US009390373B2

(12) **United States Patent**
Pescianschi

(10) **Patent No.: US 9,390,373 B2**
(45) **Date of Patent: Jul. 12, 2016**

(54) **NEURAL NETWORK AND METHOD OF NEURAL NETWORK TRAINING**

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(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 0 days.

(21) Appl. No.: **14/862,337**

(22) Filed: **Sep. 23, 2015**

(65) **Prior Publication Data**

US 2016/0012330 A1 Jan. 14, 2016

Related U.S. Application Data

(63) Continuation of application No. PCT/US2015/019236, filed on Mar. 6, 2015.

(60) Provisional application No. 61/949,210, filed on Mar. 6, 2014, provisional application No. 62/106,389, filed on Jan. 22, 2015.

(51) **Int. Cl.**
G06N 3/08 (2006.01)
G06N 3/04 (2006.01)

(52) **U.S. Cl.**
CPC .. ***G06N 3/08*** (2013.01); ***G06N 3/04*** (2013.01); ***G06N 3/084*** (2013.01)

(58) **Field of Classification Search**
None
See application file for complete search history.

(56) **References Cited**

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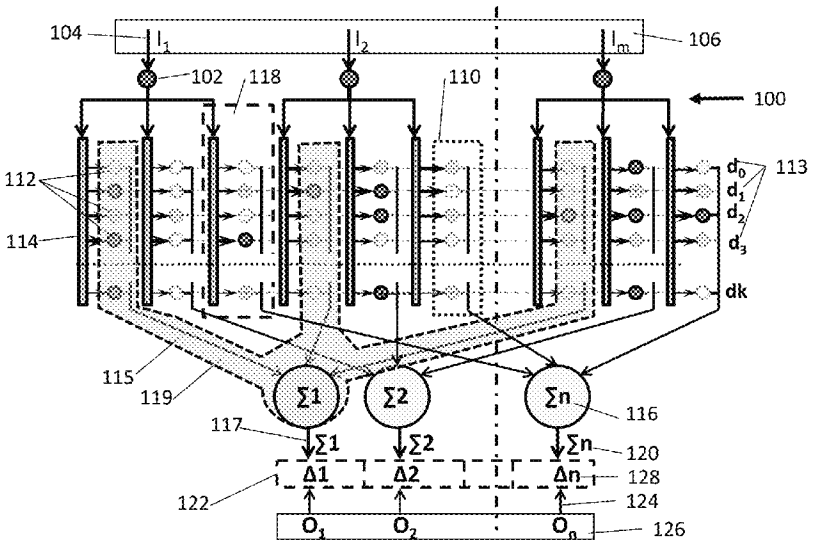
(57) **ABSTRACT**

A neural network includes a plurality of inputs for receiving input signals, and synapses connected to the inputs and having corrective weights. The network additionally includes distributors. Each distributor is connected to one of the inputs for receiving the respective input signal and selects one or more corrective weights in correlation with the input value. The network also includes neurons. Each neuron has an output connected with at least one of the inputs via one synapse and generates a neuron sum by summing corrective weights selected from each synapse connected to the respective neuron. Furthermore, the network includes a weight correction calculator that receives a desired output signal, determines a deviation of the neuron sum from the desired output signal value, and modifies respective corrective weights using the determined deviation. Adding up the modified corrective weights to determine the neuron sum minimizes the subject deviation for training the neural network.

16 Claims, 13 Drawing Sheets



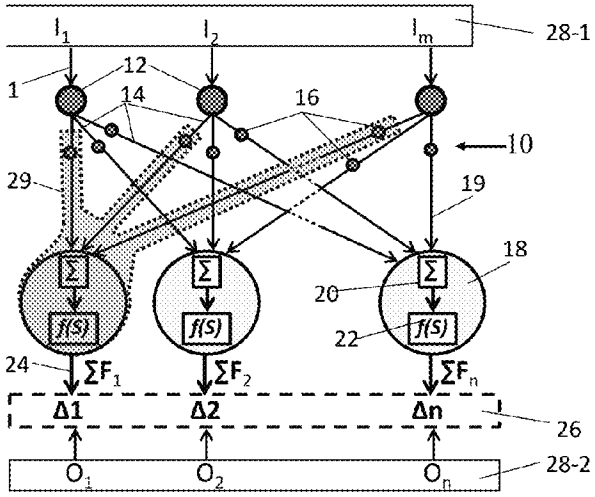


Fig. 1 (Prior Art)

