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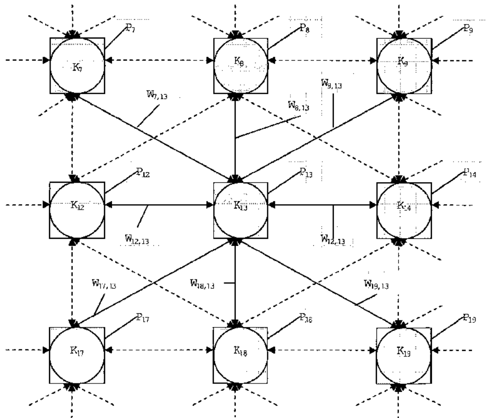
(54) **Title:** NEURAL NETWORK FOR PROCESSING ARRAYS OF DATA WITH EXISTENT TOPOLOGY, SUCH AS IMAGES, AND APPLICATION OF THE NETWORK



(57) **Abstract:** A neural network for processing arrays of data with pertinent topology comprises a n-dimensional array of cells (Ki) corresponding to the knots of the neural network! each cell having connections to the directly adjacent cells (Kj) forming the neighbourhood of a cell (Ki) ; Each cell (Ki) having inputs for each connection to directly adjacent cells; an output for the connection to one or more of the directly adjacent cells (Kj); the connection between the cells being determined by weights (wij); each cell being characterised by an internal value and being able to carry out signal processing for generating a cell output signal (ui) ; the output signal (ui) of a cell (Ki) being a function of its interna value and of the input signals form the neighbouring cells; each cell being associated univoquely to a record of a n-dimensional database (Pi) with pertinent topology and the value of each data record being the starting value of the corresponding cell;. Processing is carried out by considering the internal value or the output value (ui) of each cell (Ki) after a certain number of iterative processing steps of the neural network as the new obtained value (Ui) for the said univocally associated data records (Pi).

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AL NETWORK FOR PROCESSING ARRAYS OF DATA WITH EXISTENT TOPOLOGY, SUCH AS IMA AND APPLICATION OF THE NETWORK

A neural network for processing arrays of data with pertinent topology, an algorithm for recognising relationships between data of a database and a method for image pattern recognition based on the said neural network and on the said algorithm.

The present invention relates to a neural network for processing arrays of data with pertinent topology comprising a n-dimensional array of cells (Ki) corresponding to the knots of the neural network, each cell having connections to the directly adjacent cells (Kj) forming the neighbourhood of the a cell (Ki);

a) Each cell (Ki) having an input for each connection to a directly adjacent cell of the surrounding cells (Kj);

b) each cell (Ki) having an output for the connection to one or more of the directly adjacent cells (Kj);

c) the connection between each cell (Ki) and the directly adjacent cells being determined by weights (wij);

d) each cell being characterised by an internal value defined as the activation value or function (Ai) of the cell (Ki);

e) each cell (Ki) being able to carry out signal processing according to a signal processing function so called transfer function for generating a cell output signal (ui);

f) the transfer function determining the output signal (ui) of a cell (Ki) as a function of the activation value or function (Ai) of the cell (Ki), which transfer function comprising also the identity function which puts the activation value or function (Ai) of the cell (Ki) equal to the output signal (ui) of a cell (Ki);

g) a n-dimensional database of input data records (Pi) being provided which has to be submitted to computation by means of the neural network and in which n-dimensional database the relative position of the data records (Pi) when projected in a corresponding n-dimensional space is a relevant feature of the data records (Pi), the data records (Pi) of the database being able to be represented by an array of points in the said n-dimensional space, each point having an univocally defined position in the said array of points and being univocally related to a data record (Pi) of the said database, each data record (Pi) of the said database comprising further at least one variable or more variables each one having a certain value (Ui);

h) each data record (Pi) being univocally associated to a cell (Ki) of the n-dimensional array of cells forming the neural network which cells (Ki) has the same position in the n-dimensional array of cells (Ki) as the corresponding data record (Pi) represented by a point in the said n-dimensional array of points;

i) the value (Ui) of the variables of each data record (Pi) being considered as the initialisation value of the network being taken as the initial activation value (Ai) or the initial output value (ui) of the univocally associated cell (Ki);

j) the activation value (Ai) or the output value (ui) of each cell (Ki) after a certain number of iterative processing steps of the neural network being considered as the new obtained value (Ui) for the said univocally associated data records (Pi).

The present invention apply to the field of artificial intelligence and hence to machines having a computational unit which is able to carry out simple processes as for example learning processes from empiric experience, deductive processes, cognitive processes by means of which collected or inputted data is analysed for discovering or investigating certain relationships between the data records which at a first superficial glance may not appear evident or recognition processes by means of which voices, patterns, figures, letters or the like are recognised for further processing.

All the above mentioned processes are useful in order to put the machine in a condition to be able to take decisions on certain reactions or for simple classification aims of the data collected or inputted for example for further use.

Actually, given a database in which data are in the form of records each one being identified by related values of a certain defined number of variables, the relationships between the data records can be investigated by means of the so called "non supervised algorithms".

Known non supervised algorithm are for example the so called SOM, i.e. Self Organising Map, which as an output furnishes a grid having a certain numbers of units each one individuated by a cell and in each grid being collected a certain number of the data records belonging to a certain prototype of data record. The SOM is a known algorithm which is described in more details in KOHONEN, 1995: T. Kohonen, Self Organising Maps, Springer Verlag, Berlin, Heidelberg 1995 or Massimo Buscema & Semeion Group "Reti neurali artificiali e sistemi sociali complessi", Year 199, Edizioni Franco Angeli s.r.l. Milano, Italy, chapter 12.

This clustering can give information about the similarity of the records one with the other and so allow to carry out data classifications or to recognize relationships which can be used by a machine for deciding how to carry put a task or if a task has to be carried out or which kind of task has to be carried out.

This algorithm however are not very effective in helping for recognising relationships of certain type between data records particularly data records where the relative position of the data records in an array of data record or in a distribution of data records in a N-dimensional space, particularly a two or three dimensional space is a relevant feature of the data record. Furthermore the data records are passive elements of the process.

Different kind of traditional artificial neural networks can be used. This artificial neural networks are characterised by knots. The knots are processing cells which are connected with each other in order to for a network. The artificial neural networks are modelled on the neuron neytworks of the brain. In this case, each knot of the network representing an artifical neuron. The knots are arranged in layers. Ina a simplest configuration an inut layer of knots being connected with an output layer of knots. The number of knots corresponding normally to the different datarecords or variables of a database. In the biological case a neuron comprises three essential parts : a neuron cell body, branching extensions called dendrides for receiving input and an axon that carries the neuron's output to the dendrides of other neurons. Generally speaking a neuron sends its output to other neurons via its axon. An axon carries information through a serie of action potentials, or waves of current, that depends on the neuron's potential. This process is ofte modelled as a propagation rule represented by a net value. A neuron collects signals at its synapses by summing all the excitatory and inhibitory influences acting on it. If the excitatory influences are dominat, then the neuron fires and sends this message to other neurons via the outgoing synapses. In this sense the neuron function can be modelled as a simple threshold function. In the artificial neural networks the same model is used each knot has inputs connected to the output of some or each other knot of a preceding layer of knots and an output connected to some or each other knots of a subsequente layer of knots. The excitation or inhibition level exercised by the outputs of other knots connected to the input of a knot is determined by a connection strength which is defined by weights. If the sum of the signals inputted to a knot excides a certain threshold value the knot will fire and the output will send out a signal. The internal state or value of a knot is defined as an activation function.

By processing data with this traditional kind of artificial neural networks, the data are fed to the knots of the input layer and the result of the process is furnished at the outputs of the knots of the output layer. For better and deeper understanding of the structure of artificial neural networks see "Reti Neurali Artificiali e sistemi sociali complessi" Volume I, by Massimo Buscema & Semeion Group, Semeion Centro Ricerche, Franco Angeli Milano 1999 (ISBN 88-464-1682-1). For determining the weights defining the connection strength artifical neural network are subjected to a training process in which the data of a data base are inputted for which data the processing output data are known. The network is fed with the input data and with the known aoutput data and the connection weights are computed such that the given input and output data are matched by the weights.

When considering processing of a database which has a pertinent topology, this that the data can be projected as points in a n-dimensional space, where the relative position of the points representing the data is a relevant feature of the data themselves , such as for example the two dimensional array of pixels forming an image, the above mentioned traditional algorithm do not consider the said topologic feature, for example the position of the pixel in the image in relation to the other pixels and furthermore the processing is not carried out in parallel for each pixel.

A solution of this problem has been attempted by using so called cellular automata or their improvement as cellular neural networks. Document US 5,140,670 and document "Cellular Neural Networks: Application " by Leon o. Chua and Ling Yang, I.E.E.E. Trans. On Circuits

& Systema vol. 35 (1988) Oct., No. 10, New York, NY, US discloses a combination of a so called cellular automata and neural networks which show the features of the artificial neural network disclosed at the beginning. This new kind of information-processing system is a large scale non linear analog circuit like neural networks, which circuits processes signal in real time. Like cellular automata it is made of a massive aggregate of regulalrly spaced circuits clones, called cells, which communicate with each other directly only through its nearest neighbors. Cells not directly connected together may affect each other indirectly because of the propagation effects of the continuous-time dynamics of cellular neural network. The cellular neural networks are able to carry out feed-back and feed-forward operations. The connection among cells are uniform and local. This means that a cellular neural network can be characterized by templates of its feed-abck and feed forward operators. These operators defines the dynamic behaviour of the cellular neural network. These operators are finite constants or square matrices of coefficients, so called cloning template which defines the dynamic rule of the cellular neural network. Thus in a cellular neural network different kind of operators can be used which are predefined and independent of the particular values of the data of the array of data to be processed. Each operatore being specificly defined in order to carry out a particular operation of the data for extracting or highlighting features from the data or relations among the data. Normally a library of such operator templates, so called genes, is provided from which one or more operator templates are chosen and used to carry out the data processing desired . So for example when considering a two dimensional image an operator or a gene can be provided for detecting and highlighting edges, a further operator or gene can be provided for sharpening and so one. The peratirs can be sequentially used for processing the data in order to obtain a combination of their effects on the output image.

From the above it is clear that although the known cellular automata take into consideration the fact that the data are topologically pertinent as better defined above, nevertheless the operators are made by constants and are completely independent from the values of the data to be processed. Comparing this behaviour to a neural network, this means that the weight defining the signal propagation to the input of a knot from the output of a knot of the directly surrounding layer of knots, are predefined and independent from the internal values of the knots which corresponds to tha activation values or to the output values of a knot in an artificial neural network. Thus the intrinsic information contained in the array of data due to their topologic relation ship and to their values is lost or completely not considered.

The invention aims to provide for an improved artificial neural network which combines the advantages of the structure of a cellular neural network or of a cellular automata with the advantages of a dynamic definition of the operators which also take into account the information which is intrinsically contained in the relation fo the values of the data in an array data.

As a special case the invention aims to provide a new artificial neural network having the structure of the cellular neural network and which allows parallel processing of image data without losing the information related to the relation between the values of the pixels forming the image.

The invention ahieves the above goals by means of an artifical neural network comprising a n-dimensional array of cells (K_i) corresponding to the knots of the neural network, each cell having connections to the directly adjacent cells (K_j) forming the neighbourhood of the a cell (K_i);

a) Each cell (K_i) having an input for each connection to a directly adjacent cell of the surrounding cells (K_j);

b) each cell (K_i) having an output for the connection to one or more of the directly adjacent cells (K_j);

c) the connection between each cell (K_i) and the directly adjacent cells being determined by weights (w_{ij});

d) each cell being characterised by an internal value defined as the activation value or function (A_i) of the cell (K_i);

e) each cell (K_i) being able to carry out signal processing according to a signal processing function so called transfer function for generating a cell output signal (u_i);

f) the transfer function determining the output signal (u_i) of a cell (K_i) as a function of the activation value or function (A_i) of the cell (K_i), which transfer function comprising also the identity function which puts the activation value or function (A_i) of the cell (K_i) equal to the output signal (u_i) of a cell (K_i);

g) a n-dimensional database of input data records (P_i) being provided which has to be submitted to computation by means of the neural network and in which n-dimensional database the relative position of the data records (P_i) when projected in a corresponding n-dimensional space is a relevant feature of the data records (P_i), the data records (P_i) of the database being able to be represented by an array of points in the said n-dimensional space, each point having an univocally defined position in the said array of points and being univocally related to a data record (P_i) of the said database, each data record (P_i) of the said database comprising further at least one variable or more variables each one having a certain value (U_i);

h) each data record (P_i) being univocally associated to a cell (K_i) of the n-dimensional array of cells forming the neural network which cells (K_i) has the same position in the n-dimensional array of cells (K_i) as the corresponding data record (P_i) represented by a point in the said n-dimensional array of points;

i) the value (U_i) of the variables of each data record (P_i) being considered as the initialisation value of the network being taken as the initial activation value (A_i) or the initial output value (u_i) of the univocally associated cell (K_i);

j) the activation value (A_i) or the output value (u_i) of each cell (K_i) after a certain number of iterative processing steps of the neural network being considered as the new value (U_i) for the said univocally associated data records (P_i).

which artificial neural network further comprises the following features:

k) for each processing step of the said certain number of iterative processing steps, the weights (w_{ij}) defining the connection between each cell (K_i) and the directly adjacent cells (K_j) are determined as the function of the current values (U_j) of the variables of each data record (P_j) univocally associated to the cell (K_j) directly adjacent to the said cell (K_i), the said function being a so called learning function or rule;

l) the current activation value (A_i) or the output value (u_i) of each cell (K_i) after a processing steps of the neural network which is considered as the current new value (U_i) for the said univocally associated data records (P_i) being determined as a function of the current output values (u_j) of the directly adjacent cells (K_j) weighted by the corresponding weight (w_{ij}) defining the connection of the directly adjacent cells (K_j) with the cell (K_i).

As a variant the above mentioned aritifial neural network can be modified by determining the current activation value (A_i) or the output value (u_i) of each cell (K_i) after a processing steps of the neural network which is considered as the current new value (U_i) for the said univocally associated data records (P_i) as a function of the of the weights (w_{ij}) defining the connection of the directly adjacent cells (K_j) with the cell (K_i), the said function being a so called activation function or rule.

The current activation value (A_i) or the output value (u_i) of each cell (K_i) after a processing steps of the neural network which is considered as the current new value (U_i) for the said univocally associated data records (P_i) can be determined as a function of the current output values (u_j) of the directly adjacent cells (K_j) and of the corresponding weight (w_{ij}) defining the connection of the directly adjacent cells (K_j) with the cell (K_i), the said function being a so called activation function or rule.

Furthermore for each processing step of the said certain number of iterative processing steps, the weights (w_{ij}) defining the connection between each cell (K_i) and the directly adjacent cells (K_j) are determined as the function of the current values (U_j) of the variables of each data record (P_j) univocally associated to the cell (K_j) directly adjacent to the said cell (K_i) and of the current value (U_i) of the variables of the data record (P_i) univocally associated to the cell (K_i).

When the database is formed by the pixels of a two dimensional image, then the above neural network forms a machine for image processing according to the present invention.

Further improvements are disclosed in the following description and are subject of the dependent claims.

The above artificial neural network according to the present invention is based on the following theoretical founding:

As an example a phenomenon is defined as each space-time set which can be measured in terms of adsorbed or emitted electromagnetic frequencies. Visual phenomenon are thus a sub set of the universe of the phenomenon as defined above and which sub set varies depending on the frequencies which one desides to observe. A visual phenomenon is a phenomenon having a pertinent topology. Any phenomenon can be analyzed by means of elements which are a priori determined by a model or the phenomenon can be forced to show the relations existing between minimum elements. Any element of a phenomenon is an explicit or implicit synthesis of minimum elements. Thus an element of a model can be considered as an index reducing the original information being present in the minimum elements. This reduction can be critical since it is possible that the elements of the model ignore some properties which is present in the minimum elements and in their local interactions. Analysing visual phenomenons, or other phenomena having a pertinent topology, the reduction carried out by the elements of the model is serious. Indeed some index as for example mean values, variance and every other index basing on a mean value will non maintain the topological properties of the minimum elements being synthetized. For example the mean value of two rectangular triangles will not generate a rectangular triangle except in very rare cases.

Further every phenomenon which we can observe as a subject of scientific knowledge is a phenomenon having a pertinent topology. Due to the only fact that a shape can exist,in a theoretically isotropic space every shape shows with its topology its specific pertinence. Any kind of scientific model has the aim to let appear for every phenomenon ist inherent model by means of the interaction of minimum elements of the phenomenon. Having found the minimum elements of a phenomenon the scientific model should furnish to the said elements equations by means of which the said elements interact one with the other. When by means of the said equation the minimum elements of a phenomenon are able to reconstruct the phenomenon itself in its morphological and dynamical complexity, then the equations can be said to be a good meta-model of the model which the minimum elements has caused. Without a recnstruction proof there is no validation of the scientific activity.

Every phenomenon in order to be subject of scientific knowledge must be able to be quantitatively characterized. This means that its minimum elements and their relations must be able to be represented by numerical values. From the point of view of physics this numerical values describes "forces" and/or the "results" of the forces exercised. The interactions between these numerical values within specific equations can allow the reconstructive proof of the measure with which the meta-model (i.e. the equations) generate a model which is similar to the phenomenon which has to be understood. Thus the aim of the scientific knowledge is to define the mathematical functions being implicit in a phenomenon. When the said mathematical function is relatively complex, i.e. highly non linear, it is probable that our perception of the phenomenon oblige us to define the said phenomenon as being provided with qualitative features which cannot be reduce only to quantitative effects. This anyway only a perceptive effect due to the complexity which characterizes the function being implict in the phenomenon. It is thus possible to state that the quantitative component of every phenomenon is the perceptive effect of its highly quantitative non linearity. Considering that all the phenomenon which are present in nture evolve with highly non linear dynamics it is obvious that the perception of qualitative effects is so common to let one think that the quality is inherent in the phenomenon itself. In reality the difference between quantity and quality does not exist. Quality is the way with which the quantity expresses its virtuosity.

In any phenomenon having pertinent topology, the identity and the unity of the phenomenon is guarated by its space-time cohesion. This means that every minimum elemnt of the phenomenon is contiguous and connected directly or indirectly through specific forces to the other minimum elements. The quantitative value of each minimum element of the phenomenon which is analysed is thus the result of the action of the said forces. It can be demonstrated that in a phenomenon with pertinent topology the forces connecting each minimum elemnt with any other minimum element of the local neighbourhood are sufficient to explain the space-time cohesion of the entire phenomenon.

C onsiderin a phenomenon P comprising minimum elements p_1, p_2, … p_M in a space having D spatial dimensions, where D=2 for simplicity. Assuming now that the local neighbourhood , N, of each minimum element is formed by a first layer of directly surrounding minimum elements a so called a gradient 1 surrounding in which 1 is referred to the a step. In a boidimensional space the local neighbourhood is then formed by N=8 minimum elements. The phenomenon P can thus be represented by a matrix having M elements with M= R(rows)X C(columns).

$$\begin{matrix} p_{1,1} & p_{1,2} & p_{1,3} & \ldots\ldots p_{1,C} \\ p_{2,1} & p_{2,2} & p_{2,3} & \ldots\ldots p_{2,C} \\ \ldots. & \ldots. & \ldots. & \ldots. \\ p_{R,1} & p_{R,2} & p_{R,3} & \ldots\ldots p_{R,C} \end{matrix}$$

In this matrix each minimum element $P_{x,y}$ will, have a quantitative value for example a quantity of light which a reflector is able to reflect and which we can express as u_{xy} where $u \in \{0,1\}$. The element $p_{x,y}$ will have also connections with its local neighbourhood N.

Defining now $W_{x,y,x+k,y+z}$ (with k and z integer and such that $k \in \{-1,1\}$ and $z \in \{-1,1\}$) as the forces of its connections with the minimum elements of its local neighbourhood N. It this possible to write now

$$(3.1) \qquad u_{x,y}{}^{[n+1]} = f\left(u_{x,y}^{[n]}, u_{x+k,y+z}{}^{[n]}, W_{x,y,x+k,y+z}{}^{[n]}\right), \text{where } |k|+|z|>0;$$

from which the following equation can be derived:

$$(3.2) \qquad u_{x,y}{}^{[n]} = f^{[n]}\left(u_{x,y}^{[0]}, u_{x-k,y+z}{}^{[0]}, W_{x,y,x+k,y+z}{}^{[0]}\right)$$

In other words: the quantitative value of each minimum element $p_{x,y}$ is a function of the quantitative value of the 8 minimum elements surrounding the said element and of the forces which connects the said minimu element to the surrounding elements.

In a more analytical language:

$$\begin{aligned} u^{[n+1]}{}_{x,y} = f[&u_{x,y}^{[n]}, g_1(u^{[n]}{}_{x+1,y}, W^{[n]}{}_{x,y,x+1,y}), g_2(u^{[n]}{}_{x,y+1}, W^{[n]}{}_{x,y,x,y+1}), \\ &g_3(u^{[n]}{}_{x+1,y+1}, W^{[n]}{}_{x,y,x+1,y+1}), g_4(u^{[n]}{}_{x-1,y}, W^{[n]}{}_{x,y,x-1,y}), \\ &g_5(u^{[n]}{}_{x,y-1}, W^{[n]}{}_{x,y,x,y-1}), g_6(u^{[n]}{}_{x-1,y-1}, W^{[n]}{}_{x,y,x-1,y-1}), \\ &g_7(u^{[n]}{}_{x-1,y+1}, W^{[n]}{}_{x,y,x-1,y+1}), g_8(u^{[n]}{}_{x+1,y-1}, W^{[n]}{}_{x,y,x+1,y-1})] \end{aligned}$$

If we begin with x=1 and y=1 recursively substituting at each n-th step $u^{[n]}{}_{x+k,y+z}$ the same function $f(\cdot)$ which we have calculated above for u_{xy} than one can see that one easily reaches an index x_C and y_R, which demonstrates that the quantitative value of each element $p_{x,y}$ depends from all the other elements.

From the above it results that by defining the strength of the connections between each minimum element of a phenomenon P and the minimum elements of its local neighbourhood, one defines also the global connections strength of the etire phenomenon P.

Obviuosly this statement is valid only if assuming that the phenomeno P has a dynamic behaviour. From this it must be argued that each phenomenon having a pertinent topology is always a temporal process or the partial result of the temporal process.
By combining the ideas of local connectivity and time dynamics which characterize the phenomemnon having pertinent topology on has to argue that bthese phenomenon has at the same time a paralle and a sequential behaviour. This kind of asynchronous parallelism can be formalized.

Considering a phenomenon P with pertinent topology ina apportion of a plane having two dimensions (D=2) and which elements are squares of minimu sides L and which elements divide perfectly the plane in single tiles. In this conditions one can evaluate the function by which the two minimum elements of P being at the higher diatnce one from the other exercise a repricola influence one on the other. Assuming that each minimu elemnt of P is directly connected to ist local neighbourhood of gradient 1 (g=1), the signal diffusion of each minimum elemnt will take place t each time istant t according to the following equations:

$t=1 \qquad g=1$

$$\begin{cases} I(t)=\left(2g_{(t)}+1\right)^{p}-1 \end{cases} \tag{3.3}$$

$$g(t+1) = t+1$$

where I(t) is the number of the minimum elements pf P which are influenced at the T-th temporal cycle by the signal of the refrence minimum element. These eauations represent the diffusion functions of the signal of a minimum element of a phenomenon P of any dimension D whatever.

It is further possible to define the time delay Δt with which the two most distant minimum elements of P influence each other.

For a bidimensional situation with D=2 and knowing P_{x_1,y_1} e P_{x_2,y_2} the two minimum elements defined above, the time delay is expressed by

$$\Delta t = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} + 1 \qquad (3.4)$$

Furthermore a phenomenon having a pertinent topology is formed by minimum elements and by local connections among the said minimum elements. Each minimum elemnt is deifned by the position which it occuopies in the phenomenon and by a quantitative value which indicates at each instant for example a charatersitic effect of the phenomeno such as for example the quantity of light being emitted or reflected by a reflector.

The above can be expressed as

Minimum element= $u_{x,y,z,\ldots D}^{[t]}$

Where u is the quantitative value and x, y, z, ….D is the position and t is the time instant.

