of the tree correctly, this procedure is theoretically able to work more exactly than a usual tomographic procedure.

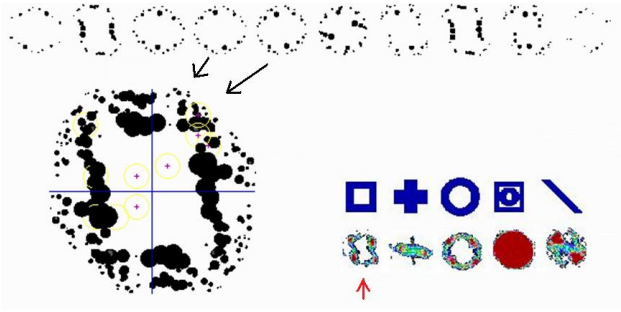

Fig. 15 Reconstruction of a pattern by overlapping 10 neural subsets (black arrows; the roots of the neural ensembles or –trees being indicated by yellow circles and purple crosses), right below: reconstruction of a pattern using 100 subsets (red arrow).

In fig. 15 we see the reconstruction of a square by overlapping 10 subsets, each having only very limited similarity to the original square. According tomographic procedures, the overlapping of more and more neural trees (ensembles or subsets) will enable the net to reconstruct the original pattern sufficiently (Fig 15 right) [6].

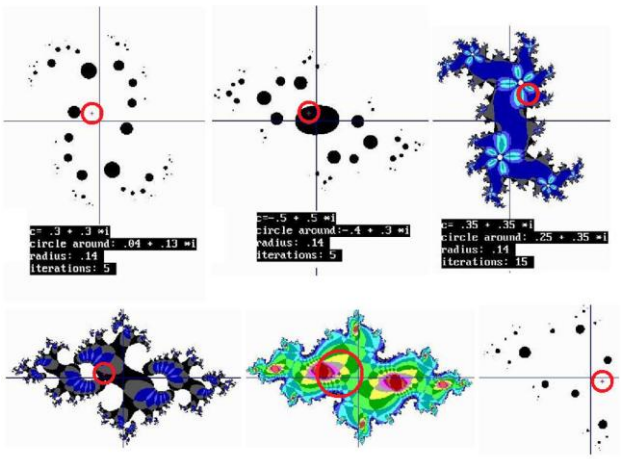

Fig. 16 Wide variety of subsets

Depending on location and size of the dendritic trees (fig. 16, red circles) of the neurons and the constant vector c of the Julia-set, the subsets, leading to maximal activation of the neurons, show a tremendous variability. There are neurons, reflecting the activity of nearly the whole net, giving general information about the presented pattern, as well as neurons, indicating activity in very small regions, connected with small details of the scene.

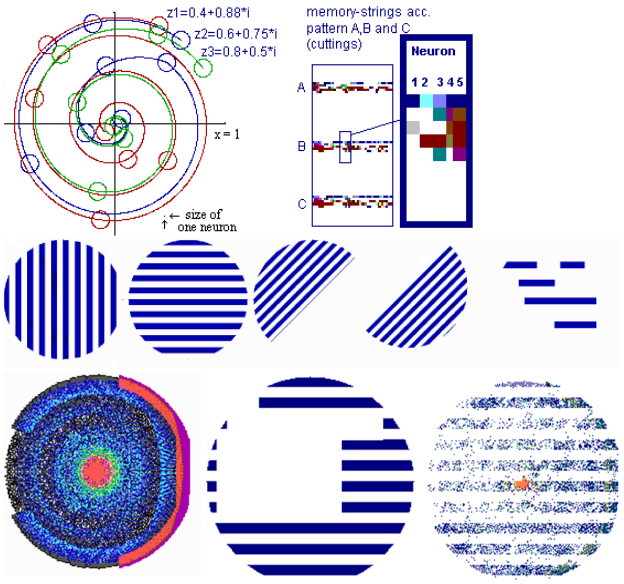

Fig. 17 Learning and reconstructing of patterns using memory-strings

Fig. 17 shows a neural net, using the squaring of complex numbers (constant vector = 0 + 0*i) for learning, for the reconstruction of the pattern only the positive square roots. Neural chains are shown in the upper left corner, some memory strings in the upper right corner. In the midline five different patterns, which are learned by the cells at the end of the neural chains (located in the pink/violet region of the net (fig. 17, left lower corner). Here we see a 'macula densa' being automatically formed by such nets, because zero represents an attractor in case of the constant vector c being zero.