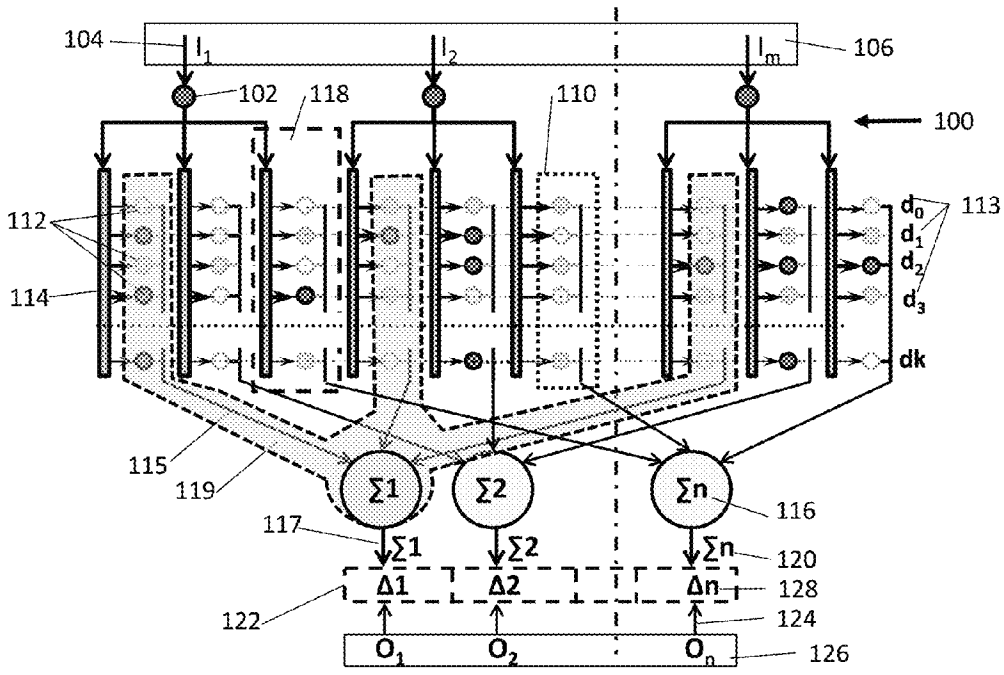


Fig. 2

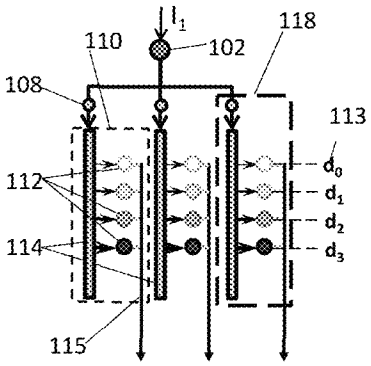


Fig. 3A

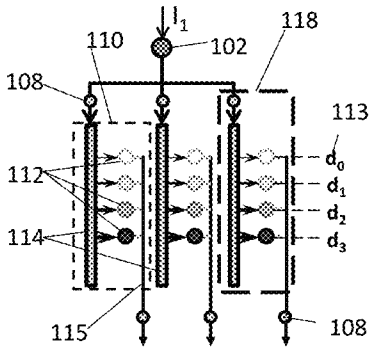


Fig. 3C

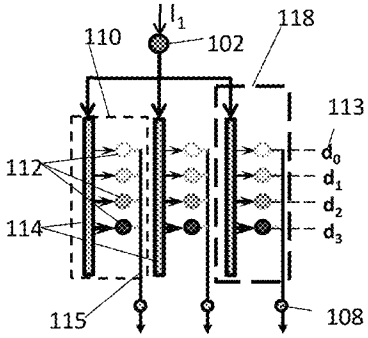


Fig. 3B

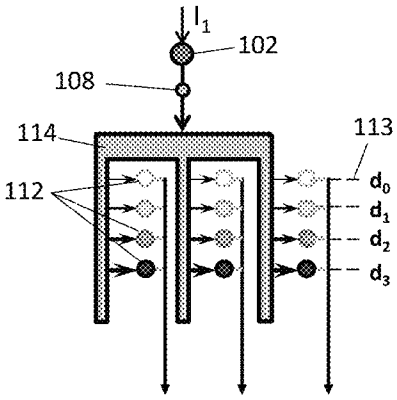