Each local connection defines the strength of the mutual influence of each minimum elemnt on each other minimum element which is directly adjacent to the said minimum element at each time instant. Each local connection is thus defined by the position of the minimum elements connecte by it and by a quantitative value at each time instant and this can be expressed as:

Local connection = $W^{[t]}_{(x,y,...D_s),(k,z,...D_d)}$

Where W is the quantitative value

X, y, D_s is the position of the source minimum element

T is the time instant and k,z D_d is the target minimum element.

Considering the above an active matrix of the connections can be defined by the system of the following equations:

$$u^{[t+1]}_{x,y,...,D_1} = f\left(u^{[t]}_{x,y,...,D_s}, u^{[t]}_{k,z,...,D_d}, W^{[t]}_{(x,y,...,D_s),(k,z,...,D_d)}\right) \quad (4a)$$

$$W^{[t+1]}_{(x,y,...,D_s),(k,z,...,D_d)} = g\left(u^{[t]}_{x,y,...,D_d}, u^{[t]}_{k,z,...,D_d}, W^{[t]}_{(x,y,...,D_s),(k,z,...,D_d)}\right) \quad (4b)$$

Equation ($a) and (4b) describes the evolution of the minimum elements and of the connections of a phenomenon with a pertinent topology towards an attracting element which represents the group of its solutions. Both equations can be presnt in two degenerated ways which request a particular attention:

As a first way

$$u^{[t+1]}_{(x,y,...,D_s)} = f\left(u^{[t=0]}_{x,y,...,D_s}, u^{[t=0]}_{k,z,...,D_d}, h(W^{[t]}_{(x,y,...,D_d),(k,z,...,D_d)})\right) \quad (4c)$$

In this case the minimum elements of the phenomenon evolve only as a function of the connections, by starting from their original or starting quantitative value which has the only effect of an impulse of the process. One particular feature of this evolution consit in the fact that the process regulating the evolution of the connections takes place in the space of the connections (equation (4b). It is in this space that the solution are found for the evolution of the minimum elements.

So in this case the starting values of the minimum elements act as simple constraint to the evolution of the connections. These last ones dynamically furnishes the values of the elements and thus the actracting element of such a process will be the new definition of any minimum elemnt as an exclusively relational element which is generated by the dynamic negotiation between its starting value and the starting value of the adjacent minimum elements.

The second degenerated case is described by the following equation:

$$u^{[t+1]}_{(x,y,\ldots,D_s),(k,z,\ldots D_d)} = f(W^{[0]}_{(x,y,\ldots D_s),(k,z,\ldots D_d)}, u^{[t]}_{(x,y,\ldots,D_s)}, u^{[t]}_{(k,z,\ldots,D_d)}) \qquad (4d)$$

In this case only the values of the minimum elements will evolve while their connections remain unchanged and the said connections will act as constraints of the evolutive process.

The above analysis of phenomena having pertinent topology basing on the example of electromagnetic or visual phenomenon demonstrates clealrly once again thye limits of the known neural networks and particularly fo the cellular neural networks. This network s deisclosed in the state of the art does not completley fit with the structure of phenomena having pertinent topology since the relation between interactions and quantitative values of the minimum elements is not considered, but the interactions are described by predefined models, i.e. the operator templates, which structure is not influenced by the values of the minimum elements of the phenomenon. On the contrary the artificial neural network according to the present invention is stepping closer to the structure of phenomena by considering the mutual relation of the quantitative value of the minimum elements formed by the data records of the database and the interactions between this minimum elements.

In the following description there are shown and described in more details different sets of rules for describing the way with which the interactions between cells or knots of the present neural network and the quantitative value of the single cells or knots, i.e. their internal value or activation value or output value are related onte to the other in order to guide the computational process of the network.

The invention realtes also to an algorithm for recognising relationships between data of a database which algorithm can be more effective, rapid and more precise in highlighting the relationships between the data of a database.

The algorithm according to the invention is an algorithm for recognizing relationships between data of a database having pertinent topology, this meaning that the data are of the kind where the relative position of the data records in an array of data records or in a distribution of data records in a N-dimensional space, particularly a two or three dimensional space is a relevant feature of the data record and where the data records can be represented as an array of cells or points, each point being univocally related to a data record of the database and having a univocally defined position in the array relatively to the cells or points of the other data records, to each data record being further associated at least one variable or more variables each one having a certain value, the algorithm being characterised by the fact that

- each cell or point in the array of cells of points representing a data records of a database is considered to be a unit or a knot of an Artificial Neural Network;
- each unit or knot formed by a cell or point of the database being successively defined as a target unit or knot and connections being defined between each target unit or knot at least to each one of the rest of the units or knots formed by the rest of cells or points of the database which are at least of gradient 1 relatively to the corresponding target unit or knot;
- a new output value of each unit or knot of the database successively defined as target unit or knot being calculated by means of the set of learning rules or functions defining the strength of the connection between the units or knots or the set of activation rules or functions of the artificial neural network defining the quantitative value of each unit or knot i.e. its activation value or its output value, or by means of the combination of both the set of learning rules or functions and the set of activation rules or functions of the artificial neural network as a function of the actual output of the units or knots connected to the target unit or knot and of the actual output of the said target unit or knot;
- The actual outputs of each unit or knot being defined as the value of the variable or as the values of the variables associated to each data record represented by a cell or a point considered as a unit or knot of the artificial neural network;

- And the new output of the target unit or knot is considered as the new value of the variable or of the variables of the data record associated to the cell or point of the array of data records corresponding to the target unit or knot;

- By carrying out the said steps for computing a new output of a target unit or knot for at least part or for each cell or point of the array of data records a new array of data records is computed where the data record of each cell or point has a new value of the at least one variable or new values for the variables as a result of a first computation cycle of the artificial neural network according to the above steps;

- The said computation cycle being repeated for each successive new array of data records until a certain prefixed number of repetitions of the computation cycle has been carried out and/or unless a certain maximum allowable error or discrepancy has been reached between the original values of the variable or of the variables of the original array of data records with respect to the values of the variable or variables of the array of data records according to the one computed in the last cycle and/or unless the difference between the value of the variable or the values of the variables of data records in the sequence of array of data records computed in the sequence of cycles is lower than a predetermined maximum rate.

Many different sets of known learning functions or rules may be used or many different sets of known activation functions or rules may be used which may also be combined each one of the said sets or combination thereof can enhance or bring to evidence certain kind of relations in a better way with respect to other kinds of relations between the data records.

According to a further improvement, the array of data records may be submitted at least twice or more times to elaboration according to the algorithm of the present invention, in a first phase being provided a first set of learning functions or rules or a first set of activation functions or rules or a combination thereof and in a second phase being provided a second set of learning functions or rules or a second set of activation functions or rules or a combination thereof and so on when more then two phases are provided while the array of data-records being used in the second or further phases of elaboration with the algorithm of the present invention with the second or further different sets of learning or activation rules or functions or with a combination thereof is the array of data records resulting respectively from the first or from the previous phase of elaboration of the array of data records.

Although there is no need that the units or knots corresponding to the cells or points related to the data records at least of gradient 1 with respect of the unit or knot actually formed by the cell or point related to the target data record be the ones spatially directly surrounding the cell or point related to the said actual target data record in a special case particularly of a two or three dimensional array of data records the cells or points related to the data records of gradient 1 with respect to the cell or point of the target data record are formed by the data records associated to the cells or points of the data record array which directly surrounds the cell or point in the array of data record related to the said target data record.

According to a further feature in the case the new array of data records computed by the algorithm is based only on a set of learning functions or rules, the new output of each target data record is defined as a function of new weights characterising the connection of each target unit or knot associated to the target data record with the units or knots represented by the cells or points of data records of gradient one relatively to the cell or point of the target data record, the set of learning rules or functions defining new weights of the connections as a function of the previous weights computed or defined in a previous computation cycle and as a function of the actual outputs of the unit or knot associated to the cell or point of target data record and of the unit or knot associated to the cells or points of the data records of gradient 1 or of the data records of the cells or points directly surrounding the cells or point of the actual target data record.

A similar result may be reached by using sets of activation functions where these functions defines the new output of the target unit or knot corresponding to the cell or point related to the target data record basing on the net input to the said target unit or knot which is a function of the outputs of the units or knots corresponding to the cells or points associated to the data records of gradient 1 with respect to the target data record, particularly to the units or knots corresponding to the cells or points of the array of data records directly surrounding the cell or point of the target data record.

The learning phase starts with a fixed predetermined value of the weights for each connection while the starting value of the unit or knot is modified according to a predetermined function which is also function of the weights and of the value of the surrounding knots or units and therefore to the data records which corresponds to cells or points in the array directly surrounding the cell or point representing a certain unit or knot of the artificial neural network.

A new data array is thus constructed in which each data record has maintained the position with respect to the other data records in the representation of the data records as cells or points in an array while each data record has changed its value as a function of its original value and of the original values of the data records relative to the surrounding points in the array.

A new cycle can thus be executed in which again each point representing a data record is set as a unit or knot of an artificial neural network, a weight is defined for each connection between units and a new value in the form of an output of each unit or knot is calculated according to the certain function.

Several different kinds and structures of known artificial neural network using different known and/or new learning functions for the definition of the weights and different functions for the calculation of the new values of each data record associated to each unit or knot may be used.

It is important to notice that since the weights of the connections between the knots of the artificial neural network are fixed at least at each cycle and eventually equal for each connection, the algorithm according to the present invention has practically no internal noise and the noise is given only by the noise of the data of the database.

Different examples of sets of learning rules or functions and of known sets of activation rules or functions and of combinations thereof are disclosed in the following detailed description of some examples.

As it will appear more clearly in the following detailed examples different learning rules for determining the weights of the connections of the artificial neural network or different functions for calculating the outputs of the units or knots of the artificial neural network which corresponds to the new values of the data records can be useful for enhancing certain kind of features of the data records.

The algorithm according to the present invention can find a simple and effective use in evaluating digital o digitalized images in order to recognize or put in evidence certain features of the said images, as for example tissue differentiation, image pattern recognition and contrast enhancement.

Particularly the algorithm according to the present invention can be used for image pattern recognition and for evidencing the different kinds of structures of the material forming a body, particularly of the tissues forming a biologic body in combination with radiological, echographic or magnetic resonance imaging or the like.

As it will appear more clearly from the detailed examples the algorithm according to the present invention can be useful evidencing different kinds of tissues and/or for substituting contrast medium in the diagnostic imaging.

In particular the different kind of revealed or enhanced information depends by the different set of learning and or activation rules applied to the neural network structure formed by the pixel array of the original image. Principally the effect obtained is similar to the one which can be obtained by using enhancing media such as contrast media in the echographic, radiographic, nuclear magnetic resonance imaging or in similar imaging methods.

The kind of information enhanced can furthermore be differentiated by the choice of a certain set of learning and/o activation rules. In general it is possible to recognize two families of this sets of rules. The two families are summarized in the table of figure 3 in which the different sets of rules are given a name which will be explained later on in the detailed description.

A first family of rules provides for weight evolution and unit activation and allow to carry out an extraction of features from a source digital or digitalized image such as for example kind of tissue in an image of biological bodies or structures of tissues or objects like for example recognizing the presence of stenosis in angiographic images.

A second family comprises rules which principally carry out a weight optimisation. After weight optimisation a further step of unit activation can be carried out. This kind of rules helps in finding out edges between different zones of an image for recognizing boundaries, for example boundaries between different kind of tissues in images of biological bodies.

The above example is not the only possible field of appliance of the algorithm according to the invention. Another example may consist in evaluating the relations and dependence between genes relatively to their common activation.

The invention relates also to a method for image pattern recognition in digital or digitalized images.

Particularly the invention relates to a method for the recognition and differentiation of different tissues in digital or digitalized images of biologic bodies, as for example in diagnostic images as for example digitalized radiographies or echographic images or magnetic resonance images.

It is important to notice that although the present description of the examples is referred particularly to a two dimensional array of data records the algorithm and the method according to the invention are not limited to such a space but can be applied also on three and N dimensional arrays of data records.

The algorithm according to the invention and the method using the said algorithm will appear more clearly form the following description of some examples by means of the annexed drawings in which:

Fig. 1 is a schematic view of a two dimensional array of cells each one representing a data record in a two dimensional array of data, for example each cell representing schematically a point (a pixel) of a digital or digitalized image.

Fig. 2 represents the step of transforming the nine central points or cells of figure 1 in units or knots of an artificial neural network.

Fig. 3 illustrates a diagram of the different families of learning and activation rules for the neural network particularly referring to a neural network structure formed by the pixel of a digital image.

Fig. 4A, 4B, 4C, and 4D illustrate respectively a mammography, the enlarged mammography, the digitalized mammography which has been subjected to the method for image pattern recognition according to the present invention and according to a particular learning law called CM and the digitalized mammography which has been subjected to the method for image pattern recognition according to the present invention and according to further particular learning law called IAC.

Figures 5A, 5B, 5C, 5D are respectively the figure 4A and a further enlargement of the figures 4B, 4C, 4D.

Figures 6A, 6B, 6C, 6D, 6E, 6F, 6G are respectively a photograph of bacteria and four digitalized images of fig. 6A subjected to known pattern recognition methods while fig. 6G illustrates the digitalized image of figure 6A subjected to the method according to the present invention using automata rules for the artificial neural network called IAC particularly enhancing contrast.

Figures 7A, 7B, 7C are a digital photo of the ventricle, the said digitalized photo subjected to a known pattern recognition method and the digitalized photo subjected to a method according to the invention called CM.

Figures 8A, 8B, 8C, 8D and 8E show a set of echographic images of the same body part where metastases are present and where figures 8A to 8D are respectively an image without contrast media, with contrast media in the arterials phase, an image with contrast media in balance, an image with contrast media with in a late phase, the image of the same body part, without contrast media and treated with the method according to the present invention.

Figures 9A, 9B, 9C, 9D are respectively a radiographic image of the lung, the digitalized image of figure 8A subjected to a known algorithm called best filter, the image of fig. 8A subjected to a treatment according to the present invention and with an rule called CM, and the image of fig. 8A subjected to a treatment according to the present invention and with an automotive rule called IAC.

Figures 10A, 10B, 10C illustrates respectively a mammography, the mammography of fig. 10A treated with a known pattern recognition method and the mammography of figure 10A treated according to the method of the present invention with an automotive rule called High CS .

Figures 11A, 11B, 11C, 11D and 11E illustrate respectively a normal photograph, the photographs according to fig. 11A treated by two different known patter recognition methods and the photograph of fig 11A treated with the method according to the present invention with two different automotive rules called IAC and IAC combined with CM.

Figures 12A to 12J illustrates respectively a radiographic source image of the anatomical district of the femoral arteria and the image elaborated according to the present invention by using different kind of rules and different combination thereof.

Figure 13 is a schematic block diagram of a typical generalised cell or knot of the neural network according to the present invention.

Referring now to figure 1, a two dimensional array of data records is schematized by an array of square cells which are identified by P_i, where i are elements of Natural Numbers. The central nine square cells P_7, P_8, P_9, P_{12}, P_{13}, P_{14}, and P_{17}, P_{18}, P_{19}, are drawn with continuous lines while the surrounding further cells are drawn with discontinuous lines for representing the fact that the array can be larger then the one represented.

Each cell of the array is a cell for a data record which has its univoquely related cell and so a univoquely related position in the array, the relative position of each cell of data record to the other cells of data record being a relevant feature of the corresponding data record. Each data record of each cell has a value U_i, where i is element of the natural numbers and where the said value can be a parametric value of only a variable of the data record or a vector comprising each data record a set of different variables. The above scheme is a representation of what is called in the specific technical language a database having a pertinent topology. This means that not only the values of the data records are relevant feature of each data record but also their relative position in a projection of the datarecord of the data base in a n-dimensional space or in an arrangement of the datarecords of the database in a n-dimensional matrix form which is just a different formalism for indicating such a projection.

For example a digital or digitalized image is a two dimensional array of pixel. Each pixel represents a data record in an array of data record and the relative position of the pixel is a relevant feature of each pixel belonging to the relevant information of the image data. The value of the pixel is a simple intensity value in a grey scale image, while in a coloured image the value is a vector comprising at least two parameters or variables namely the colour and the intensity, normally three parameter or variables in the actually used techniques of visualizing coloured images as the so called HVS or the so called RGB coding of coloured images.

Figure 2 try to schematically picture the step used by the algorithm according to the present invention which provides for treating the data records of the two dimensional array by transforming the two dimensional array of cells in an array of cells or knots of an artificial neural network. The squares represents the relation to the original cells P_i of figure 1, while the enclosed circle K_i represents the transformation or association of each cell P_i to a unit or knot K_i of an array of cells or knots of an artificial neural network.

The connection arrows w_{ij} represents the connections between the units or knots K_i and K_j of the artificial neural network. Figure 2 is related only to the nine central cells of figure 1 and the connection arrows are continuous for the central cell P_{13}, which is the cell corresponding to the actual target data record, while the discontinuous arrows are related to connection to peripheral cells which are obviously used by the present algorithm and the mechanism of which derives identically from the description of the way of working of the present algorithm as described with reference to the sole central cell P_{13}. Also the fact that the arrows are provided at both the ends of the connections represents the fact that by describing the way of working with reference of a peripheral cell to the centre cell P_{13}, this actual centre cell P_{13} will become a peripheral cell of another cell which will be the centre cell.

So by applying the algorithm according to the present invention to the array of cells the said algorithm sweeps the array cell by cell each time identifying a cell as the momentary central cell and the corresponding peripheral cells and the associated connections between the central cell and the peripheral cells and when the computation has been carried out for a certain cell momentary defined as a central cell, an adiacent cell is defined as the new central cell and new peripheral cells of this new central cells are identified with the corresponding connections, the computation being carried out this time for this new central cell and the new peripheral cells with the corresponding connections and so on. This mechanism is repeated until each cell of the array has been subjected to computation by the algorithm, thus ending a first computation cycle of the artificial neural network. The following cycles are identical with the difference that they are applied to the array of cells which has been previously treated by the algorithm.

Figure 13 illsutrates a schematic diagram of a cell or knot of the artificial neural network according to the present invention. Each knot or cell K_i comprises inputs at which the output signals u_j from other knots K_j are received by the knot or cell K_i. Furthermore each knot or cell K_i has an output u_i which is connected to the input of one or more other knots or cells K_j. The output u_i of each cell or knot is a function of an internal value A_i or state of the knot K_i also called activation value which can be also an identity function namely $A_i=u_i$.

In the present artificial neural network each knot or cell K_i has also an input for an initialisation value defining the initialisation internal value or actication value A_i of the knot or cell or the initialisation output value u_i. In this case, referring to the example of figures 1, 2 and 13, the initialisation value for the internal value or activation value A_i or the first output value u_i of the knot K_i is set equal to the value U_i of the data record P_i univocally associated as explained above to the knot K_i. Each knot or cell K_i has further an output for the computed value U_i^n for the datarecord P_i after the n-th processing cycle of a sequence of a certain number m of processing cycles. The said computed new value U_i^n corresponds either to the internal value or activation value A_i^n of the knot or cell K_i after the n-th processing cycle has been carried out or to the output value u_i^n of the knot or cell K_i after the said n-th processing cycle has been carried out.

As it appears from figure 2, the present artificial neural network comprises direct connections of a knot or cell K_i only with the knots or cells K_j directly adjacent to the said knot or cell K_i. The set of this knots or cells K_j are technically defined as the local neighbourhood of the knot or cell K_i or the knots or cells of gradient 1. The term gradient 1 refers to the stepwise difference between the position of the reference knot or cell K_i and the position of the set of knots or cells K_j forming the local neighbourhood of the said knot or cell K_i. This definition is intuitively understandable and is a widely spread technical definition. So it is clear that in a discretized array where only discrete positions are possible for the elements of the array, defining a reference element the gradient 1 neughbourhood is formed by the set of elements which position differs from the position of the reference element by a step 1 in any direction of the array. This is the simplest case. The term gradient 1 is more generic since it is not limited to the spatial coordinates, but can be referred to any kind of space in which the an n-dimensional database is projected.

The connections between the knots K_i and the knots of the local neighbourhood K_j are defined by their strength. The connection strength is quantitatively given by weights w_{ji} or w_{ij} which are multiplied with the output u_j of the knots or cells K_j of the local neighbourhood of the knot K_i, when the signals of these knots of the local neighbourhood are send to the reference knot K_i connected to them. As explained in the introduction of the description these weighted signals inputted to the reference knot K_i will have an effect on its internal state A_i in order to cause or inhibite the emission of an output signal u_i or to change the value of the said output signal u_i.

As already explained in the introduction such a neural network does not only consider as a basis for the processing the values of the knots or cells but also their relations and furthermore the interactions between the said values of the knots or cells and their relations.

Two extremes has been generally discussed in the introduction one of which considers the evolution of the internal value A_i or of the output value u_i of the knots or cells K_i only as a function of the connections w_{ji}, by starting from their original or starting quantitative value U_i which are the values of the datarecords P_i univocally associated to a corresponding knot K_i. This initial or starting value U_i has the only effect of an impulse of the process. One particular feature of this evolution consit in the fact that the process regulating the evolution of the connections w_{ji} takes place in the space of the connections (equation (4b). It is in this space that the solution are found for the evolution of the knots or cells. The starting values of the knots or cells K_i act as simple constraint to the evolution of the connections w_{ij}. These last ones dynamically furnishes the values of the knots or cells and thus the actracting element of such a process will be the new definition of any knot or cells K_i as an exclusively relational element which is generated by the dynamic negotiation between its starting value U_i and the starting value U_j of the adjacent knots or cells K_j of the local neighbourhood.

The weights w_{ji} which quantitatively defines the conncetions are the function of the internal values of the knots K_j of the local neighbourhood and/or of the reference knot K_i.

In a second extreme case as discussed form a general point of view in the introduction only the values of the knots or cells either as activation values A_i and A_j or in the form of output values u_i and u_j will evolve while their connections as represented by the weights w_{ji} remain unchanged and the said connections will act as constraints of the evolutive process.

Thus the way for determining the weights w_{ji} and the values u_i of the knots are given by set of equations called also rules.

Generally speaking, equations which defines the quantitative values of the weights are called learning rules, while equations which changes the internal state or the activation value or the output value of the knots as a function of the output values of the reference knot and of the adjacent knots of the knots of the locqal neighbourhood are called activation rules.

So as already explained computation may be carried out by only considering a set of learning rules or functions which computes new outputs of the actual centre cell P_i, by means of defining new weights w_{ij} of the connections as a function of the outputs of the centre cell and of the surrounding cells, this means of the values of the variable or of the variables of the data record corresponding to this cells. The new output of the centre cell will be then set as the new value or the new values of the variable or of the variables of the centre cell and will be a function of the outputs of the surrounding cells, this means of the values of the variable or of the variables of the data records corresponding to the said surrounding cells and of the new weights computed by the algorithm.

During computation in a first cycle the weights w_{ij} of the connections between the cells P_i and P_j used as knots K_i and K_j of the artificial neural network are set all equal to a certain value which can be randomly defined by a value for example 1 or 0.0001.

Basing on this weights the value of the actual central cell P_i, in the example of figure 2 the cell P_{13} working as a unit or knot K_{13} of an artificial neural network is changed as a function of the values of the surrounding cells P_j which are also set equal to knots K_j of the neural network (in figure 2 this are the cells and knots P_7, P_8, P_9, P_{12}, P_{14}, and P_{17}, P_{18}, P_{19} and K_7, K_8, K_9, K_{12}, K_{14}, and K_{17}, K_{18}, K_{19}) and of the weights of the connections w_{ij}.

Another way of computing the new outputs of the units or knot K_i is to use a set of activation functions or rules, which defines the output of the central knot K_{13} as a function of the values U_j (in fig. 2 U_7, U_8, U_9, U_{12}, U_{14}, and U_{17}, U_{18}, U_{19})of the data records of the cells P_j (in fig. 2 P_7, P_8, P_9, P_{12}, P_{14}, and P_{17}, P_{18}, P_{19}) surrounding the central cell P_i (in fig. 2 P_{13}) corresponding to the a unit or knot K_i (in fig. 2 K_{13}) to be activated and as a function of the weights w_{ij}. In this case new weights w_{ij} are not computed.