The memory-strings may be regarded as vectors, therefore the whole nets act as vector-machines. They learn, compare and select vectors, represented in the simulations by strings of numbers, in the biological hypothesis by chains of molecules (oligonucleotides or –peptides), which encode and represent sequences of activity, respectively, patterns.

3.31 Scanning patterns

When the iterations are performed, as a result, a special sequence of activity will arrive in each neural ensemble at the root of the neural trees, specific for each starting-pattern. A high activity at a certain region of the net will thus indicate, that the neural tree does reflect the original pattern at least in parts very well. The starting pattern will be partially represented by the neural ensemble, connected with this specific root. Depending on the underlying algorithm (spiral trajectorial system and constant vector c as well), an unlimited number of different patterns might thus be 'recognized' by different nets without prior learning. During evolution, each species may have developed suitable nets, enabling them to deal with occuring situations in an optimal way. Different species may use different fractal nets, determined by certain spiral growing pathways and different constant vectors, formed by fields of gradients of growing factors, which depend on specific locations of cells, secreting these factors.

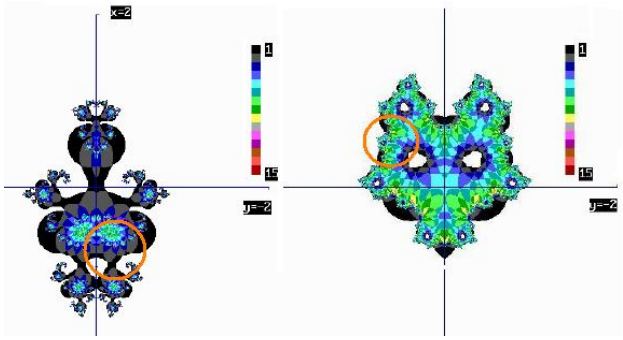

Fig. 18 Scanning patterns

Combing two fractals to get symmetric nets, these nets are able to 'recognize' very complex symmetric patterns by a high degree of activity in certain regions of the net. Within few iteration cycles, each starting pattern will be analyzed to which degree those unlimited numbers of possible complex patterns are represented within the starting pattern. Thus, this process may be regarded as a kind of Fourier- analysis of each starting-pattern. The nets will be able to analyze these patterns without any prior learning, their ability is 'inherited', ready for action as they are generated. Neurons with a dendritic tree, covering the regions of the two nets in Fig. 18 (left generated by vector c = - 0.8 + 0.32 * i, right c = 0.3255 + 0.55 *i), which are indicated by orange circles, will be maximally activated, if the complex patterns will be the starting patterns. Neighboured neurons will be activated by similar patterns, with small differences in shape and size, the differences increasing with growing distance of the neurons.

3.4 Performance

Some preliminary studies have shown, that these nets are able to perform tasks of pattern-processing quite efficiently [12],[13]. The concept of memory-strings as engrams does not only suit to fractal nets, but to nets with randomized connectivity as well (fig. 19 and fig. 20). Assuming, memory-strings, used at a certain moment, shall be blocked at the next moment, a flow of patterns will emerge, associative alternative answers of the net to a

presented pattern, with sometimes surprising effects in pattern processing:

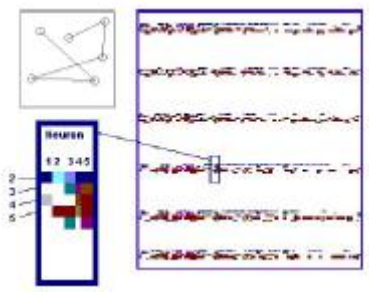

Fig. 19 Example of a net with random connectivity, formed by 10000 neuronal chains (one shown upper left) with 6 neurons each. Right: memory-strings, encoding learned patterns