Fig. 4A

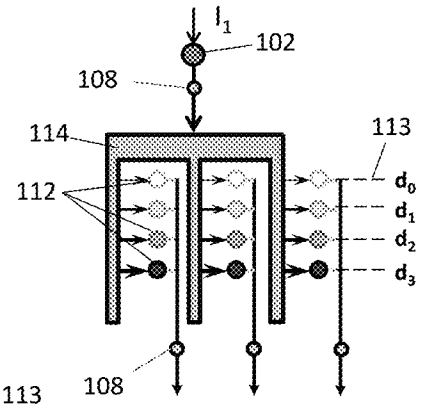


Fig. 4C

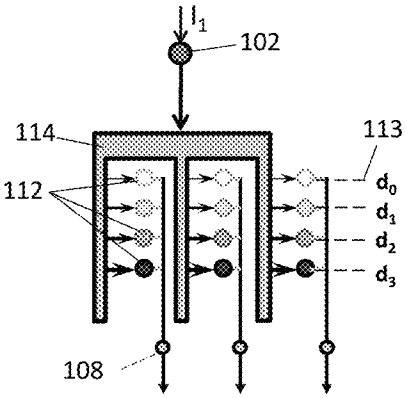


Fig. 4B

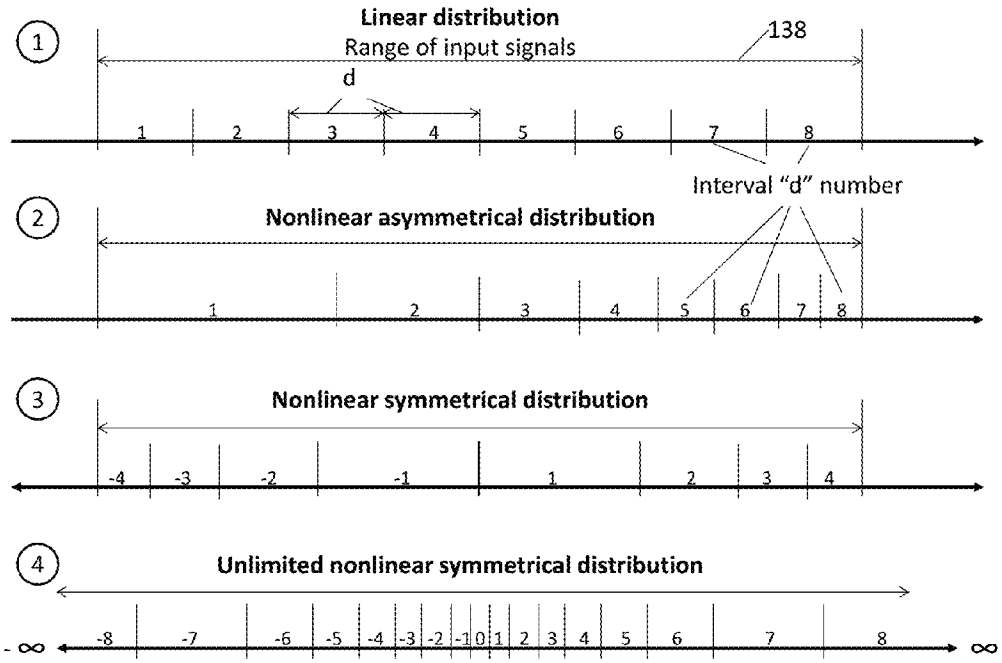


Fig. 5

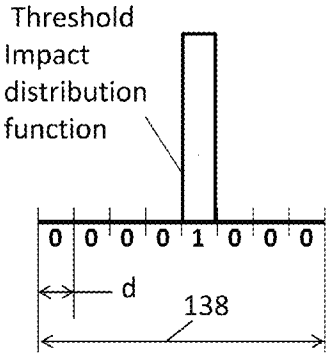


Fig. 6A

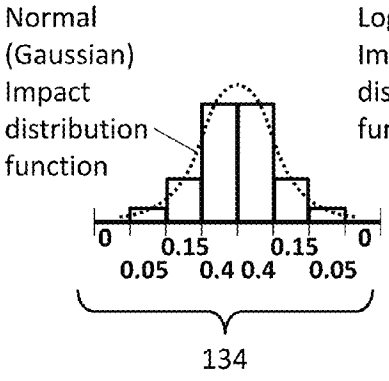