There is also the possibility to apply a combined computation using a certain set of learning rules computing new weights w_{ij} for the connection at each cycle and a certain set of activation rules computing new output values at each cycle.

Thus at the end of a cycle new outputs, this means new values of the variables for each data record of the array of data record has been computed and also new weight of the connections has be computed, both which new values of the variable or of the variables of the data records and of the weights of the connections are used in the following computation cycle.

Relating to the example of figure 2, the function defines the net input of the knot K_{13} by means of the outputs U_7, U_8, U_9, U_{12}, U_{14}, and U_{17}, U_{18}, U_{19} of the surrounding knots K_7, K_8, K_9, K_{12}, K_{14}, and K_{17}, K_{18}, K_{19} corresponding to the values of the associated cells P_7, P_8, P_9, P_{12}, P_{14}, and P_{17}, P_{18}, P_{19} surrounding the central cell P_{13} and the associated knot K_{13}. A further function is provided which basing on the differences between the previous values of the outputs and the new values calculated by the algorithm, defines new weights w_{ij} for the connections between the central knot K_i=K_{13} in fig. 2 and each one of the peripheral knots K_j equal to respectively K_7, K_8, K_9, K_{12}, K_{14}, and K_{17}, K_{18}, K_{19} in figure 2.

At the end of the first cycle when all the cells has been treated according to the above mentioned steps a new array of cells has been constructed in which each data record has maintained its cell and where each data record has a new value for the variable or for the variables computed as described before in the first cycle while also new weights for the connections has been computed.

Thus a second cycle can be carried out by using this new array of data records this time using the values of the data records computed in the first or previous cycle as outputs of the knots of the artificial neural network corresponding to the cells and where the new weights for the connection between the knots corresponding to the cells are used which has been computed in the first or previous cycle as described before. In the second or following cycle again new outputs of the knots and thus new values of the data records are computed thus forming again a new array of data records in which the data records has updated values. Similarly corresponding new weights for the connections between knots are computed to be used in a following cycle of the algorithm if this is provided or necessary.

The number (n) of following cycles can be determined as a fixed parameter. Alternatively the number of repetitions can be determined by an error or deviance calculation of the values of the new array of data records related to the original one by setting a maximum error or deviance. This calculation can be carried out by means of usual error or deviance calculation in the field of the artificial neural networks.

Another criterion might consist in the fact that the difference of the sequence of new values for the variables of the data records is monitored and the repetition of the algorithm is stopped when the differences of the said values in the sequence of cycles is not anymore significant, this mean that it is less than a predetermined value. This means also that the new values does not differ substantially from the previous one. The meaning of substantial difference has to be related to the value of the variables of the data records and to the kind of data records since in some cases very small differences might have great influence on the information of the data record while in other cases not.

In the following some examples of rules for updating the output of the knots of the artificial neural network and thus the values of the corresponding data records and for updating the weights of the connections are given. This rules which are functions are defined by a name which will help in simplifying the identification in the description of a particular rule.

In particular the different kind of revealed or enhanced information depends by the different set of learning and or activation rules applied to the neural network structure formed by the pixel array of the original image. Principally the effect obtained is similar to the one which can be obtained by using enhancing media such as contrast media in the echographic, radiographic, nuclear magnetic resonance imaging or in similar imaging methods.

The kind of information enhanced can furthermore be differentiated by the choice of a certain set of learning and/o activation rules. In general it is possible to recognize two families of this sets of rules. The two families are summarized in the table of figure 3 in which the different sets of rules are identified by a name explained later on.

A first family comprises rules which principally carry out a weight optimisation which can further be combined with a unit activation. This kind of rules helps in finding out edges between different zones of an image for recognizing boundaries, for example boundaries between different kind of tissues in images of biological bodies.

A general kind of set of rules is defined as Automata Rule (A or AR) and comprises functions for determining optimized weights, so called learning rules the following two set of rules can be used:

$$k = \frac{\sigma}{2^N}$$

$$R_{ij} = e^{-(k \cdot u_i - k \cdot u_j)^2} \qquad u \in [0, 2^N]$$

$$R'_{ij} = (R_{ij} - \frac{1-\varepsilon}{2}) \cdot C \qquad C = 5;\ \varepsilon = e^{-\frac{\sigma^2}{4}};$$

$$w_{ij} = \frac{e^{R'_{ij}} - e^{-R'_{ij}}}{e^{R'_{ij}} + e^{-R'_{ij}}}$$

where

α is a parameter which can freely defined by the user and which renders the algorithm more or less sensible to differences in the image.

R_{ij} is some sort of measure for the distance of the i-th unit from the j-th unit.

U_i are the values of the single cells P_i transformed in knots K_i of the artificial neural network and where The suffix i defines the central cell or knot and the suffix j defines the cells or knots directly surrounding the said central cell or knot.

According to the diagram of figure 3 this general rule may be further specialized or enhanced obtaining different set of rules.

The above disclosed automata rule defines the connection strength between each target or reference knot or cell K_i with each one of the knots or cells K_j of the local neighbourhood as the non linear projection of their different value u_i and u_j.Each reference knot or cell K_i is thus connected with eight symmetric weights w_{ji} to the knots or cells K_j of the local neighbourhood of gradient 1. Every bidimensional database such as a bidimensional image will so be formed by a matrix in which each element of the matrix is connected as an autonomous unit to the eight elements of its local neighbourhood, i.e. to the matrix elements directly adjacent to the reference one. Each bidimensional matrix array of data such as an image will be further formed by a specific number of symmetric connections between each element of the matrix and the elements of the local neighbourhood.

The quantitative strength value of the connections w_{ji}which are defined by the above mentioned equations forms the constraints by means of which the data arry such as an image, being in the form of an active matrix of the connection strength will cause the evolution in time of the initialisation value of each cell or knot till to the predetermined n-th processing cycle and towards the natural actractor.

A set of rule II is generally indicated as CS, i.e. Constraint Satisfaction which can be developed in different variants disclosed hereinafter:

II.1. so called CS $\overline{XOR}$

Center	*Neighbors*	*State*
1	1	1
1	0	0
0	1	0
0	0	1

$$Initialization: u_i = input_i$$

$$Net_i = (\sum_j u_j w_{ij}) \cdot \alpha$$

$$\Delta_i = Net_i \cdot (1-u_i) \cdot \alpha \quad Net_i > 0$$
$$\Delta_i = Net_i \cdot u_i \cdot \alpha \quad Net_i < 0$$
$$u_i^{[n+1]} = u_i^{[n]} + \Delta_i$$

where

U_i is the output of the central knot K_i

U_i is also defined as input of the i-th knot or cell in combination with the initialization step. This definition wants to stress out that at the first step of carrying out the neural network the i-th unit has as an output value the value of the corresponding pixel in the digitalized source image. Obviously in the starting step of the neural network this value has to be attributed to the i-th knot or cell ad is considered as an input. In the following computational cycles the value of each knot or cell is changed by the algorithm and when a certain number of repetition has been carried out the value of the i-th knot or cell corresponds or is correlated to the value of the i-th pixel in the output image.

U_j are the outputs of the surrounding knots K_j

Net_i is the net input of the central Knot K_i computed as a function of the outputs U_j of the surrounding knots K_j and the weights w_{ij} of the connections of the the surrounding knots K_j to the central Knot K_i.

n is the number of cycle

α_i is the update value of the output U_i of the central knot K_i for computing the new output value for the next cycle as a function of Net input Net_i and the actual output U_i of the central knot K_i

α is a constant.

II.2 so called CS AND

Center	*Neighbors*	*State*
1	1	1
1	0	0
0	1	0
0	0	0

$$Initialization: u_i = input_i$$

$$Net_i = (\sum_j u_j w_{ij}) \cdot \alpha$$

$$\Delta_i = Net_i \cdot (1 - u_i) \cdot \alpha \cdot (\sigma^2 - \frac{1}{2}) \quad Net_i > 0$$

$$\Delta_i = Net_i \cdot u_i \cdot \alpha \cdot (\sigma^2 - \frac{1}{2}) \quad Net_i < 0$$

$$u_i^{[n+1]} = u_i^{[n]} + \Delta_i$$

$$\bar{u} = \frac{\sum_{k \neq i}^{N} u_k}{N}; \quad \sigma^2 = \frac{\sum_{k \neq i}^{N} (\bar{u} - u_k)^2}{N}$$

in this case same definitions apply as in the previous case. The difference between this activation function and the previous lie in the fact that the function for computing α_i comprises a further term defined as α^2 and this term is defined above as a function of the mean of the outputs of all knots except the central knot K_i activated.

<u>II.3 so called CS CONTEST</u>

Center	*Neighbors*	*State*
1	1	1
1	0	0
0	1	1
0	0	0

$$Initialization: u_i = input_i$$

$$Net_i = (\sum_j u_j w_{ij}) \cdot \alpha$$

$$\Delta_i = Net_i \cdot (1-u_i) \cdot \alpha \cdot (\sigma^2 - \frac{1}{2}) \quad Net_i > 0$$

$$\Delta_i = Net_i \cdot u_i \cdot \alpha \cdot (\frac{1}{2} - \sigma^2) \quad Net_i < 0$$

$$u_i^{[n+1]} = u_i^{[n]} + \Delta_i$$

$$\bar{u} = \frac{\sum_{k \neq i}^{N} u_k}{N}; \quad \sigma^2 = \frac{\sum_{k \neq i}^{N} (\bar{u} - u_k)^2}{N}$$

Also here apply the same definitions as in the previous examples of activation functions (1) and (2).

The difference lie in the fact that the term α_i is computed in a different way for the case $Net_i<0$.

<u>II.4 so called HIGH CS $\overline{XOR}$</u>

$$Initialization: u_i = input_i$$

$$Net_i = (\sum_j u_j w_{ij} \cdot \sigma^2(w_{jk})) \cdot \alpha \quad k \in [1,N]; k \neq j$$

$$\Delta_i = Net_i \cdot (1-u_i) \cdot \alpha \quad Net_i > 0$$

$$\Delta_i = Net_i \cdot u_i \cdot \alpha \quad Net_i < 0$$

$$u_i^{[n+1]} = u_i^{[n]} + \Delta_i$$

$$\overline{w_j} = \frac{\sum_{k \neq j}^{N} w_{j,k}}{N}; \quad \sigma^2(w_{ik}) = \frac{\sum_{k \neq j}^{N} (\overline{w_j} - w_{jk})^2}{N}$$

again the symbols are defined as in the previous examples of activation functions

In this case the function for computing the net input Net_i to the knot K_i is different as in the previous cases. The function α^2 is used in the computation of the net input. In this case the function α^2 is applied to the weigths w_{ij} of the connections as it appear clearly from the above equations.

The functions for computing the update α_i value of the output U_i of the central knot K_i are identical to the case of the first example of activation function·

II.5 so called HIGH CS AND

$$Initialization: u_i = input_i$$

$$Net_i = (\sum_j u_j w_{ij} \cdot \sigma^2(w_{jk})) \cdot \alpha \quad k \in [1,N]; k \neq j$$

$$\Delta_i = Net_i \cdot (1-u_i) \cdot \alpha \cdot (\sigma^2 - \frac{1}{2}) \quad Net_i > 0$$

$$\Delta_i = Net_i \cdot u_i \cdot \alpha \cdot (\sigma^2 - \frac{1}{2}) \qquad Net_i < 0$$

$$u_i^{[n+1]} = u_i^{[n]} + \Delta_i$$

$$\overline{w_j} = \frac{\sum_{k \neq j}^{N} w_{j,k}}{N}; \ \sigma^2(w_{ik}) = \frac{\sum_{k \neq j}^{N} (\overline{w_j} - w_{jk})^2}{N}$$

$$\bar{u} = \frac{\sum_{k \neq i}^{N} u_k}{N}; \ \sigma^2 = \frac{\sum_{k \neq i}^{N} (\bar{u} - u_k)^2}{N}$$

As it will appear clearly from the comparison of this set of equations with the example of activation function (4) called High CS XOR and activation functions (2) called CS AND, this is a combination of the two set of activation functions.

II.6 so called HIGH CS CONTEST

$$Initialization: u_i = input_i$$

$$Net_i = (\sum_j u_j w_{ij} \cdot \sigma^2(w_{jk})) \cdot \alpha \quad k \in [1,N]; k \neq j$$

$$\Delta_i = Net_i \cdot (1-u_i) \cdot \alpha \cdot (\sigma^2 - \frac{1}{2}) \quad Net_i > 0$$

$$\Delta_i = Net_i \cdot u_i \cdot \alpha \cdot (\frac{1}{2} - \sigma^2) \quad Net_i < 0$$

$$u_i^{[n+1]} = u_i^{[n]} + \Delta_i$$

$$\overline{w_j} = \frac{\sum_{k \neq j}^{N} w_{j,k}}{N}; \quad \sigma^2(w_{ik}) = \frac{\sum_{k \neq j}^{N} (\overline{w_j} - w_{jk})^2}{N}$$

$$\bar{u} = \frac{\sum_{k \neq i}^{N} u_k}{N}; \quad \sigma^2 = \frac{\sum_{k \neq i}^{N} (\bar{u} - u_k)^2}{N}$$

Also this case represents a combination of two of the previous examples of activation functions, namely the activation functions (3) called CS CONTEST and the activation functions (4) called High CS XOR.

The above disclosed different variation of set of rules follow a common general concept. The basic idea as explained by means of the example of a two dimensional image consist in considering each pixel of the matrix as an hypotesis which can be gradually true or false in relation to the luminosity of each pixel. Also this system inherits the local connections between each pixel and its local neighbourhood the strength of the said connection being expressed by means of the weights as computed by the above disclosed automata rule. This conncections work as constraints during the evolution of the active matrix of the connections. The function of cost of the above discloses system of equation consist in attempting to make true each hypotesis of the matrix and thus to bring luminosity of each pixel to a maximum. During this process the weights defining the connection which has been previously computed will act as constraints.

As an example above there is shown the behaviour of the pixels in some border line cases:

Value of the reference pixel	Value of the neighbour pixel	connections	Evolutions
high	high	(+)	Rapid increase
high	low	(-)	Slow decrease
Low	high	(-)	Rapid decrease
Low	Low	(+)	Slow increase

A further special set of rules differing from the CS set of rules is the set of rules III identified by the name IAC, i.e. Interaction and Activation Competition

IAC

$$MaxPixelRange = 2^{M} \; ; \; u_i \in [0,1] \; ; \qquad \alpha = \beta = \frac{Sigma}{2^{M}} ; \; N = Intorno \; ;$$

$$Max = 1; Min = 0; rest = 0.1; decay = 0.1;$$

$$ecc_i = \sum_{j}^{N} u_j \cdot w_{ij} ; \qquad w_{ij} > 0$$

$$ini_i = \sum_{j}^{N} u_j \cdot w_{ij} ; \qquad w_{ij} < 0$$

$$Net_i = (ecc_i \cdot \alpha) + (ini_i \cdot \beta)$$

$$Act_i = \frac{e^{Net_i} - e^{-Net_i}}{e^{Net_i} + e^{-Net_i}}$$

$$\Delta_i = (Max - u_i) \cdot Act_i - decay \cdot (u_i - rest); \qquad Act_i > 0$$

$$\Delta_i = (u_i - Min) \cdot Act_i - decay \cdot (u_i - rest); \qquad Act_i < 0$$

$$u_i^{[n+1]} = u_i^{[n]} + \frac{e^{\Delta_i} - e^{-\Delta_i}}{e^{\Delta_i} + e^{-\Delta_i}}$$

Here the net input Net_i of the central knot K_i is defined as a combination, more precisely as a sum of two different functions for computing the net input depending on the fact if the weights w_{ij} of the connections are positive or negative. More precisely the functions ecc_i and ini_i are identical only a selection is made between inputs associated to positive and to negative weight connections. This is expressed by the two functions ecc_i and ini_i. This two components of Net_i are related to an excitation or enhancement in the case of the component ecc_i and to an inhibition in the case of ini_i. The net input Net_i is a combination of the ecc_i and ini_i in which ecc_i and ini_i are multiplied respectively by a parameter α and by a parameter ß. The two parameters determines the influence of the positive weigt connections and of the negative weight connections on the net input Net_i .

Furthermore an activation parameter Act_i is provided as a function of the net input Net_i to the knot K_i.

This parameter is used for choosing one of two different function for computing the update value α_i of the output U_i of the knot K_i depending on the fact whether Act_i is negative or positive. The enhancing and inhibiting clearly appears also from the two functions for computing α_i since Act_i is present as a parameter in the said functions.

The said functions further comprises the following expressions:

Max and Min which are defined as the top and the bottom range of the activation value.

Decay which is a function defined as the usual decay value along the time of each unit.

Rest which is defined as the default value toward each unit tends for.

The new output value of the knot K_i is defined by a particular exponential function which further enhances the excitation and inhibition mechanism of this example of activation functions.

Generally speaking as referred to an example of an image formed by an arry of pixels as the database to be processed, the above equations defines an Active matrix of the connections in which every pixel is an agent which receives dynamically excitation and inhibition impulses from the other pixels and which modifies correspondingly its internal state. The above equation system can be defined as a collective auto-coordinating system between agent-pixels. The pixels having an high luminosity tend to support oneselves, while the other pixels are drawn towards low values of luminosity. The fixed connection weights between each agent-pixel and its local neighbourhood act as constraints which modulate the communication between each pixel. The said communication is formed by exciting and inhibiting messages. The evolution causes by discrete steps transformation of the original image that the pixel which are in a situation of a sudden change of luminosity will left isolated and are drawn to low values of luminosity. Thus, the entire system will highlight the edges which are present in an image without using function which is explicitly designed for this task. Where the pixel are in competition with each other some sort of walls are visualized which we often perceive as walls between different figures. The advantage of the above system of ruels lies in the fact that the edge detection effect takes place due to a local auto-coordination. Furthermore also a function as an adapve threshold filter occurs. For each edge a line is represented having a thickness which corresponds to the difference in local luminosity which the image shows in every area.

A further alternative of the above mentioned sets of rules is the set IV so called Pixel Mexican Hat PmH

$$MaxPixelRange = 2^M \; ; \;\; u_i \in [0,1] \; ; \qquad N = Surroundings;$$

$$Max = 1; Min = 0; rest = 0.1; decay = 0.1;$$

$$ecc_i = \sum_j^N (u_i - u_j \cdot w_{ij})^2; \quad w_{ij} > 0$$

$$ini_i = \sum_j^N (u_i - u_j \cdot w_{ij})^2; \quad w_{ij} < 0$$

$$Net_i = ((1 - \frac{ecc_i}{1 + ini_i}) \cdot e^{-\frac{ecc_i}{1+ini_i}}) - ((1 - \frac{ini_i}{1 + ecc_i}) \cdot e^{-\frac{ini_i}{1+ecc_i}})$$

$$Act_i = \frac{e^{Net_i} - e^{-Net_i}}{e^{Net_i} + e^{-Net_i}}$$

$$\Delta_i = (Max - u_i) \cdot Act_i - decay \cdot (u_i - rest); \quad Act_i > 0$$

$$\Delta_i = (u_i - Min) \cdot Act_i - decay \cdot (u_i - rest); \quad Act_i < 0$$

$$u_i^{[n+1]} = u_i^{[n]} + \frac{e^{\Delta_i} - e^{-\Delta_i}}{e^{\Delta_i} + e^{-\Delta_i}}$$

Here the same definition apply as to the previous set III called IAC.

It is important to notice that the more specialized sets II.1 to II.6, III, and IV differs from the general one called AR by the fact that not only a weight optimization is carried out but also a units activation.

This system of rules act as a magnifying lens having a local and adaptive threshold. The effect referred to an image is that all the pixels are highlighted which are in a minimal conflict relating to luminosity but ehich have a regular and persiten luminosity so that the visual effect is to illuminate the edges which often are not visible with the eyes.

A second family of rules provides for weight evolution and unit activation and allow to carry out an extraction of features from a source digital or digitalized image such as for example kind of tissue in an image of biological bodies or structures of tissues or objects like for example recognizing the presence of stenosis in angiographic images.

Two sub groups of sets of learning and activation rules are provided.

A first one indicated as the set V so called CM, Contractive map can be defined as a recirculation neural network and comprises a learning phase and a recall phase. (for deeper information see Massimo Buscema & Semeion Group "Reti Neurali Arificiali e Sistemi Sociali Complessi" Volume I, Edizione Franco Angeli Milano 1999).

The set of rules V so called CM comprises the following functions:

a) Learning

$u \in [0,1]$; C = neighbors ; $w_{ij} = 0.0001$ Initialization

$$\Delta w_{ij} = u_i - (u_j \cdot w_{ij}) \cdot (1 - \frac{w_{ij}}{C}) \cdot u_j$$

$$w_{ij}^{[n+1]} = w_{ij}^{[n]} + \Delta w_{ij}$$

$$Out_i(rem, quot) = \mathrm{mod}(\frac{\sum_{k \neq i}^{N} w_{i,k}}{N} \cdot MaxPixel, MaxPixel)$$

b) Recall

$$NewW_{ji} = NewW_{ij} = w_{ij} - \overline{w}$$

where

U_i is the value of the central cell or knot K_i

U_j are the values of the surrounding knots K_j

W_{ij} indicates the weights of the connection of the surrounding knots K_j and the central knot K_i.

W_{ij}^{n} defines the weights of the connection in the n-th cycle.

W_{ij}^{n+1} defines the weight of the connections in the n+1-th cycle.

α W_{ij} is the value which has to be added to the weights W_{ij} in order to update then for the next cycle.

Out_i is the output value of the i-th unit corresponding to the i-th pixel which is the target unit or pixel

New W_{ji} is the new weight of the connection between j-th and i-th unit

New W_{ij} is the new weight of the connection between i-th and j-th unit

$\overline{w}$ is the mean value of the weight.

The arguments rem and quot relates to a particular function applied to the value of each pixel, this means to the output of each unit u_i.

Considering only a grey scale image, the value of each pixel and thus the output of each corresponding unit can be divided by the number of grey scale levels.

If one considers for example 256 grey scale levels than the value of each pixel can be divided by this number. By considering only solutions of the division belonging to the integer numbers this division gives rise to a certain reduced number of classes to which the pixels, i.e. the units belong and furthermore to a rest. The rest is indicated by variable rem.

This kind of operation allow to classify the units an thus the pixels in a certain reduced number of classes and to visualize each class in the output image by giving to the class a certain uniform colour or grey level. The rest, this means the rem value is further used to differentiate the intensity of the colour or grey level. For example considering four classes for the pixel or units each class can be given a colour such as red, green, blue, yellow or four grey levels. The rest of each pixel can be used for varying each colour between dark red or the light or pale red and so on. These allow to further differentiate the pixels of the output image which belong to the same class.

It is possible to compare the rem function as a function for modulating the values given to unit output and sou to the pixels of the output image within certain value range characterising each class defined by the quot function.

Obviously the quot and rem function apply also to pixels values corresponding to coloured pixels, where normally the pixel value is a vector providing three parameters as for example RGB definition of colured pixel values or HSV, or the like.

As it might appear evident from the above listed equations, the pixels value and correspondingly the output value of the units of the image transformed in a neural network are normalized at the beginning for maintaining the possible output values within an interval between 0 and 1.

During definition of the classification by means of the quot function and the corresponding rem function the output values are again denormalized, i.e. rescaled from the interval between 0 1nd 1 to the original interval.

Not using the classification of the functions quot and the modulation of the function rem and not denormalizing the output values of the units of the neural network, this means the pixel values, particularly the pixel values of the output image and by defining a scale of greys or of colours which scale is correlated to the values of the units of the neural network or the above mentioned pixel values of the output image it is possible to obtain a modified rule which is defined as "CM true color", while the other rules are defined as "CM quot", when only the classification with the quot function is applied or "CM quot + rem" when also the rem function is applied in combination with the quot function.

Referred to the example of the image made of an array of pixels, the basic idea of the above disclosed set of rule is that processing starts from the initialisation value of each pixel: the said value will be left invariant through the cycles. Indeed the evolution takes place on the weight defining the connections and at each processing cycle each pixel takes its new value of brightness as a function of the said weights which characterise the pixel at the current instant. Here connections between the reference pixel and the pixel of its local neighbourhood are bidirectional. Each pixel has a connection with which it communicates with another pixel and a second connection for receiving communications form this last pixel.