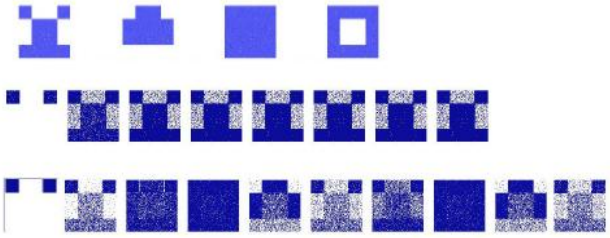

Fig. 20 Four patterns (row above) are learned. Reconstruction of a (shown at the left) presented pattern, middle row: without - , row below: with inhibition of the memory-strings, actually used to reconstruct a pattern, for the next three working-cycles, causing a vivid sequence of sensible patterns and subpatterns.

At first, the memory-strings with the best fitting sequence will be chosen to reconstruct the pattern. The most similar pattern will be reconstructed (fig. 20 middle row). If these strings are blocked for a certain number of working-cycles, the net will 'play' with patterns and subpatterns, which are not learned directly, but are included within the learned patterns (fig. 20 row below).
Thus, a way to process informations, additionally to changing synapses, will become possible: an intracellular processing by ordering the memory-strings by similarity, or e.g. producing average memory-strings out of a sample of memory-strings, all connected with related patterns. After learning patterns/pictures of different cars, the net could for each cell build a memory-string as an average of all 'car-related' memory-strings, now representing 'the idea' of a car. The concept proves in case of 'biomorph' neural nets with more than 3 million (though very simplified) neurons (fig. 21).

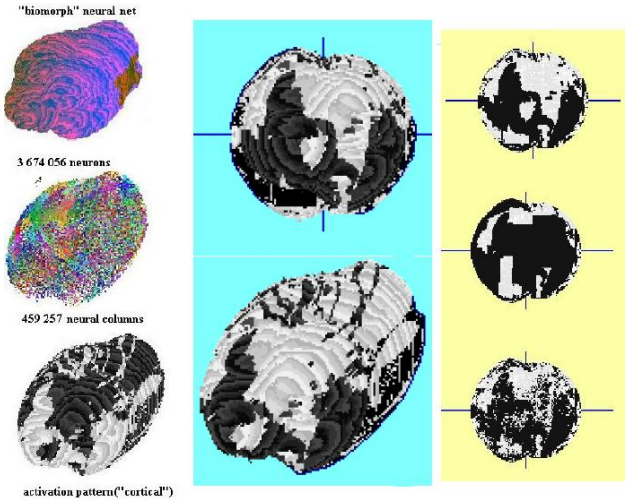

Fig. 21 Large fractal neural net with maximally simplified neurons, patterns learned (middle column), are reconstructed, when presented partially (right column)

Even moving, animated patterns might be learned and reproduced by nets working on base of memory-strings [14]. In figure 22, the blown up medial-right columns show the reproduction of a sequence of moving patterns, presented only partially for three working-cycles.

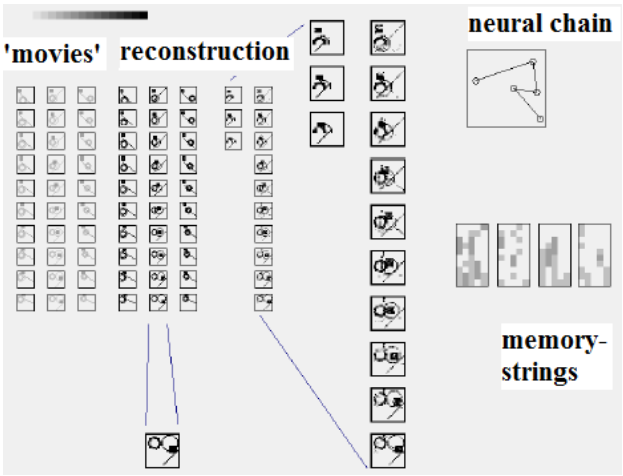

Fig 22 Learning and reconstruction of animated sequences of patterns by a net with random connectivity, processing of patterns using memory-strings

3.5 Inheritance of behaviour

The fractal algorithm determines the connectivity of the neural net, the 'central nervous system' of the simulated worm. A starting pattern, represented by the pattern of activity within the 'sensory-neurons' will be distributed over the whole net, causing a sequence of activity, arriving at the 'motoneurons' during the cycles of activation (figs 23 and 24).