The evolution law or rule of the weights defining the connections is in this set of rules of the deterministic type and the weights are intialized with values which are proximate to zero.

The new values of brightness for each pixel in every process cycle are defined in the space of the weights. Thus each value of each pixel is defined by the weights defining the connection of this pixel with the pixels of the local neighbourhood.

A further different set of rules which is the set VI and is defined as Local Sine LS belongs also to the above mentioned second family of set of rules.

The local sine set can be provided according to two variants called Local Sine 1 LS1 and Local Sine 2 LS2 These two sets differs only in one equation and the set of rules is described by the following equations:

$$k = \frac{\sigma}{2^M};$$

$$w_{ij} = \pi;$$

$$Net_i = \left[\sum_j^N \sin\left(u_j \cdot w_{ij}\right) \right] \cdot k; \qquad u_j \in [0,1];$$

$$d_{ij} = \left(u_i - u_j \cdot w_{ij}\right)^2;$$

$$\Delta_{ij} = d_{ij} \cdot Net_i \cdot \cos\left(u_j \cdot w_{ij}\right) \cdot u_j; \qquad \text{(LS1)}$$

$$\Delta_{ij} = d_{ij} \cdot Net_i \cdot \cos\left(u_j \cdot w_{ij}\right) \cdot -\sin\left(u_j \cdot w_{ij}\right); \qquad \text{(LS2)}$$

$$w_{ij}^{[t+1]} = w_{ij}^{[t]} + \Delta_{ij};$$

$$\overline{w_i} = \frac{\sum_{j}^{N} w_{ij}}{N};$$

$$W_{Max} = Max\{w_{ij}\}; \qquad W_{Min} = Min\{w_{ij}\};$$

$$Scale = \frac{2^M}{W_{Max} - W_{Min}}; \quad Offset = -\frac{W_{Min} \cdot 2^M}{W_{Max} - W_{Min}};$$

$$Out_i = Scale \cdot \overline{w_i} + Offset;$$

Most of the variables or functions of the above equations have already been defined in the disclosure of the previous set of rules I to V.

D_{ij} represents some sort of distance of the i-th unit form the j-th unit.

α is the standard variation.

As already disclosed it is possible to use only a set of learning rules, only a set of activation rules or both a set of learning rules and of activation rules for applying the algorithm to the array of data records.

As it will appear clearly form the following examples illustrated also in the figures, different kinds of sets of learning rules or of activation rules or of combinations thereof will lead to different outputs which will enhance particular relationships between the data records of the array with respect to other relation ships.

It is important to notice that the present algorithm does not consist in a non supervised mapping algorithm but transforms an array of data records in an active artificial neural network capable of working in a supervised or non supervised manner depending on the rules or functions for learning and activating. In any case a learning phase is present which normally does not occur in non supervised mapping algorithm.

Any kind of known or future artificial neural network may be applied for actuating the principle of the algorithm according to the present invention which is independent from the structure of the artificial neural network itself.

Furthermore it is possible to subject an array of data records to a first learning phase according to a certain known set of learning rules and then a first time to a first set of activation functions. The result so obtained is obviously again an array of data records which may be subjected once again to computation with the algorithm according to the present invention this time choosing equal or different learning rules and a different set of activation functions. In this way an elaboration of the original array of data records is carried out by means of a sequence of two algorithm according to the present invention which are different relating to the learning rules and/or to the sets of activation functions.

The different sets of rules applied in the first computation cycle and in a second computation cycle does not belong necessary to only one family of set of rules, but the set of learning and activation rules of both families may be combined in as two, three or more stage algorithm for elaborating digital or digitalized images.

The effectiveness of the algorithm according to the invention will be shown by means of some practical examples. In this examples the array of data records is formed by image date of a digital image or a digitalize image. Each cell or point P_i of the schematic example of figures 1 and 2 is formed by a pixel of the image and the value of each cell of point P_i is formed by the intensity parameter, i.e. by the parameter influencing the level of grey of the pixel.

It must be noticed that the examples could be also carried out for coloured image in this case the value of each pixel would have be defined by a set of parameter in the form of a vector defining the intensity and the colour.

Figures 4A illustrate a mammography taken according to traditional techniques. Figure 4B is an enlargement of figure 4A. The traditional image of analogical type was digitalized with a scanner and treated with the algorithm according to the present invention.

Figure 4C illustrates the image resulting from the treatment of the mammography of figure 4B where the algorithm was applied using only the set of learning rules and activation rules defined above as CM. As it appears clearly from figure 4C, the rule CM has the effect of enhancing contrast and putting into evidence image zones having equal intensity or level of grey scale by defining clear boredom lines. Equal intensities or grey scale level are defined within a certain range of intensities or grey scale level in a discretized scale of intensities or grey levels.

As it appears clearly from the comparison of figures 4B and 4C, the nodulus or the zone of higher vascolarization in figure 4B is highlighted by the treatment with the algorithm according to the invention and the boredom of this zones are sharply depicted in figure 4C. Figures 5A to 5D are enlargement of this zone of the nodule to better evidence the clear boredom of the image zones furnished by the treatment of traditional mammography with the algorithm according to the present invention. It is also to notice that the image resulting from the treatment with the algorithm according to the present invention is able to extract also more information from the analogical mammography. Indeed the edges of the breast in the analogical image is not clearly differentiated from the background of the image. As it appears from figure 4C the algorithm according to the invention is able to set a more defined boredom clearly differentiating the background from the image of the breast. This is important in order to make measurement of the position of the nodule if an intervention has to be carried out, particularly a reduced invasive intervention by means of microsurgical techniques.

The use only of the set of functions defined above as CM for applying the algorithm according to the present invention to the analogical image somehow inverts the black and white zones of the image for certain zones and being set for enhancing contrast gives some sort of very discretized image defining sharply differentiated image zones.

Figure 4D and the corresponding enlargement of figure 5D illustrate the image obtained by a double treatment of the analogical image of figure 4C and 5C with the algorithm according to the present invention.

In this case the first treatment is carried out by applying the algorithm using only the set of functions which has been defined above as CM. The image data, this means the array of image data obtained by this treatment is further subjected to a treatment with the algorithm according to the present invention where use is made of a combination of learning and activation functions and more precisely of the set defined above as Automata rules AR and of the set of functions defined above as IAC.

At first it is to be noticed that an inversion of black and white zones has been obtained with respect to the image of figures 4C and 5C and partially with respect of the images of figures 4B and 5B. Particularly, the background is white instead of black. Furthermore the nodule is white as in the original analogical image of the mammography (figures 4B and 5B). A more miniaturized discretization of the image is obtained and also the internal structure of the nodule, which in the image of figures 4C and 5C was not subjected to a differentiation in relation to the appearance of this structure in the original mammography except for the inversion of black and white, is subjected to a differentiation and the more important structures are highlighted.

Figures 6A illustrate a analogical image of bacteria. The image has been taken with an electronic microscope. The figure 6B to 6F illustrates the images resulting from the treatment of the image of figure 6A with different known image pattern recognition algorithms. Figure 6G illustrates the image resulting from the treatment of image of figure 6A by means of the algorithm according to the present invention which is applied using only the set of rules named AR and the evolutionary rule named IAC as defined above.

The difference and superiority of the image obtained by the algorithm according to the present invention appears clearly and without doubts form the comparison of the image according to figure 6G with the images according to figures 6B to 6F. again it is important to notice how the particular set of learning rules applied enhances the contrasts and sets clear boredom of the different image zones.

The same effect can be observed in relation to figures 7A to 7C. Here figure 7A is a digital image of the ventricle of the heart. Figure 7B illustrates the image treated by a known image recognition algorithm called Snake. Figure 7C illustrates the image obtained by treatment of image of figure 7A with the algorithm according to the present invention using only the set of functions defined above as CM. Clear and well defined boredoms of the image zones are obtained and the different areas are well differentiated in the image.

The about resulting capability of the algorithm according to the present invention of evidencing contrasts and setting clear boredom to different image zones and differentiating the image zones has a surprising effect. This effect can be appreciated by comparing the images of figures 8A to 8E.

Figures 8A to 8D illustrates ecographic images of metastases taken at different instants in relation to the instant of injection of so called contrast media, i.e. of substances capable of enhancing the revelation of vascular activity by reflecting the ultrasound beam in a non linear way, namely at a frequency different from the fundamental frequency of the impinging beam, normally at a frequency of the order of the second harmonics of the fundamental frequency of the impinging beam.

Figure 8A is an image taken at an instant before the contrast media are present in the imaged zone.

Figure 8B is an image taken during the arterial phase where the contrast medium has reached the imaged zone.

Figure 8C is an image of the same zone of figures 8A and 8B taken at an instant where the arterial and venal phase are at a balance.

Figure 8D is an image taken at a late instant relating to the injection of the contrast medium.

In figure 8D a white circle illustrates the metastases which appears as a darker spot relating to the surrounding image ones.

Figure 8E is the image resulting form the treatment of image 8A, i.e. before the injection of the contrast medium in the zone to be imaged, with the algorithm according to the present invention using the set of functions defined as CM in the above description.

It appears clearly how the metastases has been highlighted, particularly the ones enclosed by the white circle of figure 8D. Also some more little dots above the bigger spot in the white circle and at the right hand side of the said bigger spot are clearly highlighted. This spots can be seen with different evidence in the zone encircled by the white circle in the different images of figures 8B to 8D. In the original image according to figure 8A the bigger spots and dots can be seen very badly and the smaller ones are practically very difficult to be identified as alterations of the tissue.

Thus the treatment of a digital or digitalized image with the algorithm according to the present invention can substitute with a high reliance and precision contrast media imaging. This is a very important advantage since on the first hand it is possible to avoid invasive interventions during imaging. Furthermore the use of contrast media during imaging requires the presence of a specialized medical assistant for injecting the contrast medium in a patient. Contrast media imaging, also known as harmonic imaging in the field of ultrasound imaging requires also longer times to be carried out since after injection of the contrast media some time is needed until the contrast media reaches the tissue to be imaged. Furthermore there is also difficult to predict when the contrast media will reach the tissue to be imaged and sometimes it happens that no image can be taken at the correct instant coinciding with the presence of the contrast media in the tissue to be imaged. Thus the algorithm according to the present invention allows to overcome all the difficulties and drawbacks related to imaging with contrast media which are more than the most important ones disclosed above. This can be appreciated by every expert of the field of diagnostic imaging, where a lot of arrangements must be provided in the imaging apparati for allowing to acquire images with contrast media, particularly real time images.

Figures 9A to 9D illustrates respectively an analogic image, namely a radiography of the lung. The image obtained by treatment with the algorithm according to the present invention respectively using only a set of functions defined above as CM (figure 9C) and a treatment of the image of figure 9A by means of the algorithm according to the present invention using a combination of the above mentioned set of functions defined as CM and of the set of functions defined above as IAC (figure 9D) are compared with the analogical radiographic image of figure 9A and with an image obtained by treating the image of figure 9A with a known filtering algorithm called best filter.

The already effects of the algorithm according to the present invention disclosed several times above can be appreciated. Particularly the image of figure 9D shows how the filament structure present in the lung is highlighted. In this case the to roughly discretized image of figure 9C does not allow to highlight this filament structure, which is depicted in figure 9D as black traces in the lower half of the lungs and at the sides of the two lungs facing each other. While the filament structure can be seen in the image according to figure 9A, the image according to figure 9B does not show this structure. In the image according to figure 9C the structure is present however the differentiation of the image zones is to sharp and rough.

Figure 10 illustrates three images 10A, 10B, 10C put one beside the other and related to a mammography.

The left hand figure 10A is the original mammography, the right hand image 10C is the original mammography, where some nodules are identified by highlighting them with white dots and encircling in white circles. The comparison of the left hand image 10A with the right hand image 10C allow to appreciate the very tiny level of differentiation of the image of the nodules from the surrounding image zone. The centre image of figure 10B is the result of the treatment of the digitalized figure 10A by means of the algorithm according to the present invention using only a set of activation rules defined in the above description as High CS.

It appears evident that the algorithm has revealed and clearly highlighted in the obtained treated image the nodules which has been identified by the human eye and to this a further great number of nodules which where not apparent by human eye in the original image of figures 10A and 10C.

The example of figures 11A to 11E relates to an image of a landscape and not to a diagnostic image and is choosen in order to appreciate the accuracy of the algorithm according to the present invention differentiating image zones by maintaining the relevant structure of the original image. This means that the objects depicted in the image can still be recognized after treatment of the image by means of the algorithm according to the invention.

Figure 11A is a seascape image with a boat in the foreground.

The image may be an image acquired by means of digital techniques such as digital cameras or the like or an image which has been acquired by means of analogical techniques and which has been digitalized by means of a scanner or the like.

Figure 11B and 11C illustrates the image obtained by treating the image according to figure 11A by means of two different known image elaboration algorithms. It appears evident that the subjects of the seascape can hardly be recognized in the images according to figures 11B and 11C.

Figure 11D illustrates the image according to figure 11A after treatment with the algorithm according to the present invention, where only the set of functions has been used defined as IAC in the above description. In this image the subjects of the original image can be recognized much better than in the images of figures 11B and 11C and the different image zones are very good differentiated and recognized.

Figure 11E illustrates the image obtained by the treatment of figure 11A with the algorithm according to the present invention where a set of functions defined as CM in the above description has been used in combination with a set of functions defined as IAC in the above description. The result of this treatment is that the image zones having a certain impact on the viewer are enhanced. So the land in the background and the boat in the foreground are enhanced with respect to the see.

It is further to be noticed that the present algorithm can be applied in combination with other algorithm such as artificial neural networks or other prediction algorithm which are trained and tested to recognize kind of tissue or structure of the material composing and image.

In this case instead of feeding to the image recognition algorithm using the image data array as passive information for training and testing the image data of the digital or digitalized original image, this data can be subjected previously to treatment by means of the present algorithm in one of the forms disclosed above.

In order to ensure greater accuracy of the prediction the treatment of the image data of the original image by means of the algorithm according to the present invention can be carried out several times each time using a different set of learning functions or rules or a different set of activation functions or rules or a different combination thereof or using a sequence of treatment of the original image data in which each treatment phase uses different set of learning functions or rules or a different set of activation functions or rules or a different combination thereof. The prediction algorithm being applied to the image data obtained by each treatment and then the results of each prediction may be combined together or compared one with the other.

Figures 12A to 12J illustrates further examples of elaboration of a same source image by means of the method according to the invention in which different set or rules or combination thereof are applied.

Figure 12A is the source image which is a radiography of the femoral arteria.

In the source image a circle and two ellipse indicated respectively with 1, 2 and 3 encircles particulars of the vessels where a stenosis could be revealed. While the stenosis identified by the circle 1 appears in a sure way also in the source image, the zones encircled by the ellipses 2 and 3 does not give sure information.

The first image 12B is obtained by the method according to the invention in which the set of rules V using the rem function. Here The constriction at 2 and 3 of the right hand branch of the arterial can be seen much better while also the central branch indicated by a rectangle 4 appear visible. The structure at the interior of the arterial branches does not appear very clearly.

Figure 12C illustrate the image obtained by elaborating the source image with the set of rules V so called CM this time using only the option quot. Four classes of grey levels can be seen indicating different zones, namely three grey levels and white. The zones classified by quot does not show any further structure. In an y case the constrictions at 1, 2, 3, and 4 can be already identified in the output image.

Figure 12D shows the result of applying rules V by taking into consideration both the quot and the rem function. In this case the four image zones having one of the four grey level of the image according to figure 12C are modulated by the rem function, namely the grey scale of image 12A. The four image zones having different grey levels are further modulated by the rem function and so a structure can be recognized. The constrictions at 1, 2, 3 and 4 appear more clearly than in the previous images.

Figure 12E illustrates the result of elaborating the source image 12A by means of the rules according to example V and by using the true color option, where the pixel values elaborated are maintained normalized within the interval between 0 and 1. also in this case it is possible to recognize the constrictions of the arterial at 1, 2, 3 and 4.

Figure 12F is the image obtained by elaborating the source image with the local sine algorithm according to the first option. Also in this case the presence of the constrictions appears evident at 1, 2, 3 and 4.

The four figures 12G to 12J illustrates the result obtained by elaborating the source image 12A by a combination of two elaboration steps or stages each one carried out by means of the set of rules according to example V or VI.

Image of figure 12G is obtained by first carrying out an elaboration with the set of rules according to example VI second option, namely the so called LS2 set of rules and by submitting the output image obtained by this first elaboration to a second elaboration this time using the set of rules V so called CM applying the Rem and Quot functions.

Figure 12H illustrates a variant of the elaboration carried out for figure 12G in which the output image obtained by the elaboration with the set of rules according to example VI second option the so called LS2 set of rules is further elaborated with the set of rules according to example V, the so called CM, this time using only the rem function.

Fig. 12I is a similar way of elaborating the source image 12A as in figure 12H, this time the second elaboration stage is carried out by using the set of rules of example V by applying only the quot function.

Fig. 12J is still another variant of the two stage elaboration according to the previous examples of figure 12G to 12I, where the set of rules of example V is used for the second elaboration, this time by applying the True Colour variant.

Although the images are all shown in a grey scale palette, it is possible to define colours and to correlate the different zones of the image to a specific colour, thus obtaining an artificially coloured image which better enhances the different zones of the image and the different objects identified by the elaboration according to the method of the present invention.

Furthermore it has to be stressed out that although the example described is limited to applying the algorithm according to the present invention to an array of image data, this is not the only field where this algorithm can be applied, since treatment is permitted of every kind of database where the data are of the kind that can be represented as an array of points or cells, each point or cell being univocally related to a data record of the database and the position of each point or cell in the array relatively to the other points or cell being a relevant feature of the data record associated to the said point in order to reveal any sort of relation between the data records of the database.

CLAIMS

1. An artificial neural network comprising a n-dimensional array of cells (K_i) corresponding to the knots of the neural network, each cell having connections to the directly adjacent cells (K_j) forming the neighbourhood of the a cell (K_i);

a) Each cell (K_i) having an input for each connection to a directly adjacent cell of the surrounding cells (K_j);

b) each cell (K_i) having an output for the connection to one or more of the directly adjacent cells (K_j);

c) the connection between each cell (K_i) and the directly adjacent cells being determined by weights (w_{ij});

d) each cell being characterised by an internal value defined as the activation value or function (A_i) of the cell (K_i);

e) each cell (K_i) being able to carry out signal processing according to a signal processing function so called transfer function for generating a cell output signal (u_i);

f) the transfer function determining the output signal (u_i) of a cell (K_i) as a function of the activation value or function (A_i) of the cell (K_i), which transfer function comprising also the identity function which puts the activation value or function (A_i) of the cell (K_i) equal to the output signal (u_i) of a cell (K_i);

g) a n-dimensional database of input data records (P_i) being provided which has to be submitted to computation by means of the neural network and in which n-dimensional database the relative position of the data records (P_i) when projected in a corresponding n-dimensional space is a relevant feature of the data records (Pi), the data records (P_i) of the database being able to be represented by an array of points in the said n-dimensional space, each point having an univocally defined position in the said array of points and being univocally related to a data record (P_i) of the said database, each data record (P_i) of the said database comprising further at least one variable or more variables each one having a certain value (U_i);

h) each data record (P_i) being univocally associated to a cell (K_i) of the n-dimensional array of cells forming the neural network which cells (K_i) has the same position in the n-dimensional array of cells (K_i) as the corresponding data record (P_i) represented by a point in the said n-dimensional array of points;

i) the value (U_i) of the variables of each data record (P_i) being considered as the initialisation value of the network being taken as the initial activation value (A_i) or the initial output value (u_i) of the univocally associated cell (K_i);

j) the activation value (A_i) or the output value (u_i) of each cell (K_i) after a certain number of iterative processing steps of the neural network being considered as the new value (U_i) for the said univocally associated data records (P_i).

characterised in that

k) for each processing step of the said certain number of iterative processing steps, the weights (w_{ij}) defining the connection between each cell (K_i) and the directly adjacent cells (K_j) are determined as the function of the current values (U_j) of the variables of each data record (P_j) univocally associated to the cell (K_j) directly adjacent to the said cell (K_i), the said function being a so called learning function or rule;

l) the current activation value (A_i) or the output value (u_i) of each cell (K_i) after a processing steps of the neural network which is considered as the current new value (U_i) for the said univocally associated data records (P_i) being determined as a function of the current output values (u_j) of the directly adjacent cells (K_j) weighted by the corresponding weight (w_{ij}) defining the connection of the directly adjacent cells (K_j) with the cell (K_i).

2. A neural network as claimed in claim 1, characterised in that it is modified by determining the current activation value (A_i) or the output value (u_i) of each cell (K_i) after a processing steps of the neural network which is considered as the current new value (U_i) for the said univocally associated data records (P_i) as a function of the of the weights (w_{ij}) defining the connection of the directly adjacent cells (K_j) with the cell (K_i), the said function being a so called activation function or rule.

3. A neural network as claimed in claim 1, characterised in that the current activation value (A_i) or the output value (u_i) of each cell (K_i) after a processing steps of the neural network which is considered as the current new value (U_i) for the said univocally associated data records (P_i) being determined as a function of the current output values (u_j) of the directly adjacent cells (K_j) and of the corresponding

weight (w_{ij}) defining the connection of the directly adjacent cells (K_j) with the cell (K_i), the said function being a so called activation function or rule.

4. A neural network as claimed in claims 1 or 2, characterised in that for each processing step of the said certain number of iterative processing steps, the weights (w_{ij}) defining the connection between each cell (K_i) and the directly adjacent cells (K_j) are determined as the function of the current values (U_j) of the variables of each data record (P_j) univocally associated to the cell (K_j) directly adjacent to the said cell (K_i) and of the current value (U_i) of the variables of the data record (P_i) univocally associated to the cell (Ki);

5. A neural network as lcaime in one or more fo the preceding claims characterised in that only the following learning rules are used:

$$k = \frac{\sigma}{2^N}$$

$$R_{ij} = e^{-(k \cdot u_i - k \cdot u_j)^2} \qquad u \in [0, 2^N]$$

$$R'_{ij} = (R_{ij} - \frac{1-\varepsilon}{2}) \cdot C \qquad C = 5;\ \varepsilon = e^{-\frac{\sigma^2}{4}};$$

$$w_{ij} = \frac{e^{R'_{ij}} - e^{-R'_{ij}}}{e^{R'_{ij}} + e^{-R'_{ij}}}$$

where

α is a parameter which can freely defined by the user and which renders the algorithm more or less sensible to differences in the image.

R_{ij} is some sort of measure for the distance of the i-th unit from the j-th unit.

U_i are the values of the single cells P_i transformed in knots K_i of the artificial neural network and where

The suffix i defines the central cell or knot and the suffix j defines the cells or knots directly surrounding the said central cell or knot.

6. A neural network according to one or more of the preceding claims 1 to 4 characterised in that the following rules are used:

a) Learning

$u \in [0,1]$; C = neighbors ; $w_{ij} = 0.0001$ Initialization

$$\Delta w_{ij} = u_i - (u_j \cdot w_{ij}) \cdot (1 - \frac{w_{ij}}{C}) \cdot u_j$$

$$w_{ij}^{[n+1]} = w_{ij}^{[n]} + \Delta w_{ij}$$

$$Out_i(rem, quot) = \mathrm{mod}(\frac{\sum_{k \neq i}^{N} w_{i,k}}{N} \cdot MaxPixel, MaxPixel)$$

b) Recall

$$NewW_{ji} = NewW_{ij} = w_{ij} - \overline{w}$$

where

U_i is the value of the central cell or knot K_i

U_j are the values of the surrounding knots K_j

W_{ij} indicates the weights of the connection of the surrounding knots K_j and the central knot K_i.

W_{ij}^{n} defines the weights of the connection in the n-th cycle.

W_{ij}^{n+1} defines the weight of the connections in the n+1-th cycle.

α W_{ij} is the value which has to be added to the weights W_{ij} in order to update then for the next cycle.

Out_i is the output value of the i-th unit corresponding to the i-th pixel which is the target unit or pixel

New W_{ji} is the new weight of the connection between j-th and i-th unit

New W_{ij} is the new weight of the connection between i-th and j-th unit

$\overline{w}$ is the mean value of the weight.

The argument quot relating to the integer quotient of the output value of each unit and the number of steps in a scale of representing the said value.

The argument rem relating to the rest of the above mentioned quotient.

7. A neural network according to one or more of the preceding claims 1 to 4 characterised in that only the following activation rules are used:

Center	*Neighbors*	*State*
1	1	1
1	0	0
0	1	0
0	0	1

$$Initialization : u_i = input_i$$

$$Net_i = (\sum_j u_j w_{ij}) \cdot \alpha$$

$$\Delta_i = Net_i \cdot (1-u_i)\cdot\alpha \quad Net_i > 0$$
$$\Delta_i = Net_i \cdot u_i \cdot\alpha \quad Net_i < 0$$
$$u_i^{[n+1]} = u_i^{[n]} + \Delta_i$$

where

U_i is the input at the first step and the output of the central knot K_i at the following steps

U_j are the outputs of the surrounding knots K_j

Net_i is the net input of the central Knot K_i computed as a function of the outputs U_j of the surrounding knots K_j and the weights w_{ij} of the connections of the the surrounding knots K_j to the central Knot K_i.

n is the number of cycle

α_i is the update value of the output U_i of the central knot K_i for computing the new output value for the next cycle as a function of Net input Net_i and the actual output U_i of the central knot K_i

α is a constant.

8. A Neural Network according to one or more of the preceding claims 1 to 4, characterised in that only the following activation rules are used:

Center	*Neighbors*	*State*
1	1	1
1	0	0
0	1	0
0	0	0

$$Initialization: u_i = input_i$$

$$Net_i = (\sum_j u_j w_{ij})\cdot\alpha$$

$$\Delta_i = Net_i \cdot (1-u_i) \cdot \alpha \cdot (\sigma^2 - \frac{1}{2}) \quad Net_i > 0$$

$$\Delta_i = Net_i \cdot u_i \cdot \alpha \cdot (\sigma^2 - \frac{1}{2}) \quad Net_i < 0$$

$$u_i^{[n+1]} = u_i^{[n]} + \Delta_i$$

$$\bar{u} = \frac{\sum_{k \neq i}^{N} u_k}{N}; \quad \sigma^2 = \frac{\sum_{k \neq i}^{N} (\bar{u} - u_k)^2}{N}$$

where

U_i is the input at the first step and the output of the central knot K_i at the following steps

U_j are the outputs of the surrounding knots K_j

Net_i is the net input of the central Knot K_i computed as a function of the outputs U_j of the surrounding knots K_j and the weights w_{ij} of the connections of the the surrounding knots K_j to the central Knot K_i.

n is the number of cycle

α_i is the update value of the output U_i of the central knot K_i for computing the new output value for the next cycle as a function of Net input Net_i and the actual output U_i of the central knot K_i

α is a constant.

9. A Nerual Network according to one or more of the preceding claims 1 to 4, characterised in that only the following activation rules are used:

Center	*Neighbors*	*State*
1	1	1
1	0	0
0	1	1
0	0	0

$$Initialization: u_i = input_i$$

$$Net_i = \left(\sum_j u_j w_{ij}\right) \cdot \alpha$$

$$\Delta_i = Net_i \cdot (1 - u_i) \cdot \alpha \cdot \left(\sigma^2 - \frac{1}{2}\right) \quad Net_i > 0$$

$$\Delta_i = Net_i \cdot u_i \cdot \alpha \cdot \left(\frac{1}{2} - \sigma^2\right) \quad Net_i < 0$$

$$u_i^{[n+1]} = u_i^{[n]} + \Delta_i$$

$$\bar{u} = \frac{\sum_{k \neq i}^{N} u_k}{N}; \quad \sigma^2 = \frac{\sum_{k \neq i}^{N} (\bar{u} - u_k)^2}{N}$$

where

U_i is the input at the first step and the output of the central knot K_i at the following steps

U_j are the outputs of the surrounding knots K_j

Net_i is the net input of the central Knot K_i computed as a function of the outputs U_j of the surrounding knots K_j and the weights w_{ij} of the connections of the the surrounding knots K_j to the central Knot K_i.

n is the number of cycle

α_i is the update value of the output U_i of the central knot K_i for computing the new output value for the next cycle as a function of Net input Net_i and the actual output U_i of the central knot K_i

α is a constant.

10 A neural Network according to one or more of the preceding claims 1 to 4, characterised in that only the following activation rules are used:

$$Initialization: u_i = input_i$$

$$Net_i = (\sum_j u_j w_{ij} \cdot \sigma^2(w_{jk})) \cdot \alpha \quad k \in [1,N]; k \neq j$$

$$\Delta_i = Net_i \cdot (1-u_i) \cdot \alpha \quad Net_i > 0$$

$$\Delta_i = Net_i \cdot u_i \cdot \alpha \quad Net_i < 0$$

$$u_i^{[n+1]} = u_i^{[n]} + \Delta_i$$

$$\overline{w_j} = \frac{\sum_{k \neq j}^{N} w_{j,k}}{N}; \; \sigma^2(w_{ik}) = \frac{\sum_{k \neq j}^{N} (\overline{w_j} - w_{jk})^2}{N}$$

where

U_i is the input at the first step and the output of the central knot K_i at the following steps

U_j are the outputs of the surrounding knots K_j

Net_i is the net input of the central Knot K_i computed as a function of the outputs U_j of the surrounding knots K_j and the weights w_{ij} of the connections of the the surrounding knots K_j to the central Knot K_i.

n is the number of cycle

α_i is the update value of the output U_i of the central knot K_i for computing the new output value for the next cycle as a function of Net input Net_i and the actual output U_i of the central knot K_i

11. A Neural Network according to one or more of the preceding claims 1 to 4, characterised in that only the following activation rules are used:

$$Initialization: u_i = input_i$$

$$Net_i = (\sum_j u_j w_{ij} \cdot \sigma^2(w_{jk})) \cdot \alpha \quad k \in [1,N]; k \neq j$$

$$\Delta_i = Net_i \cdot (1-u_i) \cdot \alpha \cdot (\sigma^2 - \frac{1}{2}) \quad Net_i > 0$$

$$\Delta_i = Net_i \cdot u_i \cdot \alpha \cdot (\sigma^2 - \frac{1}{2}) \quad Net_i < 0$$

$$u_i^{[n+1]} = u_i^{[n]} + \Delta_i$$

$$\overline{w_j} = \frac{\sum_{k \neq j}^{N} w_{j,k}}{N}; \quad \sigma^2(w_{ik}) = \frac{\sum_{k \neq j}^{N} (\overline{w_j} - w_{jk})^2}{N}$$

$$\bar{u} = \frac{\sum_{k \neq i}^{N} u_k}{N}; \quad \sigma^2 = \frac{\sum_{k \neq i}^{N} (\bar{u} - u_k)^2}{N}$$

where

U_i is the input at the first step and the output of the central knot K_i at the following steps

U_j are the outputs of the surrounding knots K_j

Net_i is the net input of the central Knot K_i computed as a function of the outputs U_j of the surrounding knots K_j and the weights w_{ij} of the connections of the the surrounding knots K_j to the central Knot K_i.

n is the number of cycle

α_i is the update value of the output U_i of the central knot K_i for computing the new output value for the next cycle as a function of Net input Net_i and the actual output U_i of the central knot K_i

12. A Neural Network according to one or more of the preceding claims 1 to 4, characterised in that only the following activation rules are used:

$$Initialization: u_i = input_i$$

$$Net_i = (\sum_j u_j w_{ij} \cdot \sigma^2(w_{jk})) \cdot \alpha \quad k \in [1, N]; k \neq j$$

$$\Delta_i = Net_i \cdot (1 - u_i) \cdot \alpha \cdot (\sigma^2 - \frac{1}{2}) \quad Net_i > 0$$

$$\Delta_i = Net_i \cdot u_i \cdot \alpha \cdot (\frac{1}{2} - \sigma^2) \quad Net_i < 0$$

$$u_i^{[n+1]} = u_i^{[n]} + \Delta_i$$

$$\overline{w_j} = \frac{\sum_{k \neq j}^{N} w_{j,k}}{N}; \ \sigma^2(w_{ik}) = \frac{\sum_{k \neq j}^{N} (\overline{w_j} - w_{jk})^2}{N}$$

$$\bar{u} = \frac{\sum_{k \neq i}^{N} u_k}{N}; \ \sigma^2 = \frac{\sum_{k \neq i}^{N} (\bar{u} - u_k)^2}{N}$$

where

U_i is the input at the first step and the output of the central knot K_i at the following steps

U_j are the outputs of the surrounding knots K_j

Net_i is the net input of the central Knot K_i computed as a function of the outputs U_j of the surrounding knots K_j and the weights w_{ij} of the connections of the the surrounding knots K_j to the central Knot K_i.

n is the number of cycle

α_i is the update value of the output U_i of the central knot K_i for computing the new output value for the next cycle as a function of Net input Net_i and the actual output U_i of the central knot K_i

α is a constant.

13. A Neural Network according to one or more of the preceding claims 1 to 4, characterised in that only the following activation rules are used:

$$MaxPixelRange = 2^M \ ; \ u_i \in [0,1] \ ; \qquad \alpha = \beta = \frac{Sigma}{2^M}; \ N = Intorno;$$

$$Max = 1; Min = 0; rest = 0.1; decay = 0.1;$$

$$ecc_i = \sum_j^N u_j \cdot w_{ij}; \qquad w_{ij} > 0$$

$$ini_i = \sum_j^N u_j \cdot w_{ij}; \qquad w_{ij} < 0$$

$$Net_i = (ecc_i \cdot \alpha) + (ini_i \cdot \beta)$$

$$Act_i = \frac{e^{Net_i} - e^{-Net_i}}{e^{Net_i} + e^{-Net_i}}$$

$$\Delta_i = (Max - u_i) \cdot Act_i - decay \cdot (u_i - rest); \qquad Act_i > 0$$

$$\Delta_i = (u_i - Min) \cdot Act_i - decay \cdot (u_i - rest); \qquad Act_i < 0$$

$$u_i^{[n+1]} = u_i^{[n]} + \frac{e^{\Delta_i} - e^{-\Delta_i}}{e^{\Delta_i} + e^{-\Delta_i}}$$

U_i is the output of the central knot K_i

U_j are the outputs of the surrounding knots K_j

Net_i is the net input of the central Knot K_i computed as a function of the outputs U_j of the surrounding knots K_j and the weights w_{ij} of the connections of the the surrounding knots K_j to the central Knot K_i.

N is the number of cycle

α_i is the update value of the output U_i of the central knot K_i for computing the new output value for the next cycle as a function of Net input Net_i and the actual output U_i of the central knot K_i

α is a constant.

And where the functions ecc_i and ini_i are identical only a selection is made between inputs associated to positive and to negative weight connections and where an activation parameter Act_i is provided as a function of the net input Net_i to the knot $K_{iJ;}$

this parameter being used for choosing one of two different function for computing the update value α_i of the output U_i of the knot K_i depending on the fact whether Act_i is negative or positive

two functions being provided for computing α_i comprising the following expressions:

Max and Min which are defined as the top and the bottom range of the activation value.

Decay which is a function defined as the usual decay value along the time of each unit.

Rest which is defined as the default value toward each unit tends for.

14. A Neural Network according to one or more of the preceding claims 1 to 4, characterised in that only the following activation rules are used:

$$MaxPixelRange = 2^M\ ;\ \ u_i \in [0,1]\ ;\quad N = Surroundings;$$

$$Max = 1; Min = 0; rest = 0.1; decay = 0.1;$$

$$ecc_i = \sum_j^N (u_i - u_j \cdot w_{ij})^2; \quad w_{ij} > 0$$

$$ini_i = \sum_j^N (u_i - u_j \cdot w_{ij})^2; \quad w_{ij} < 0$$

$$Net_i = ((1 - \frac{ecc_i}{1 + ini_i}) \cdot e^{-\frac{ecc_i}{1+ini_i}}) - ((1 - \frac{ini_i}{1 + ecc_i}) \cdot e^{-\frac{ini_i}{1+ecc_i}})$$

$$Act_i = \frac{e^{Net_i} - e^{-Net_i}}{e^{Net_i} + e^{-Net_i}}$$

$$\Delta_i = (Max - u_i) \cdot Act_i - decay \cdot (u_i - rest); \qquad Act_i > 0$$

$$\Delta_i = (u_i - Min) \cdot Act_i - decay \cdot (u_i - rest); \qquad Act_i < 0$$

$$u_i^{[n+1]} = u_i^{[n]} + \frac{e^{\Delta_i} - e^{-\Delta_i}}{e^{\Delta_i} + e^{-\Delta_i}}$$

U_i is the output of the central knot K_i

U_j are the outputs of the surrounding knots K_j

Net_i is the net input of the central Knot K_i computed as a function of the outputs U_j of the surrounding knots K_j and the weights w_{ij} of the connections of the the surrounding knots K_j to the central Knot K_i.

N is the number of cycle

α_i is the update value of the output U_i of the central knot K_i for computing the new output value for the next cycle as a function of Net input Net_i and the actual output U_i of the central knot K_i

α is a constant.

And where the functions ecc_i and ini_i are identical only a selection is made between inputs associated to positive and to negative weight connections and where an activation parameter Act_i is provided as a function of the net input Net_i to the knot $K_{iJ;}$

this parameter being used for choosing one of two different function for computing the update value α_i of the output U_i of the knot K_i depending on the fact whether Act_i is negative or positive two functions being provided for computing α_i comprising the following expressions:

Max and Min which are defined as the top and the bottom range of the activation value.

Decay which is a function defined as the usual decay value along the time of each unit.

Rest which is defined as the default value toward each unit tends for.

14. A Neural Network to one or more of the preceding claims 1 to 4, characterised in that only the following activation rules are used:

$$k = \frac{\sigma}{2^M};$$

$$w_{ij} = \pi;$$

$$Net_i = \left[\sum_j^N \sin(u_j \cdot w_{ij})\right] \cdot k; \qquad u_j \in [0,1];$$

$$d_{ij} = (u_i - u_j \cdot w_{ij})^2;$$

$$\Delta_{ij} = d_{ij} \cdot Net_i \cdot \cos(u_j \cdot w_{ij}) \cdot u_j;$$

or

$$\Delta_{ij} = d_{ij} \cdot Net_i \cdot \cos(u_j \cdot w_{ij}) \cdot -\sin(u_j \cdot w_{ij});$$

$$w_{ij}^{[t+1]} = w_{ij}^{[t]} + \Delta_{ij};$$

$$\overline{w_i} = \frac{\sum_j^N w_{ij}}{N};$$

$$W_{Max} = Max\{w_{ij}\}; \qquad W_{Min} = Min\{w_{ij}\};$$

$$Scale = \frac{2^M}{W_{Max} - W_{Min}}; \quad Offset = -\frac{W_{Min} \cdot 2^M}{W_{Max} - W_{Min}};$$

$$Out_i = Scale \cdot \overline{w_i} + Offset;$$

where

U_i is the value of the central cell or knot K_i

U_j are the values of the surrounding knots K_j

W_{ij} indicates the weights of the connection of the surrounding knots K_j and the central knot K_i.

Out_i is the output value of the i-th unit corresponding to the i-th pixel which is the target unit or pixel

New W_{ji} is the new weight of the connection between j-th and i-th unit

$\overline{w}$ is the mean value of the weight.

15. A Neural Network according to one or more of the preceding claims characterized in that at each computation cycle a combination of a set or learning rules or functions and of a set of activation functions according to one or more of the preceding claims 5 to 14 is used for providing a new array of data records in which the value of each data record has been changed as a function of the outputs of the actual target data record and of the data records of the surrounding cells or points and as a function of the weights defining the connections between the target data record and the data records of the surrounding cells or points and for providing new values for the weights of the said connections which new array of data record and which new weights for the connections are used for carrying out the following computation cycle.

16. An artificial neural network according to one ro more of the preceding claims characterized in tha it is a image processing machine, the data records of the database univoquely associated or acting as knots of an array of knots (K_i) being formed by the pixels (P_i) while tha initialisation values of the knots being formed by the pixels values (U_i.

17. An artificial neural Network as claimed in claim 16, characterised in that the pixel value is a scalar elemnt or a vector elemnt the pixel being characterised by different variables forming a component of the vector each variable being related to a physical and/or visual feature characterising the pixle and its visual aspect.

18. A Neural Network as claimed in claim 17, characterized in that the pixel is of the grey scale image and is characterized by its brightness.

19. A neural Network as claimed in claims 16 or 17, characterized in that the pixels are of a colour image and the variables characterising the pixel are at least three corresponding to a HSV or a RGB or another conventiona coding of pixel appearance.

20. An algorithm for recognizing relationships between data of a database the data being of the kind where the relative position of the data records in an array of data records or in a distribution of data records in a N-dimensional space, particularly a two or three dimensional space is a relevant feature of the data record and where the data records can be represented as an array of cells or points, each point being univocally related to a data record of the database and having a univocally defined position in the array relatively to the cells or points of the

other data records, to each data record being further associated at least one variable or more variables each one having a certain value, the algorithm being characterised by the fact that

- each cell or point in the array of cells of points representing a data records of a database is considered to be a unit or a knot of an Artificial Neural Network.

21. An artificial neural network according to claim 20, in which

- each unit or knot formed by a cell or point of the database being successively defined as a target unit or knot and connections being defined between each target unit or knot at least to each one of the rest of the units or knots formed by the rest of cells or points of the database which are at least of gradient 1 relatively to the corresponding target unit or knot;

- a new output value of each unit or knot of the database successively defined as target unit or knot being calculated by means of the set of learning rules or functions or the set of activation rules or functions of the artificial neural network or by means of the combination of both the set of learning rules or functions and the set of activation rules or functions of the artificial neural network as a function of the actual output of the units or knots connected to the target unit or knot and of the actual output of the said target unit or knot;

- The actual outputs of each unit or knot being defined as the value of the variable or as the values of the variables associated to each data record represented by a cell or a point considered as a unit or knot of the artificial neural network;

- And the new output of the target unit or knot is considered as the new value of the variable or of the variables of the data record associated to the cell or point of the array of data records corresponding to the target unit or knot;

- By carrying out the said steps for computing a new output of a target unit or knot for at least part or for each cell or point of the array of data records a new array of data records is computed where the data record of each cell or point has a new value of the at least one variable or new values for the variables as a result of a first computation cycle of the artificial neural network according to the above steps;

- The said computation cycle being repeated for each successive new array of data records until a certain prefixed number of repetitions of the computation cycle has been carried out and/or unless a certain maximum allowable error or discrepancy has been reached between the original values of the variable or of the variables of the original array of data records with respect to the values of the variable or variables of the array of data records according to the one computed in the last cycle and/or unless the difference between the value of the variable or the values of the variables of data records in the sequence of array of data records computed in the sequence of cycles is lower than a predetermined maximum rate.

22. An algorithm according to claim 20 or 21, characterised in that the array of data records is submitted at least twice or more times to elaboration with the said algorithm in a first elaboration phase being provided a first set of learning functions or rules or a first set of activation functions or rules or a combination thereof and in a second elaboration phase being provided a second set of learning functions or rules or a second set of activation functions or rules or a combination thereof and so on when more then two phases are provided while the array of data records being used in the second or further elaboration phases with the algorithm with the second or further different sets of learning or activation rules or functions or with a combination thereof is the array of data records resulting respectively from the first or from the previous elaboration phase of the array of data records.

23. An algorithm according to one or more of the preceding claims 20 to 22, characterised in that particularly in a two or three dimensional array of data records, the cells or points related to the data records of gradient 1 with respect to the cell or point of the target data record are formed by the data records associated to the cells or points of the data record array which directly surrounds the cell or point in the array of data record related to the said target data record.

24. An algorithm according to one or more of the preceding claims 20 to 23, characterised in that the new array of data records computed by the algorithm is based only on a set of learning functions or rules for optimizing the weights of te connections, the new

output of each target data record being defined as a function of new weights characterising the connection of each target unit or knot associated to the target data record with the units or knots represented by the cells or points of data records of gradient one relatively to the cell or point of the target data record, the set of learning rules or functions defining new weights of the connections as a function of the previous weights computed or defined in a previous computation cycle and as a function of the actual outputs of the unit or knot associated to the cell or point of target data record and of the unit or knot associated to the cells or points of the data records of at least of gradient 1 or of the data records of the cells or points directly surrounding the cells or point of the actual target data record.

25. An algorithm according to one or more of the preceding claims 20 to 23, characterised in that the new array of data records computed by the algorithm is based only on a set of activation functions where these functions defines the new output of the target unit or knot corresponding to the cell or point related to the target data record basing on the net input to the said target unit or knot which is a function of the outputs of the units or knots corresponding to the cells or points associated to the data records at least of gradient 1 with respect to the target data record, particularly to the units or knots corresponding to the cells or points of the array of data records directly surrounding the cell or point of the target data record.

26. An algorithm according to one or more of the preceding claims 20 to 25 characterised in that

computation in the first computation cycle starts with a fixed predetermined value of the weights for each connection while the starting value of the unit or knot is modified according to a predetermined function which is also function of the weights and of the value of the surrounding knots or units and therefore to the data records which corresponds to cells or points in the array directly surrounding the cell or point representing a certain unit or knot of the artificial neural network.

27. An algorithm according to one or more of the preceding claims 20 to 26 characterised in that only the following learning rules are used:

$$k = \frac{\sigma}{2^N}$$

$$R_{ij} = e^{-(k \cdot u_i - k \cdot u_j)^2} \qquad u \in [0, 2^N]$$

$$R'_{ij} = (R_{ij} - \frac{1-\varepsilon}{2}) \cdot C \qquad C = 5; \ \varepsilon = e^{-\frac{\sigma^2}{4}};$$

$$w_{ij} = \frac{e^{R'_{ij}} - e^{-R'_{ij}}}{e^{R'_{ij}} + e^{-R'_{ij}}}$$

where

α is a parameter which can freely defined by the user and which renders the algorithm more or less sensible to differences in the image.

R_{ij} is some sort of measure for the distance of the i-th unit from the j-th unit.

U_i are the values of the single cells P_i transformed in knots K_i of the artificial neural network and where

The suffix i defines the central cell or knot and the suffix j defines the cells or knots directly surrounding the said central cell or knot.

28. An algorithm according to one or more of the preceding claims 20 to 27 characterised in that the following learning rules are used:

a) Learning

$u \in [0,1]$; C = neighbors ; $w_{ij} = 0.0001$ Initialization

$$\Delta w_{ij} = u_i - (u_j \cdot w_{ij}) \cdot (1 - \frac{w_{ij}}{C}) \cdot u_j$$

$$w_{ij}^{[n+1]} = w_{ij}^{[n]} + \Delta w_{ij}$$

$$Out_i(rem, quot) = \mathrm{mod}(\frac{\sum_{k \neq i}^{N} w_{i,k}}{N} \cdot MaxPixel, MaxPixel)$$

b) Recall

$$NewW_{ji} = NewW_{ij} = w_{ij} - \overline{w}$$

where

U_i is the value of the central cell or knot K_i

U_j are the values of the surrounding knots K_j

W_{ij} indicates the weights of the connection of the surrounding knots K_j and the central knot K_i.

W_{ij}^n defines the weights of the connection in the n-th cycle.

W_{ij}^{n+1} defines the weight of the connections in the n+1-th cycle.

α W_{ij} is the value which has to be added to the weights W_{ij} in order to update then for the next cycle.

Out_i is the output value of the i-th unit corresponding to the i-th pixel which is the target unit or pixel

New W_{ji} is the new weight of the connection between j-th and i-th unit

New W_{ij} is the new weight of the connection between i-th and j-th unit

$\overline{w}$ is the mean value of the weight.

The argument quot relating to the integer quotient of the output value of each unit and the number of steps in a scale of representing the said value.

The argument rem relating to the rest of the above mentioned quotient.