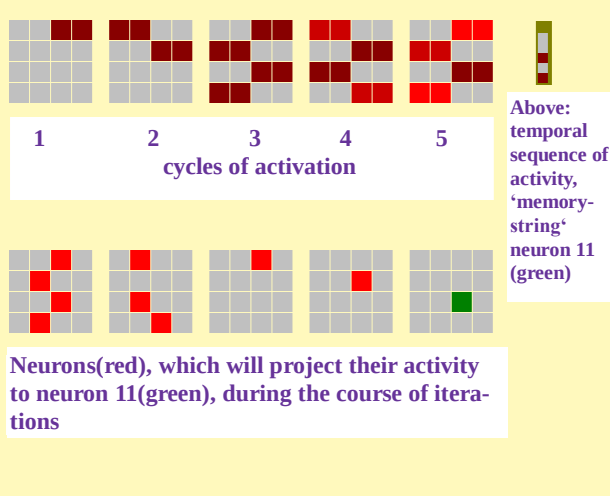

Fig. 23 The neural net of the simulated organism, distribution of a starting pattern (above), connected neurons (below), 'memory-string' (above-right)

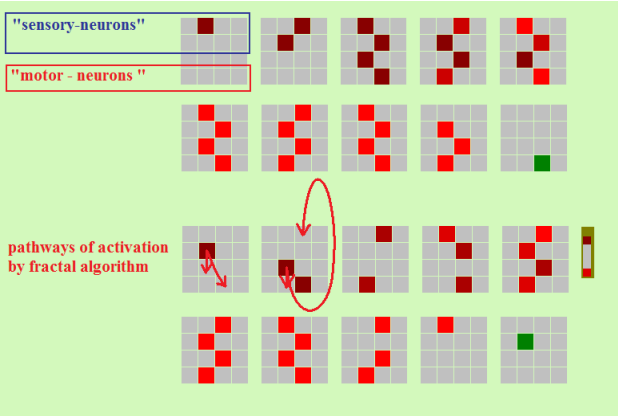

Fig. 24 The fractal connectivity of the neurons

The activation of two neurons by each neuron in the course of iterations resembles to the connectivity of the pyramidal cells of the CA3-layer of the hippocampus, which project by their axons as well with the fornix to the limbic system and as well by Schaffer collaterals to pyramidal cells of the CA1-layer of the hippocampus.

As shown in figs 25 and 26, the 'worm' will move in the world, its movements, except in case of a random movement (20 percent of the moves to avoid endless loops), completely determined by the process of selecting best fitting memory-strings according to the sequence of activity, arriving at each motoneuron and the hierarchy of motoneurons

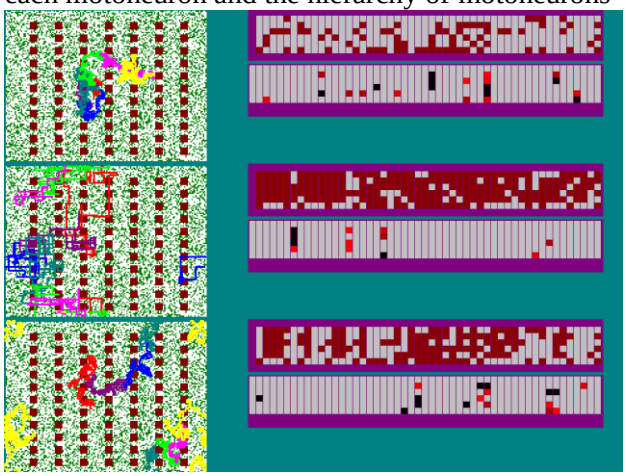

Fig. 25 Left: course of the simulated 'worm' through the cellular world (3000 moves). Food: green, enemies: dark red squares. Right: three sets of 'genes', above and in the middle determined by random procedures, below, 'genes' of the 'child', mixed from the sets of memory-strings of its parents. Below each set of memory strings: the memory-strings used by the motoneurons are shown.