29. An Algorithm according to one or more of the preceding claims 20 to 28 characterised in that only the following activation rules are used:

Center	*Neighbors*	*State*
1	1	1
1	0	0
0	1	0
0	0	1

$$Initialization: u_i = input_i$$

$$Net_i = (\sum_j u_j w_{ij}) \cdot \alpha$$

$$\Delta_i = Net_i \cdot (1 - u_i) \cdot \alpha \quad Net_i > 0$$

$$\Delta_i = Net_i \cdot u_i \cdot \alpha \quad Net_i < 0$$

$$u_i^{[n+1]} = u_i^{[n]} + \Delta_i$$

where

U_i is the input at the first step and the output of the central knot K_i at the following steps

U_j are the outputs of the surrounding knots K_j

Net_i is the net input of the central Knot K_i computed as a function of the outputs U_j of the surrounding knots K_j and the weights w_{ij} of the connections of the the surrounding knots K_j to the central Knot K_i.

n is the number of cycle

α_i is the update value of the output U_i of the central knot K_i for computing the new output value for the next cycle as a function of Net input Net_i and the actual output U_i of the central knot K_i

α is a constant.

30. An Algorithm according to one or more of the preceding claims 20 to 27, characterised in that only the following activation rules are used:

Center	*Neighbors*	*State*
1	1	1
1	0	0
0	1	0
0	0	0

$$Initialization: u_i = input_i$$

$$Net_i = (\sum_j u_j w_{ij}) \cdot \alpha$$

$$\Delta_i = Net_i \cdot (1 - u_i) \cdot \alpha \cdot (\sigma^2 - \frac{1}{2}) \quad Net_i > 0$$

$$\Delta_i = Net_i \cdot u_i \cdot \alpha \cdot (\sigma^2 - \frac{1}{2}) \quad Net_i < 0$$

$$u_i^{[n+1]} = u_i^{[n]} + \Delta_i$$

$$\bar{u} = \frac{\sum_{k \neq i}^{N} u_k}{N}; \quad \sigma^2 = \frac{\sum_{k \neq i}^{N} (\bar{u} - u_k)^2}{N}$$

where

U_i is the input at the first step and the output of the central knot K_i at the following steps

U_j are the outputs of the surrounding knots K_j

Net_i is the net input of the central Knot K_i computed as a function of the outputs U_j of the surrounding knots K_j and the weights w_{ij} of the connections of the the surrounding knots K_j to the central Knot K_i.

n is the number of cycle

α_i is the update value of the output U_i of the central knot K_i for computing the new output value for the next cycle as a function of Net input Net_i and the actual output U_i of the central knot K_i

α is a constant.

31. An Algorithm according to one or more of the preceding claims 20 to 27, characterised in that only the following activation rules are used:

Center	*Neighbors*	*State*
1	1	1
1	0	0
0	1	1
0	0	0

$$Initialization: u_i = input_i$$

$$Net_i = (\sum_j u_j w_{ij}) \cdot \alpha$$

$$\Delta_i = Net_i \cdot (1-u_i) \cdot \alpha \cdot (\sigma^2 - \frac{1}{2}) \quad Net_i > 0$$

$$\Delta_i = Net_i \cdot u_i \cdot \alpha \cdot (\frac{1}{2} - \sigma^2) \quad Net_i < 0$$

$$u_i^{[n+1]} = u_i^{[n]} + \Delta_i$$

$$\bar{u} = \frac{\sum_{k \neq i}^{N} u_k}{N}; \quad \sigma^2 = \frac{\sum_{k \neq i}^{N} (\bar{u} - u_k)^2}{N}$$

where

U_i is the input at the first step and the output of the central knot K_i at the following steps

U_j are the outputs of the surrounding knots K_j

Net_i is the net input of the central Knot K_i computed as a function of the outputs U_j of the surrounding knots K_j and the weights w_{ij} of the connections of the the surrounding knots K_j to the central Knot K_i.

n is the number of cycle

α_i is the update value of the output U_i of the central knot K_i for computing the new output value for the next cycle as a function of Net input Net_i and the actual output U_i of the central knot K_i

α is a constant.

32. An Algorithm according to one or more of the preceding claims 20 to 27, characterised in that only the following activation rules are used:

$$Initialization: u_i = input_i$$

$$Net_i = (\sum_j u_j w_{ij} \cdot \sigma^2(w_{jk})) \cdot \alpha \quad k \in [1, N]; k \neq j$$

$$\Delta_i = Net_i \cdot (1-u_i) \cdot \alpha \quad Net_i > 0$$
$$\Delta_i = Net_i \cdot u_i \cdot \alpha \qquad Net_i < 0$$
$$u_i^{[n+1]} = u_i^{[n]} + \Delta_i$$

$$\overline{w_j} = \frac{\sum_{k \neq j}^{N} w_{j,k}}{N}; \quad \sigma^2(w_{ik}) = \frac{\sum_{k \neq j}^{N} (\overline{w_j} - w_{jk})^2}{N}$$

where

U_i is the input at the first step and the output of the central knot K_i at the following steps

U_j are the outputs of the surrounding knots K_j

Net_i is the net input of the central Knot K_i computed as a function of the outputs U_j of the surrounding knots K_j and the weights w_{ij} of the connections of the the surrounding knots K_j to the central Knot K_i.

n is the number of cycle

α_i is the update value of the output U_i of the central knot K_i for computing the new output value for the next cycle as a function of Net input Net_i and the actual output U_i of the central knot K_i

33. An Algorithm according to one or more of the preceding claims 20 to 27, characterised in that only the following activation rules are used:

$$Initialization: u_i = input_i$$

$$Net_i = (\sum_j u_j w_{ij} \cdot \sigma^2(w_{jk})) \cdot \alpha \quad k \in [1,N]; k \neq j$$

$$\Delta_i = Net_i \cdot (1-u_i) \cdot \alpha \cdot (\sigma^2 - \frac{1}{2}) \quad Net_i > 0$$

$$\Delta_i = Net_i \cdot u_i \cdot \alpha \cdot (\sigma^2 - \frac{1}{2}) \qquad Net_i < 0$$

$$u_i^{[n+1]} = u_i^{[n]} + \Delta_i$$

$$\overline{w_j} = \frac{\sum_{k \neq j}^{N} w_{j,k}}{N}; \quad \sigma^2(w_{ik}) = \frac{\sum_{k \neq j}^{N} (\overline{w_j} - w_{jk})^2}{N}$$

$$\bar{u} = \frac{\sum_{k \neq i}^{N} u_k}{N}; \quad \sigma^2 = \frac{\sum_{k \neq i}^{N} (\bar{u} - u_k)^2}{N}$$

where

U_i is the input at the first step and the output of the central knot K_i at the following steps

U_j are the outputs of the surrounding knots K_j

Net_i is the net input of the central Knot K_i computed as a function of the outputs U_j of the surrounding knots K_j and the weights w_{ij} of the connections of the the surrounding knots K_j to the central Knot K_i.

n is the number of cycle

α_i is the update value of the output U_i of the central knot K_i for computing the new output value for the next cycle as a function of Net input Net_i and the actual output U_i of the central knot K_i

34. An Algorithm according to one or more of the preceding claims 20 to 27, characterised in that only the following activation rules are used:

$$Initialization: u_i = input_i$$

$$Net_i = (\sum_j u_j w_{ij} \cdot \sigma^2(w_{jk})) \cdot \alpha \quad k \in [1, N]; k \neq j$$

$$\Delta_i = Net_i \cdot (1-u_i) \cdot \alpha \cdot (\sigma^2 - \frac{1}{2}) \quad Net_i > 0$$
$$\Delta_i = Net_i \cdot u_i \cdot \alpha \cdot (\frac{1}{2} - \sigma^2) \quad Net_i < 0$$

$$u_i^{[n+1]} = u_i^{[n]} + \Delta_i$$

$$\overline{w_j} = \frac{\sum_{k \neq j}^{N} w_{j,k}}{N}; \quad \sigma^2(w_{ik}) = \frac{\sum_{k \neq j}^{N} (\overline{w_j} - w_{jk})^2}{N}$$

$$\bar{u} = \frac{\sum_{k \neq i}^{N} u_k}{N}; \quad \sigma^2 = \frac{\sum_{k \neq i}^{N} (\bar{u} - u_k)^2}{N}$$

where

U_i is the input at the first step and the output of the central knot K_i at the following steps

U_j are the outputs of the surrounding knots K_j

Net_i is the net input of the central Knot K_i computed as a function of the outputs U_j of the surrounding knots K_j and the weights w_{ij} of the connections of the the surrounding knots K_j to the central Knot K_i.

n is the number of cycle

α_i is the update value of the output U_i of the central knot K_i for computing the new output value for the next cycle as a function of Net input Net_i and the actual output U_i of the central knot K_i

α is a constant.

35. An Algorithm according to one or more of the preceding claims 20 to 27, characterised in that only the following activation rules are used:

$$MaxPixelRange = 2^M \; ; \; u_i \in [0,1] \; ; \qquad \alpha = \beta = \frac{Sigma}{2^M}; \; N = Intorno;$$

$$Max = 1; Min = 0; rest = 0.1; decay = 0.1;$$

$$ecc_i = \sum_j^N u_j \cdot w_{ij}; \quad w_{ij} > 0$$

$$ini_i = \sum_j^N u_j \cdot w_{ij}; \quad w_{ij} < 0$$

$$Net_i = (ecc_i \cdot \alpha) + (ini_i \cdot \beta)$$

$$Act_i = \frac{e^{Net_i} - e^{-Net_i}}{e^{Net_i} + e^{-Net_i}}$$

$$\Delta_i = (Max - u_i) \cdot Act_i - decay \cdot (u_i - rest); \quad Act_i > 0$$

$$\Delta_i = (u_i - Min) \cdot Act_i - decay \cdot (u_i - rest); \quad Act_i < 0$$

$$u_i^{[n+1]} = u_i^{[n]} + \frac{e^{\Delta_i} - e^{-\Delta_i}}{e^{\Delta_i} + e^{-\Delta_i}}$$

U_i is the output of the central knot K_i

U_j are the outputs of the surrounding knots K_j

Net_i is the net input of the central Knot K_i computed as a function of the outputs U_j of the surrounding knots K_j and the weights w_{ij} of the connections of the the surrounding knots K_j to the central Knot K_i.

N is the number of cycle

α_i is the update value of the output U_i of the central knot K_i for computing the new output value for the next cycle as a function of Net input Net_i and the actual output U_i of the central knot K_i

α is a constant.

And where the functions ecc_i and ini_i are identical only a selection is made between inputs associated to positive and to negative weight connections and where an activation parameter Act_i is provided as a function of the net input Net_i to the knot $K_{iJ;}$

this parameter being used for choosing one of two different function for computing the update value α_i of the output U_i of the knot K_i depending on the fact whether Act_i is negative or positive

two functions being provided for computing α_i comprising the following expressions:

Max and Min which are defined as the top and the bottom range of the activation value.

Decay which is a function defined as the usual decay value along the time of each unit.

Rest which is defined as the default value toward each unit tends for.

36. An Algorithm according to one or more of the preceding claims 20 to 27, characterised in that only the following activation rules are used:

$$MaxPixelRange = 2^M ; \ u_i \in [0,1] ; \quad N = Surroundings;$$

$$Max = 1; Min = 0; rest = 0.1; decay = 0.1;$$

$$ecc_i = \sum_j^N (u_i - u_j \cdot w_{ij})^2; \quad w_{ij} > 0$$

$$ini_i = \sum_j^N (u_i - u_j \cdot w_{ij})^2; \quad w_{ij} < 0$$

$$Net_i = ((1 - \frac{ecc_i}{1 + ini_i}) \cdot e^{-\frac{ecc_i}{1+ini_i}}) - ((1 - \frac{ini_i}{1 + ecc_i}) \cdot e^{-\frac{ini_i}{1+ecc_i}})$$

$$Act_i = \frac{e^{Net_i} - e^{-Net_i}}{e^{Net_i} + e^{-Net_i}}$$

$$\Delta_i = (Max - u_i) \cdot Act_i - decay \cdot (u_i - rest); \quad Act_i > 0$$

$$\Delta_i = (u_i - Min) \cdot Act_i - decay \cdot (u_i - rest); \quad Act_i < 0$$

$$u_i^{[n+1]} = u_i^{[n]} + \frac{e^{\Delta_i} - e^{-\Delta_i}}{e^{\Delta_i} + e^{-\Delta_i}}$$

U_i is the output of the central knot K_i

U_j are the outputs of the surrounding knots K_j

Net_i is the net input of the central Knot K_i computed as a function of the outputs U_j of the surrounding knots K_j and the weights w_{ij} of the connections of the the surrounding knots K_j to the central Knot K_i.

N is the number of cycle

α_i is the update value of the output U_i of the central knot K_i for computing the new output value for the next cycle as a function of Net input Net_i and the actual output U_i of the central knot K_i

α is a constant.

And where the functions ecc_i and ini_i are identical only a selection is made between inputs associated to positive and to negative weight connections and where an activation parameter Act_i is provided as a function of the net input Net_i to the knot $K_{iJ;}$

this parameter being used for choosing one of two different function for computing the update value α_i of the output U_i of the knot K_i depending on the fact whether Act_i is negative or positive

two functions being provided for computing α_i comprising the following expressions:

Max and Min which are defined as the top and the bottom range of the activation value.

Decay which is a function defined as the usual decay value along the time of each unit.

Rest which is defined as the default value toward each unit tends for.

37. An Algorithm according to one or more of the preceding claims 20 to 27, characterised in that only the following activation rules are used:

$$k = \frac{\sigma}{2^M};$$

$$w_{ij} = \pi;$$

$$Net_i = \left[\sum_j^N \sin(u_j \cdot w_{ij}) \right] \cdot k; \qquad u_j \in [0,1];$$

$$d_{ij} = (u_i - u_j \cdot w_{ij})^2;$$

$$\Delta_{ij} = d_{ij} \cdot Net_i \cdot \cos(u_j \cdot w_{ij}) \cdot u_j;$$

or

$$\Delta_{ij} = d_{ij} \cdot Net_i \cdot \cos(u_j \cdot w_{ij}) \cdot - \sin(u_j \cdot w_{ij});$$

$$w_{ij}^{[t+1]} = w_{ij}^{[t]} + \Delta_{ij};$$

$$\overline{w_i} = \frac{\sum_j^N w_{ij}}{N};$$

$$W_{Max} = Max\{w_{ij}\}; \qquad W_{Min} = Min\{w_{ij}\};$$

$$Scale = \frac{2^M}{W_{Max} - W_{Min}}; \qquad Offset = -\frac{W_{Min} \cdot 2^M}{W_{Max} - W_{Min}};$$

$$Out_i = Scale \cdot \overline{w_i} + Offset;$$

where

U_i is the value of the central cell or knot K_i

U_j are the values of the surrounding knots K_j

W_{ij} indicates the weights of the connection of the surrounding knots K_j and the central knot K_i.

Out_i is the output value of the i-th unit corresponding to the i-th pixel which is the target unit or pixel

New W_{ji} is the new weight of the connection between j-th and i-th unit

$\overline{w}$ is the mean value of the weight.

38. An Algorithm according to one or more of the preceding claims 20 to 37 characterized in that at each computation cycle a combination of a set or learning rules or functions and of a set of activation functions according to one or more of the preceding claims 5 to 16 is used for providing a new array of data records in which the value of each data record has been changed as a function of the outputs of the actual target data record and of the data records of the surrounding cells or points and as a function of the weights defining the connections between the target data record and the data records of the surrounding cells or points and for providing new values for the weights of the said connections which new array of data record and which new weights for the connections are used for carrying out the following computation cycle.

39. A method for image processing in which the image is formed by a two or three dimensional array of pixels and in which each pixel of the array forms a unit or knot of an artificial neural network, the input and the output of the artificial neural network being formed by the original values of the pixels corresponding to each unit and by the computed value of each pixel, the computation of the output value of each one of the knots being carried out as a function of the

values at least of the pixels surrounding the said knot.

40. A method according to claim 39, characterised in that between each knot or unit of the artificial neural network corresponsing univoquely to a pixel of the array of pixels forming the image and the related units or knots of at least gradient 1 weighted connections are provided.

41. A method according to claims 39 and 40, characterised in that a weight optimization is carried out.

42. A method according to claim 41, characterised in that unit activation is carried out after weight optimization.

43. A method according to one or more of the preciding claims 39 to 42, characterized in that weight evolution and unit activation is carried out.

44. A method according to one or more of the preceding claims 39 to 43 characterized in that it is carried out by means of an artificial neural network according to claims 1 to 19 eventually implemented as an algorithm according to claims 20 to 38.

45 A method according to one or more of claims 39 to 44, characterised in that it is a method for image pattern recognition in which the image is a digital image or an analogical image which has been digitalized, the array of image data being formed by a finite number of points or cells each one corresponding to an image unitary element so called pixel or voxel and each one pixel or voxel being related to a value of a parametric variable describing the intensity or the level of grey of the pixels in a grey scale image or each pixel or voxel being related to a vector each

component of the said vector being a parametric variable describing the intensity of the pixel or voxel and the colour of the pixel or voxel, characterised in that the said array of image data is subjected to processing with an artificial neural network according to one or more of the preceding claims 1 to 19, being the cells or points of the data records of gradient 1 formed by the pixels or voxels directly surrounding a target pixel or voxel, the said algorithm being applied a certain number of times for carrying out a certain number of repetitions of the computation cycle, which number is a fixed defined number, or is computed on the basis of a variance or difference of the output values for the pixels at a certain repetition of the computation cycle and of the original values of the image data array, or which number of repetitions of the computation cycle is determined as the number of repetition at which the following computation cycles furnishes an output for the image data array which difference from the output for the image data array of the previous computation cycle is less than a certain predetermined difference.

46. A method for image pattern recognition according to claim 45, in which the artificial neural network is implemented as an algorithm according to claims 20 to 39.

47 A method according to claim 46, charaterised in that the algorithm according to claims 20 to 39 is applied two times in succession one of the other at each time being used a different set of learning rules or functions or a different set of activation rules or functions or a different combination thereof.

48. A method for image pattern recognition according to one or more of the preceding claims 45 to 47, characterised in that the algorithm according to claims 20 to 39 is applied in combination with a predictive algorithm learned for recognising features of different zones of an imaged subject.

49. A method according to one or more of the preceding claims 45 to 47 wherein the predictive algorithm is an artificial neural network and the learning and testing database is formed by a set of images of identical subjects, the different imaged zones of the said image subject being univoquely identified for each image of the training and testing database, while the prediction algorithm is carried out on the image data array obtained as an output of the elaboration carried out with the algorithm according to one or more of claims 20 to 39.

50. The method according to claim 49, in which the prediction algorithm is carried out also using the original image data array as an input data while the prediction results obtained by the carrying out of the prediction algorithm on the image data array computed with the algorithm according to one or more of the preceding claims 20 to 39 and the prediction results obtained carrying out the prediction algorithm on the original image data array are combined or compared.

51. A method for carrying out contrast imaging or harmonic imaging in biological tissues without providing the presence of contrast media, characterised in that an ultrasound or MRI or radiographic image of a certain body or of a certain part of a body is acquired and the acquired image data array is subjected to a method according to one or more of the preceding claims

39 to 50 using a neural network according to one or more of the preceding claims 1 to 19 eventually implemented as an algorithm according to one or more of the preceding claims 20 to 39.

52. A method according to claim 51, characterized in that the neural network according to claims 1 to 4 is provided with a set of rules according to claim 5 eventually implemented as an algorithm according to one or more of the preceding claims 20 to 27 in combination with at least a set of learning rules according to claim 28.

53. A method according to claim 52, characterised in that the neural network neural network according to claims 1 to 4 is provided with a combination of rules according to claim 5 with a set of rules according to one of the claims 6 to 19 and eventually being the said neural network implemented as an algorithm according to one or more of the preceding claims 20 to 27 in combination with a set of learning rules or functions according to claim 28 and with a set of learning rules or functions according to one of the claims 29 to 17.

54 A method according to claim 52, characterised in that it uses a set of learning and or activation rules according to one or more of the preceding claims 28 to 38.

55. A method according to claim 54, characterised in that at least two image elaboration stages are provided the first elaboration stage being carried out with one set of learning and /or activation rules while the second elaboration stage is carried out by submitting the pixel values of the output image elaborated in the first stage to a second elaboration with a second set of learning and/or activation rules.

56 A method according to claims 54 or 55, characterised in that at least a third or more elaboration stages are provided each one carried out with a different set of learning and/or activation rules.

57 A method according to one or more of the claims 54 to 56, characterised in that the learning and/or activation rules are according to claims 5 to 19 or 27 to 38.

58. A method for helping in identifying tumoral tissues characterised in that it provides the steps of

acquiring a digital image or a digitalized analogical image of the anatomical district containing the tumoral tissues;

elaborating the said digital or digitalize image by means of the method according to one or more of the preceding claims 39 to 57.

59. A method for helping in identifying stenosis in blood vessels characterised in that it provides the steps of

acquiring a digital image or a digitalized analogical image of the anatomical district containing the tumoral tissue;

elaborating the said digital or digitalize image by means of the method according to one or more of the preceding claims 39 to 57.

60. A method for helping in identifying calcifications in biological tissues characterised in that it provides the steps of

acquiring a digital image or a digitalized analogical image of the anatomical district containing the tumoral tissue;

elaborating the said digital or digitalize image by means of the method according to one or more of the preceding claims 39 to 57.

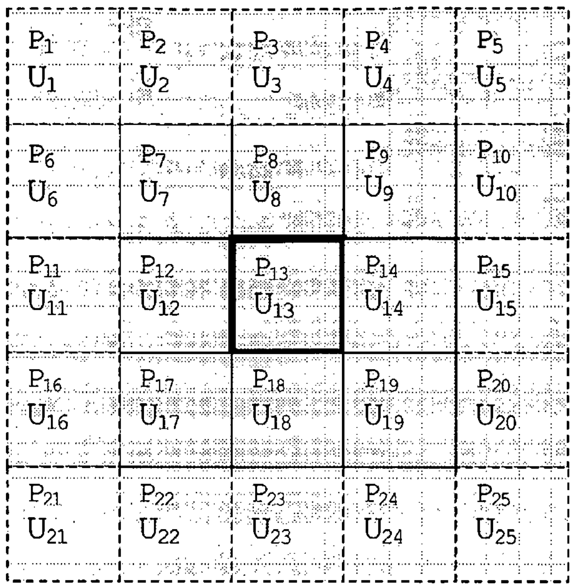
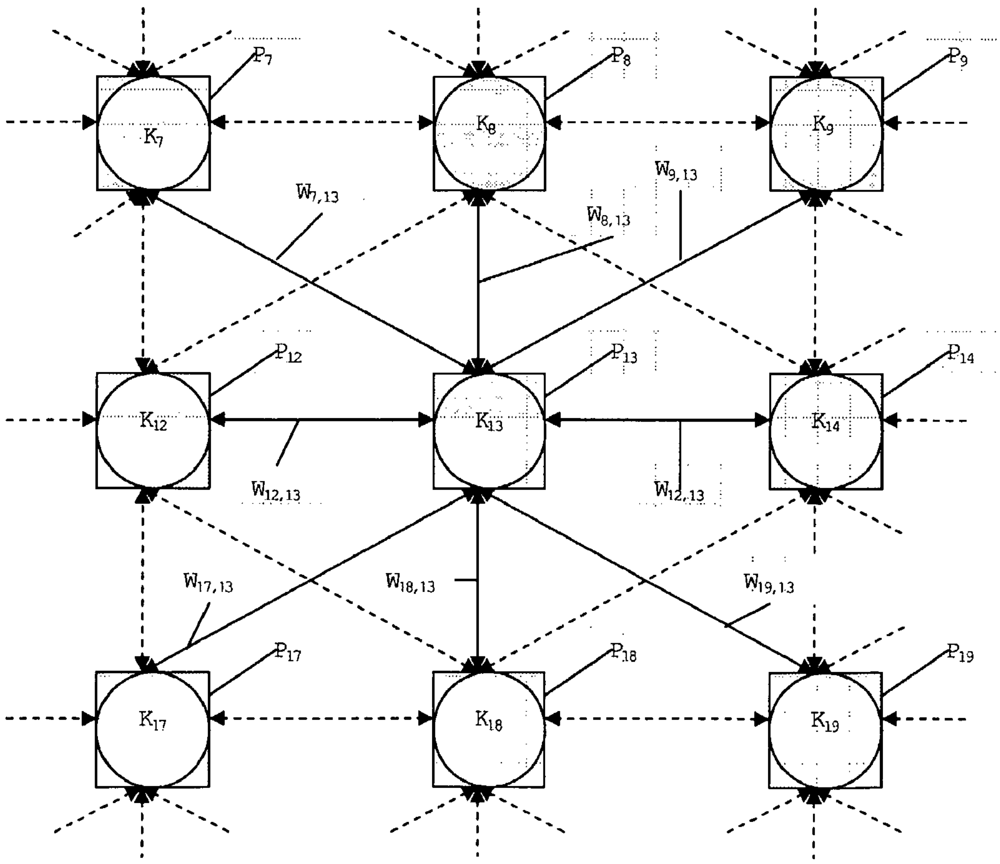

P1 U1
P2 U2
P3 U3
P4 U4
P5 U5
P6 U6
P7 U7
P8 U8
P9 U9
P10 U10
P11 U11
P12 U12
P13 U13
P14 U14
P15 U15
P16 U16
P17 U17
P18 U18
P19 U19
P20 U20
P21 U21
P22 U22
P23 U23
P24 U24
P25 U25

Fig.1


P7
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K18
K19

Fig. 2

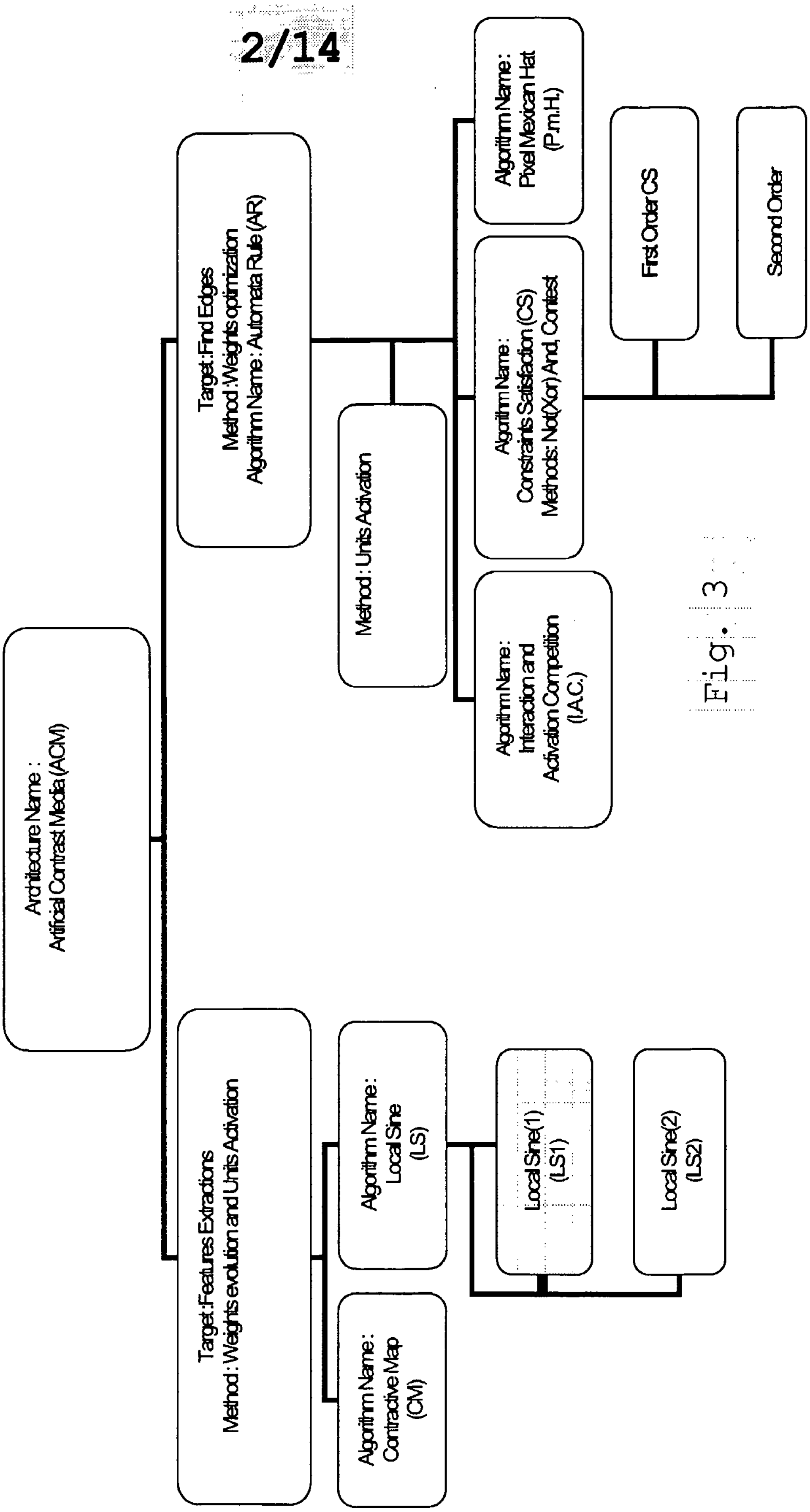

Architecture Name :
Artificial Contrast Media (ACM)
Target : Features Extractions
Method : Weights evolution and Units Activation
Algorithm Name :
Contractive Map
(CM)
Algorithm Name :
Local Sine
(LS)
Local Sine(1)
(LS1)
Local Sine(2)
(LS2)
Target : Find Edges
Method : Weights optimization
Algorithm Name : Automata Rule (AR)
Method : Units Activation
Algorithm Name :
Interaction and
Activation Competition
(I.A.C.)
Algorithm Name :
Constraints Satisfaction (CS)
Methods: Not(Xor) And, Contest
First Order CS
Second Order
Algorithm Name :
Pixel Mexican Hat
(P.m.H.)

Fig. 3

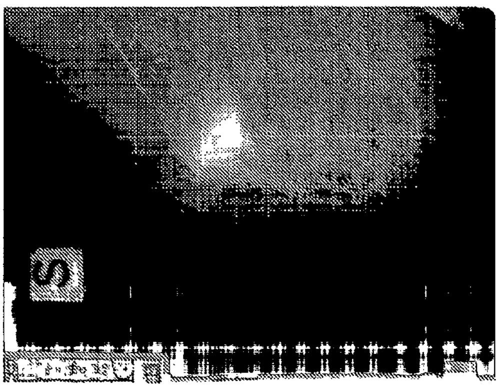


Fig. 4A

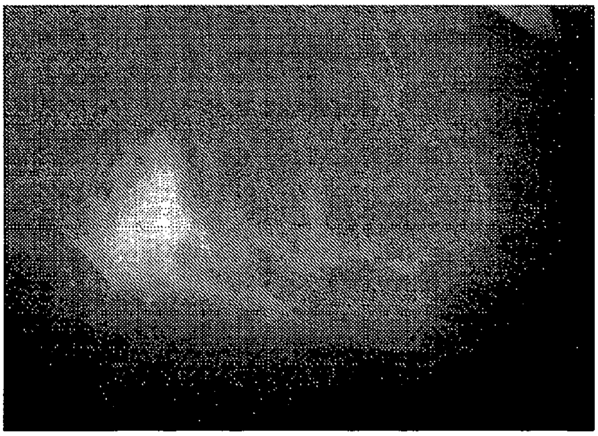
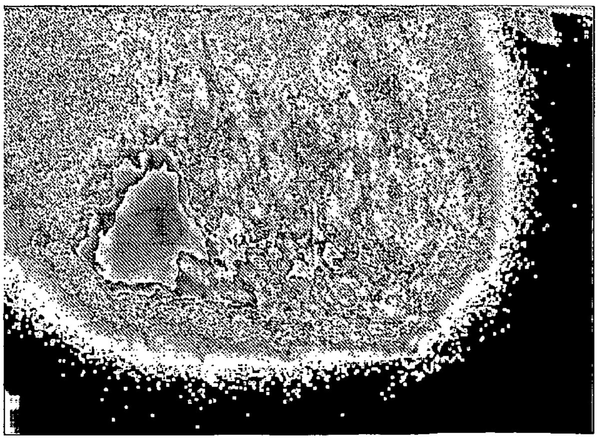


Fig. 4B
Reduction about 80%



CM
Fig. 4C

IAC with
Ar on Cm
Fig. 4D

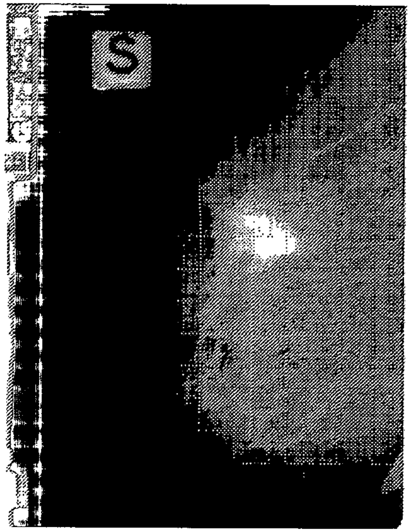


Fig. 5A

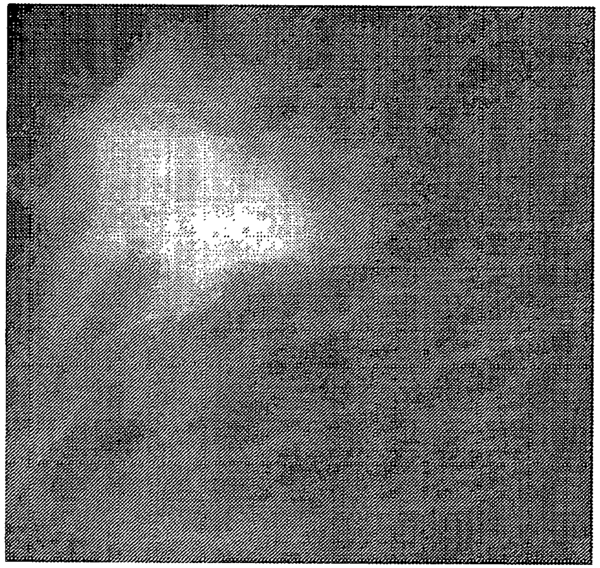
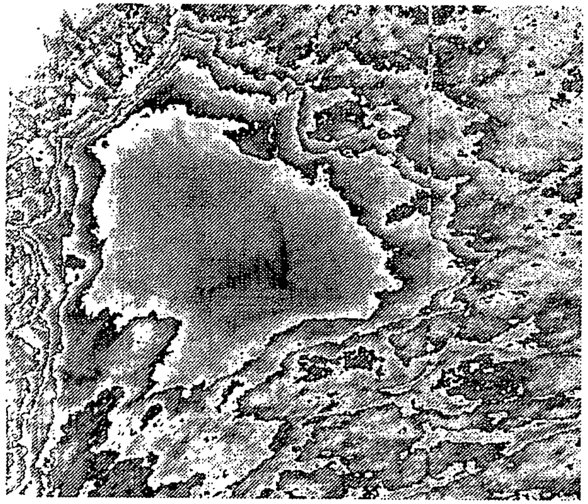
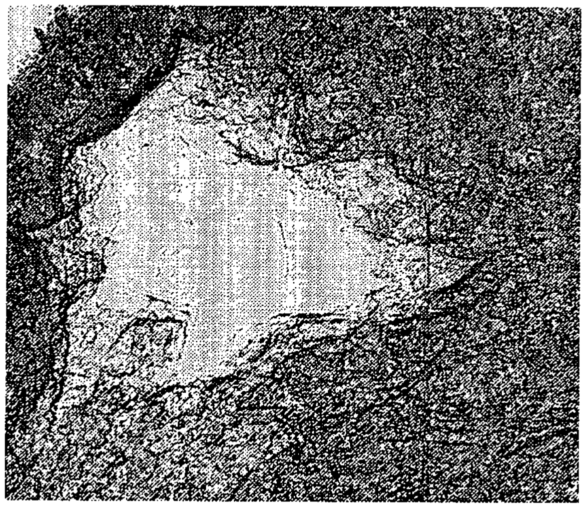


Fig. 5B
Zooming



CM
Fig. 5C

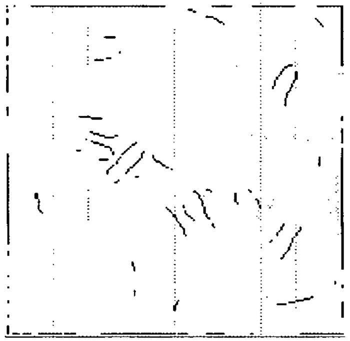


IAC with
Ar on Cm

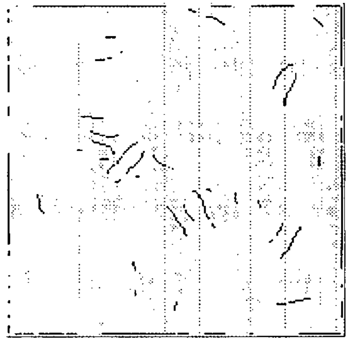
Fig. 5D

Bacteria Image

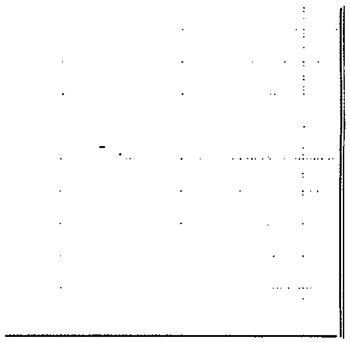
Original
Fig. 6A



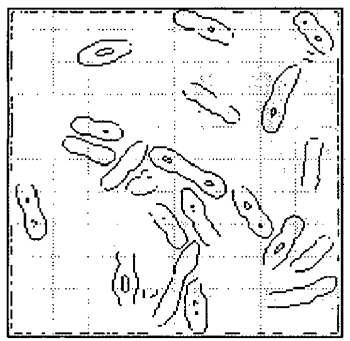
Sobel
Fig. 6B



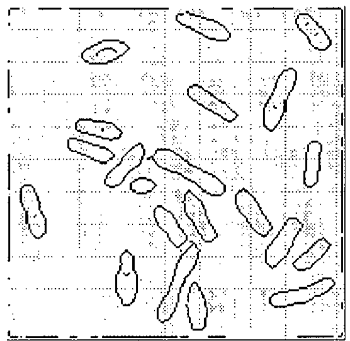
Prewitt
Fig. 6C



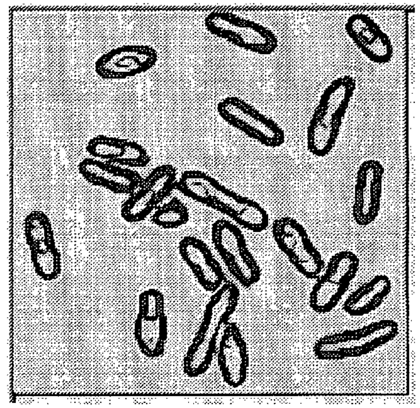
Roberts
Fig. 6 D



LoG
Fig. 6E

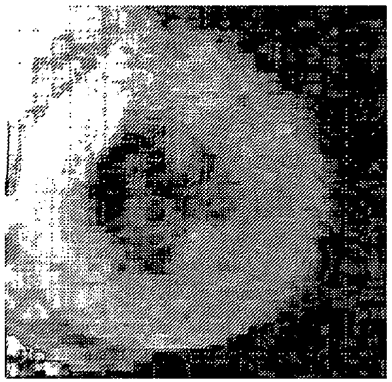


Canny
Fig. 6F

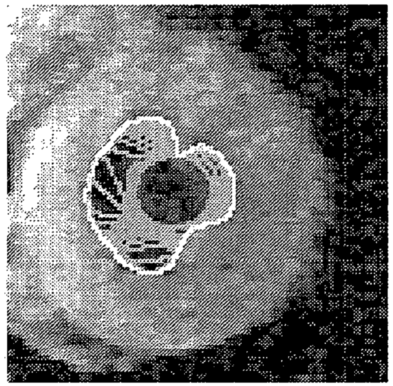


CM
Fig. 6G

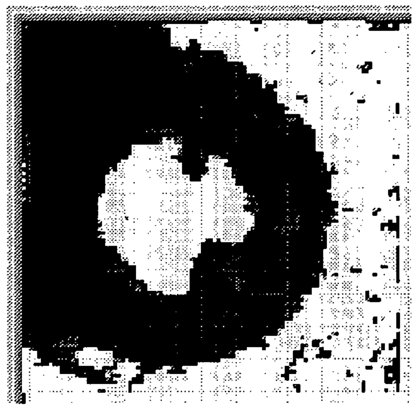
Ventricle



Original
Fig. 7A

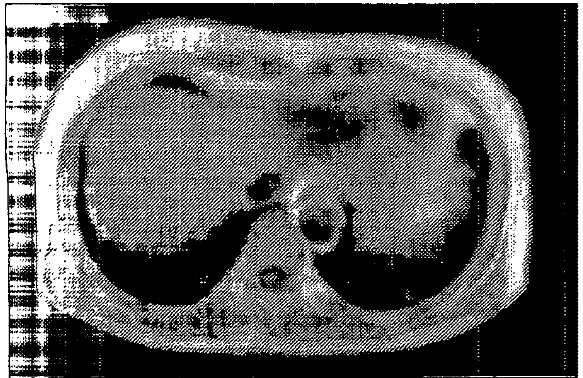


Snake
Fig. 7B



ACM
Fig. 7C

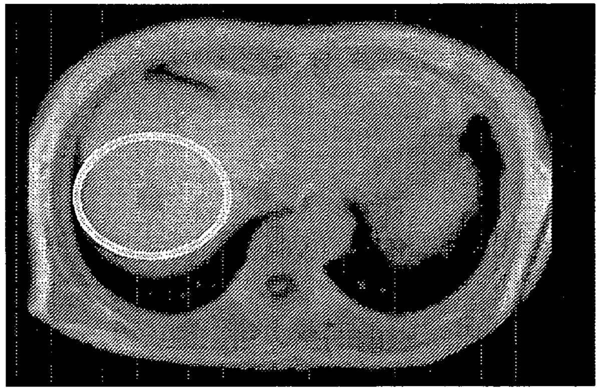
DYNAMIC IMAGING OF METASTASES



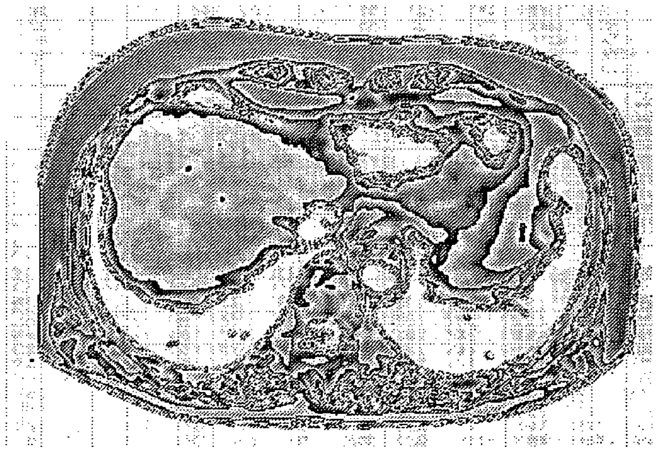
Precontrast
Fig. 8A

Arterial phase
Fig. 8B

Balance Phase
Fig. 8C



Late phase Fig. 8D



Precontrast - CM
Fig. 8E

Lung

Original

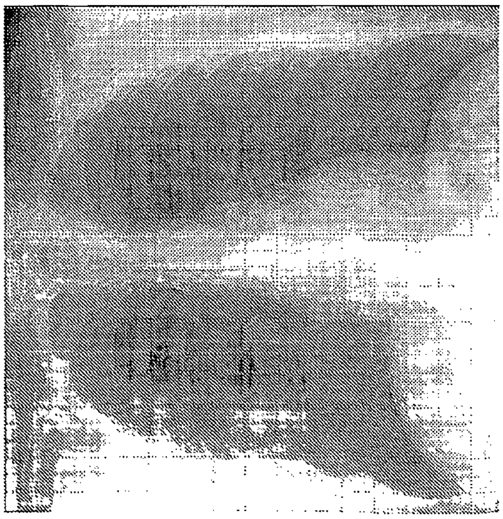


Fig. 9A

Best Filter

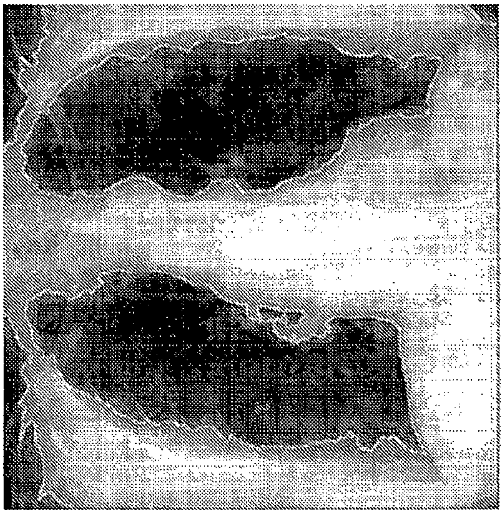


Fig. 9C

CM

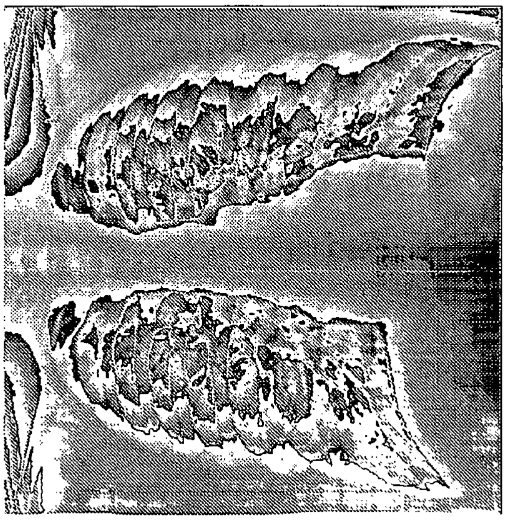


Fig. 9B

ACM (Iac con Cm)

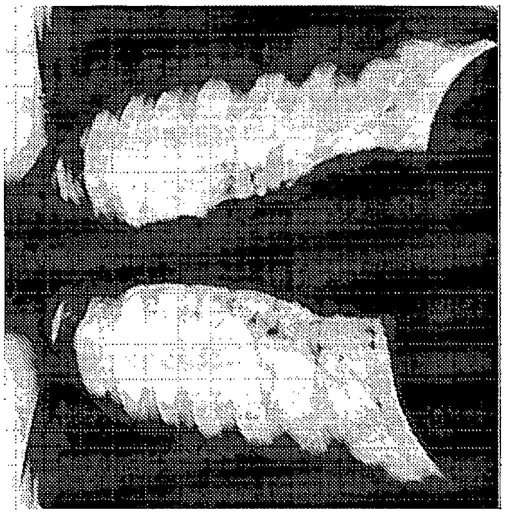


Fig. 9D

Mam1 (High CS)