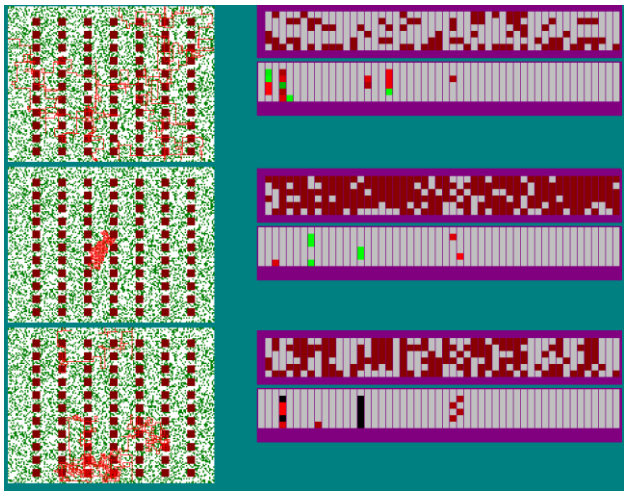

Fig. 26 Another example suggesting a 'mixture' of behaviour (more nested or long-ranging), when inheriting to equal parts the memory-strings, 'genes' of the 'parents' (above and middle) to the 'child' (below).

(if several motoneurons will be active at the same moment, the first choice will be to move forward, next choices to move the left, to the right or backwards). Thus, different sets of memory-strings will result in different behaviour in identical

situations (respective identical patterns of activity of the sensory-neurons). Learning will be performed either by marking memory-strings, which will have caused a sensible or dangerous move. Such markers (encoded at an additional position of the memory-string) will influence the process of selecting the memory-string, improving its chances to be selected, if it is marked as having caused useful former moves and, on the contrary, diminuishing its chances in case of negative effects in former moves.

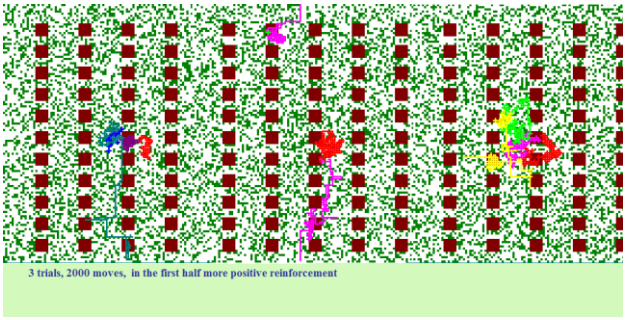

Fig. 27 Changing parameters of reinforcement during the course of movements might result in a change of behaviour (in the first half of moves more positive reinforcements).

Changing the parameters of reinforcement (more positive reinforcement after a useful move in the first half of moves) resulted in a change of behaviour (fig. 27). This figure may suggest the effect of such a change of 'psychological' parameters, but further studies are needed to confirm the result, excluding possible artefacts or random-effects more strictly.

Some courses may suggest an 'inheritance' of certain aspects of behaviour (e.g. movements in a more nested ore a more long-ranging manner) from parents to a child, when mixing the memory-strings of the parents to form the child´s 'genes' (fig. 26).

These results are very preliminary and limited in their expressiveness. Nevertheless they might offer a hypothetical model, how organisms could inherit behaviour, using molecular chains (RNA or DNA-molecules or oligopeptides in the biological hypothesis respectively vectors, chains or sets of numbers, in computer-simulations) as base of information processing. In the course of generations, evolutionary effects may optimize such behaviours in regard to the demands of the environment by selecting useful sets of memory-strings.