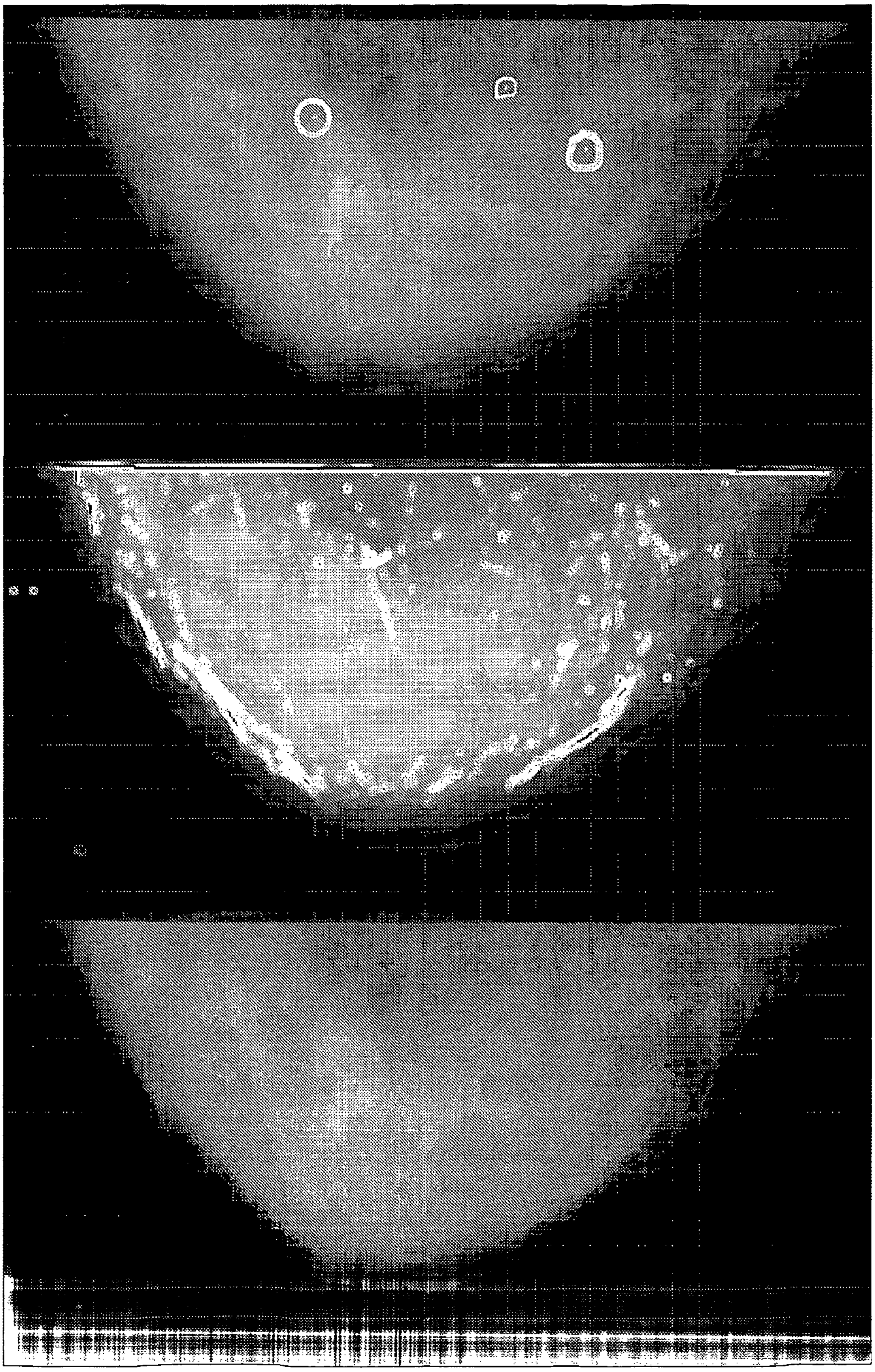
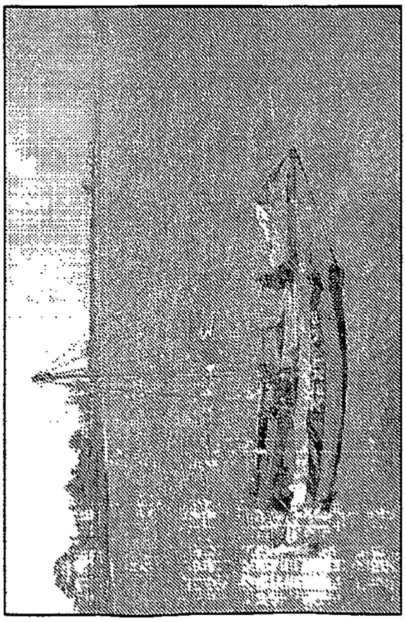


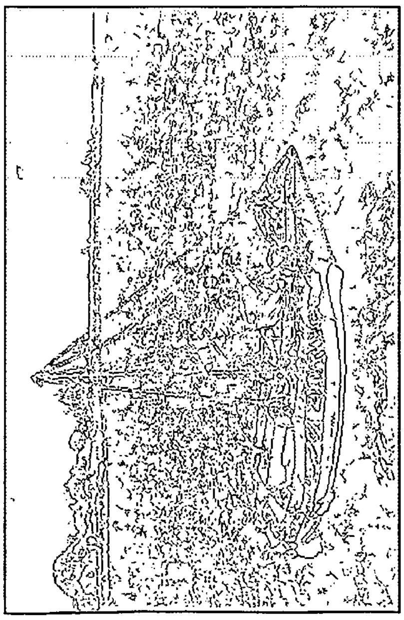
Fig. 10A

Fig. 10B

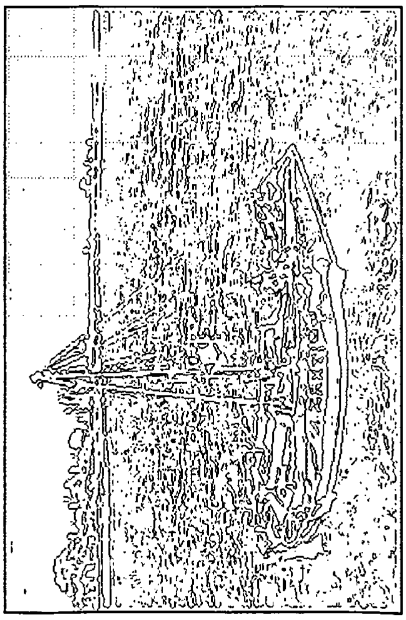
Fig. 10C



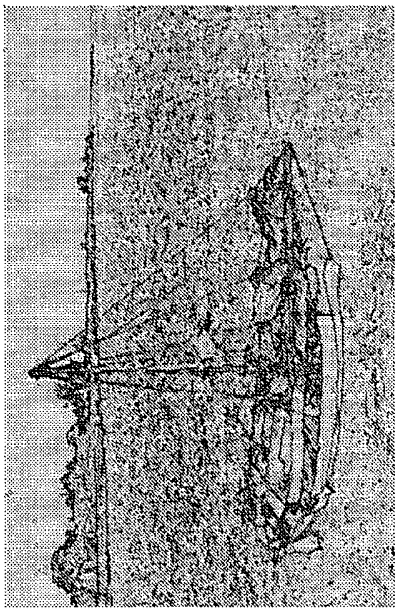
Original
Fig. 11A



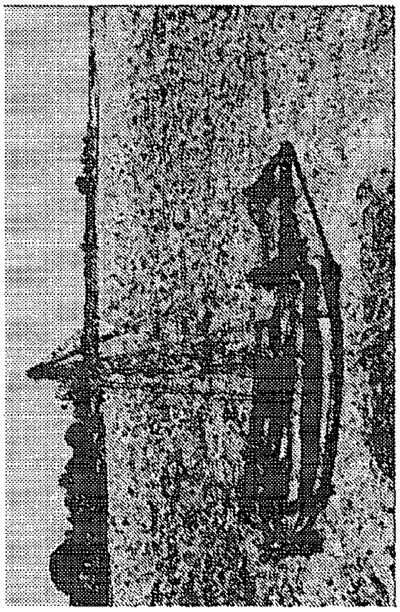
Canny
Fig. 11B



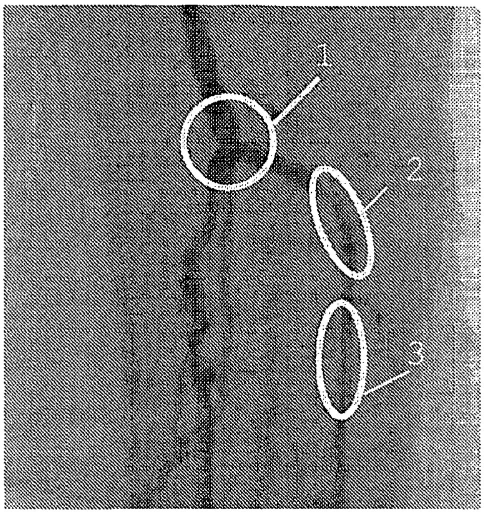
Log
Fig. 11C



IAC
Fig. 11D

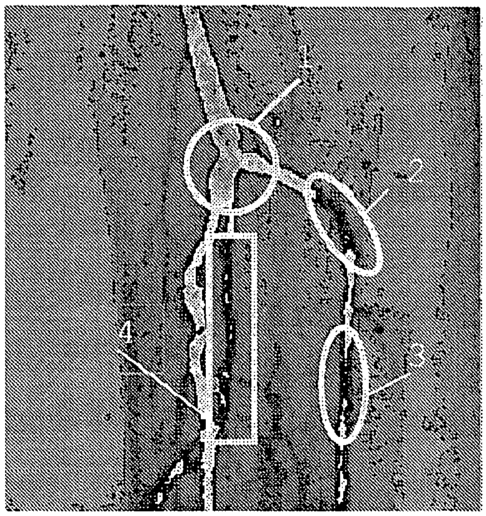


IAC on Cm
Fig. 11E



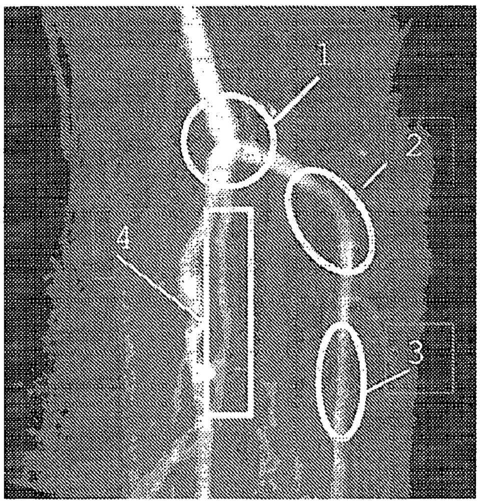
SOURCE

Fig. 12A



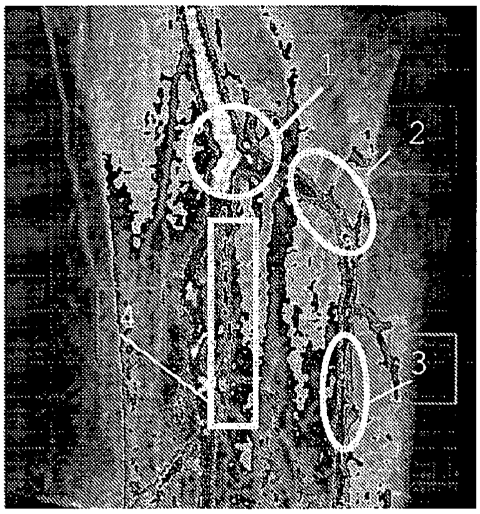
CM Rem

Fig. 12B



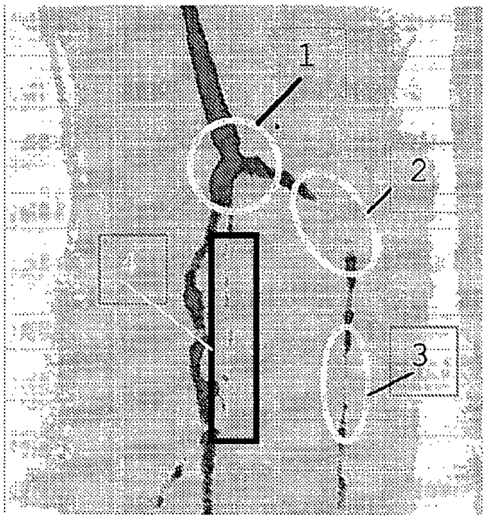
CM Quot

Fig. 12C



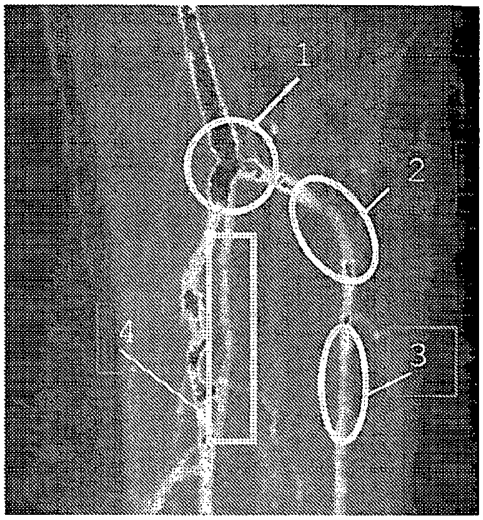
CM Quot + Rem

Fig. 12D



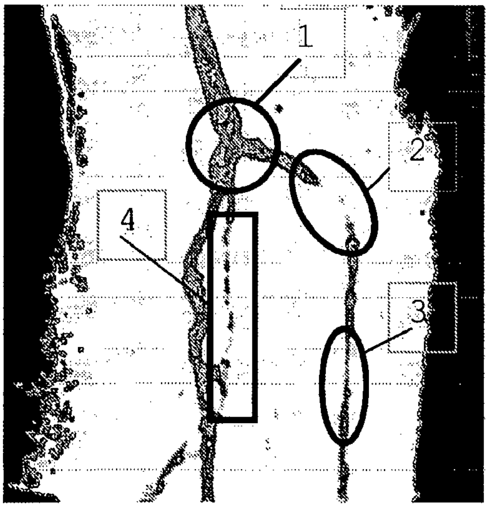
CM True Color

Fig. 12E



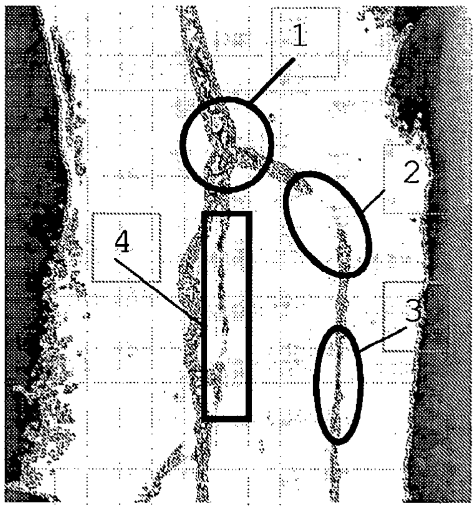
LS1

Fig. 12F



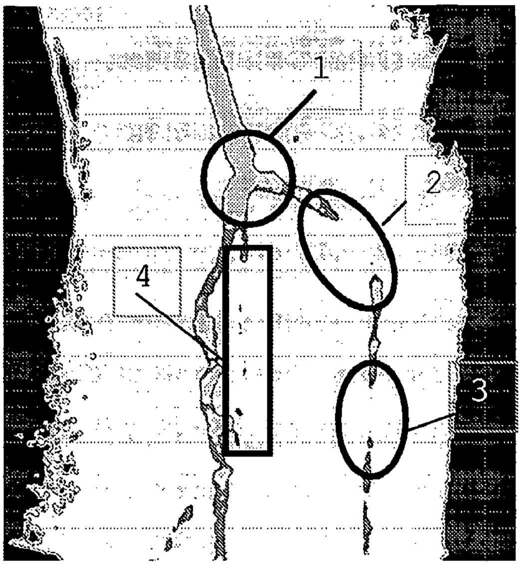
CM Rem + Quot on LS2

Fig. 12G



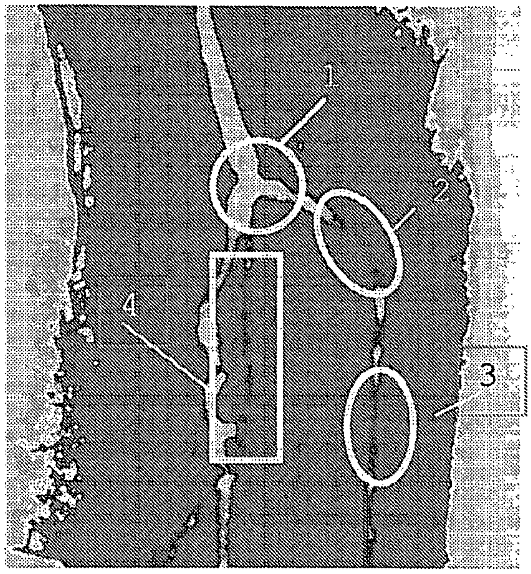
CM Rem on LS2

Fig. 12H



CM Quot on LS2

Fig. 12I



CM True Color on LS2

Fig. 12J

14/14

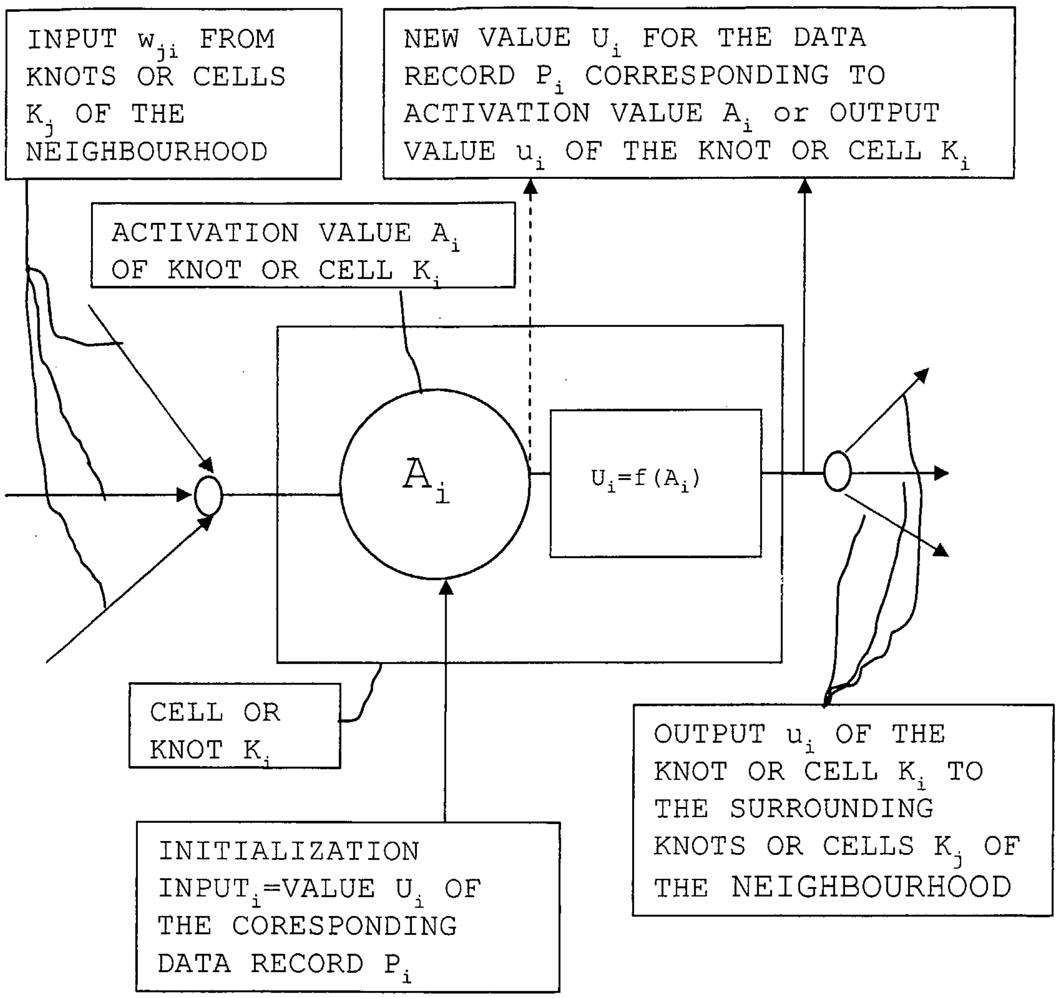

INPUT w_{ji} FROM KNOTS OR CELLS K_j OF THE NEIGHBOURHOOD
NEW VALUE U_i FOR THE DATA RECORD P_i CORRESPONDING TO ACTIVATION VALUE A_i or OUTPUT VALUE u_i OF THE KNOT OR CELL K_i
ACTIVATION VALUE A_i OF KNOT OR CELL K_i
A_i
$U_i=f(A_i)$
CELL OR KNOT K_i
OUTPUT u_i OF THE KNOT OR CELL K_i TO THE SURROUNDING KNOTS OR CELLS K_j OF THE NEIGHBOURHOOD
INITIALIZATION INPUT$_i$=VALUE U_i OF THE CORESPONDING DATA RECORD P_i

Fig. 13

INTERNATIONAL SEARCH REPORT

International Application No
PCT/EP2004/051821

A. CLASSIFICATION OF SUBJECT MATTER
IPC 7 G06K9/66 G06N3/04 G06T5/00

According to International Patent Classification (IPC) or to both national classification and IPC

B. FIELDS SEARCHED

Minimum documentation searched (classification system followed by classification symbols)
IPC 7 G06K G06N G06T

Documentation searched other than minimum documentation to the extent that such documents are included in the fields searched

Electronic data base consulted during the international search (name of data base and, where practical, search terms used)

EPO-Internal, INSPEC

C. DOCUMENTS CONSIDERED TO BE RELEVANT

Category °	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
X	CHUA L O ET AL: "CELLULAR NEURAL NETWORKS: APPLICATIONS" IEEE TRANSACTIONS ON CIRCUITS AND SYSTEMS, IEEE INC. NEW YORK, US, vol. 35, no. 10, 1 October 1988 (1988-10-01), pages 1273-1290, XP000119052	20,39,40
Y	* the whole document, in particular sections III and IV *	41-43
A		1-19, 21-38, 44-60
X	US 5 140 670 A (CHUA LEON O ET AL) 18 August 1992 (1992-08-18) abstract column 13, line 40 - line 56	20,39,40

-/--

[X] Further documents are listed in the continuation of box C.

[X] Patent family members are listed in annex.

° Special categories of cited documents :

"A" document defining the general state of the art which is not considered to be of particular relevance

"E" earlier document but published on or after the international filing date

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"O" document referring to an oral disclosure, use, exhibition or other means

"P" document published prior to the international filing date but later than the priority date claimed

"T" later document published after the international filing date or priority date and not in conflict with the application but cited to understand the principle or theory underlying the invention

"X" document of particular relevance; the claimed invention cannot be considered novel or cannot be considered to involve an inventive step when the document is taken alone

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"&" document member of the same patent family

Date of the actual completion of the international search	Date of mailing of the international search report
21 October 2004	05/11/2004

Name and mailing address of the ISA	Authorized officer
European Patent Office, P.B. 5818 Patentlaan 2 NL – 2280 HV Rijswijk Tel. (+31-70) 340-2040, Tx. 31 651 epo nl, Fax: (+31-70) 340-3016	Kessler, C

C.(Continuation) DOCUMENTS CONSIDERED TO BE RELEVANT

Category °	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
Y	GUZELIS C ET AL: "Recurrent perceptron learning algorithm for completely stable cellular neural networks" CELLULAR NEURAL NETWORKS AND THEIR APPLICATIONS, 1994. CNNA-94., PROCEEDINGS OF THE THIRD IEEE INTERNATIONAL WORKSHOP ON ROME, ITALY 18-21 DEC. 1994, NEW YORK, NY, USA,IEEE, 18 December 1994 (1994-12-18), pages 177-182, XP010131320 ISBN: 0-7803-2070-0	41-43
A	the whole document	1-40, 44-60
A	WEICKERT J: "FOUNDATIONS AND APPLICATIONS OF NONLINEAR ANISOTROPIC DIFFUSION FILTERING" ZEITSCHRIFT FUER ANGEWANDTE MATHEMATIK UND MECHANIK, VDI VERLAG, BERLIN, DE, vol. 76, no. 1, 3 July 1995 (1995-07-03), pages 283-286, XP008024946 ISSN: 0044-2267 the whole document	1-60
A	SAHOTA P ET AL: "Training genetically evolving cellular automata for image processing" SPEECH, IMAGE PROCESSING AND NEURAL NETWORKS, 1994. PROCEEDINGS, ISSIPNN '94., 1994 INTERNATIONAL SYMPOSIUM ON HONG KONG 13-16 APRIL 1994, NEW YORK, NY, USA,IEEE, 13 April 1994 (1994-04-13), pages 753-756, XP010121398 ISBN: 0-7803-1865-X the whole document	41-43
A	L. DIAPPI, M. BUSCEMA ET AL.: "The urban sprawl dynamics: does a Neural Network understand the spatial logic better than a Cellular Automata?" 42ND ERSA CONGRESS, 'Online! 27 August 2002 (2002-08-27), - 31 August 2002 (2002-08-31) pages 1-20, XP002267589 Dortmund Retrieved from the Internet: URL:http://www.raumplanung.uni-dortmund.de/rwp/ersa2002/cd-rom/papers/033.pdf> 'retrieved on 2004-01-21! * The whole document, in particular page 12, table 1, learning law "Cm" *	1-60

INTERNATIONAL SEARCH REPORT

Information on patent family members

International Application No
PCT/EP2004/051821

Patent document cited in search report		Publication date	Patent family member(s)	Publication date
US 5140670	A	18-08-1992	NONE	

Form PCT/ISA/210 (patent family annex) (January 2004)