5 Conclusion

Two- and three-dimensional fractal neural nets offer numerous interesting features concerning richness of connectivity of the neurons even over long distances, the emerging of neural ensembles enabling tomographic ways of pattern - processing as well as morphologic similarities to biological structures. During growth (or generating in simulation), the connectivity arises inborn, without any prior learning. Thus the nets are, without learning, able to 'recognize' (different patterns will cause maximal activity in certain distinct neurons) a great variety of complex patterns by the neuronal ensembles, which will be formed by the fractal connectivity itself. Storage and processing of patterns by intracellular memory-strings in all or in specialized neurons enable the nets to perform extraordinary ways of learning, comparing, extracting and reconstructing patterns. Their ability to, at least theoretically, reconstruct the patterns in each neural ensemble (if these are pure chains, not trees) perfectly, not only associatively, offers advantages compared to nets, based upon changing of synapses. In those, the structure of the net will be changed by the learning procedure, which will not be the case for nets, working on memory-strings. Their connectivity will remain unchanged by all procedures of pattern processing. Several preliminary studies have shown the applicability of these principles. Only very hypothetically these concepts play a major role in biology. The obvious similarity of these structures in terms of their connectivity and morphology (strictly topographic projections, decussationes, occurence of nuclei like a thalamus (fig. 28), of lobi, gyri, sulci and ventricular systems, the similarity between the trajectorial system of the segments of logarithmic spirals with the course of the fibres of the optic nerve within the eye), but also their dynamics (activation of one neuron by many other neurons of distant regions with con- and divergence (fig. 29), the emergence of neural ensembles, enabling these nets to perform a tomographic way to process patterns) let this idea appear to be not completely fantastic. Memory-strings could, though completely hypothetically, explain, how complex behavioural patterns could be inherited from one generation to the next without need for learning. This concept is confirmed by the results of the very preliminary simulations, presented here. Means to generate and process such engrams, to compare and select them accordingly, are at least principally available in biological cells with regard to the genetic apparatus and Calcium-dependent Kinases and others.

Nevertheless they are strictly hypothetical, but they may work as alternative models, performing well in simulations, to widen our horizon and our concepts of the function of biological nervous systems. Further studies seem to be worth to explore the properties of these neural nets, which act as fractal neural vector-machines.

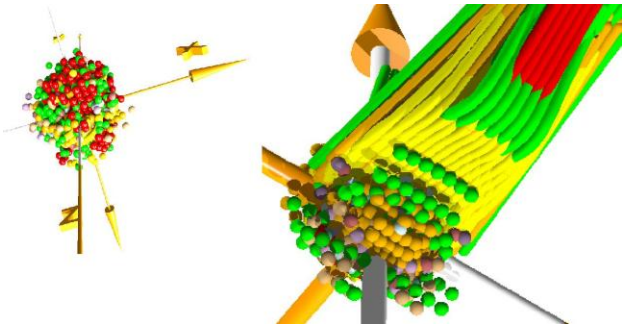

Fig. 28 Central nuclei in a three-dimensional analogue of a Mandelbrot-set with a subset of 'efferent' topographic projections forming tracts of fibres

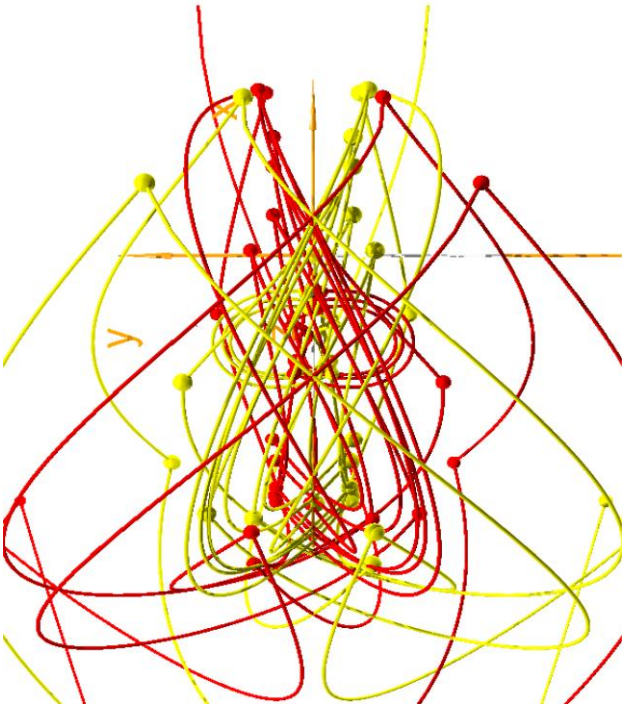

Fig. 29 Dynamics of fractal pathways

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