Fig. 6B

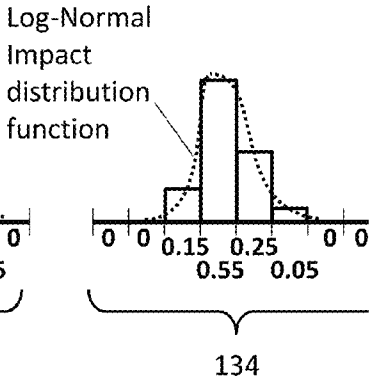


Fig. 6C

Original image

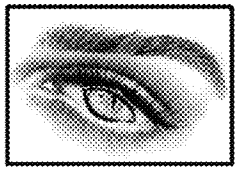


Image in digital codes

127	109	91	82
142	113	85	77
112	125	71	15
101	112	92	5

Image in interval format

12	10	9	8
14	11	8	7
11	12	7	1
10	11	9	0

Fig. 7

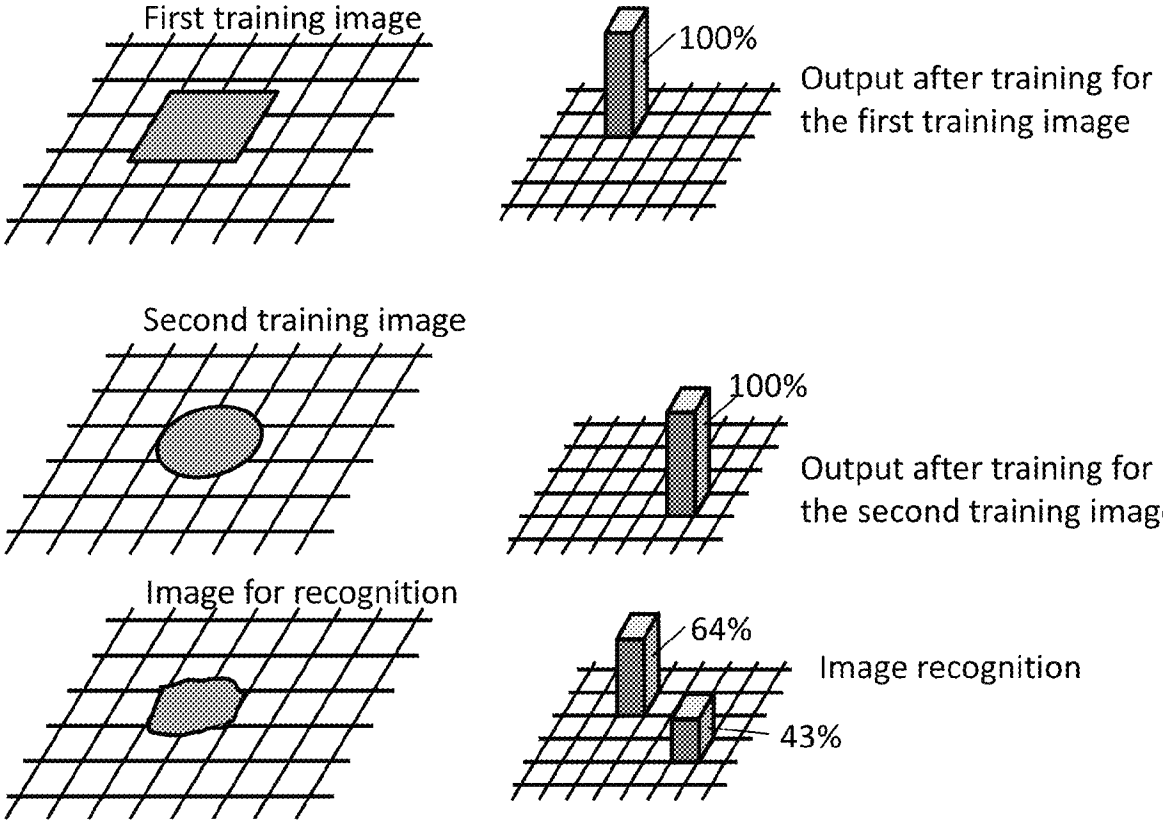


Fig. 8

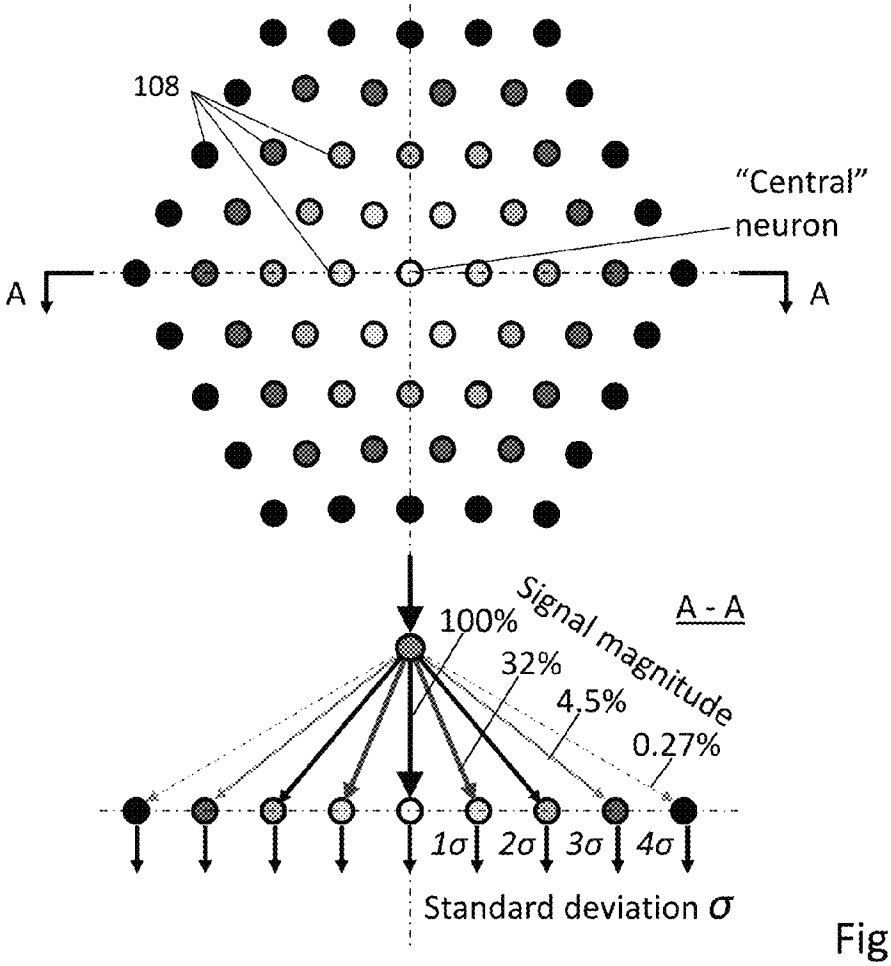

108
"Central" neuron
A
A
A - A
Signal magnitude
100%
32%
4.5%
0.27%
1σ
2σ
3σ
4σ
Standard deviation σ

Fig. 9

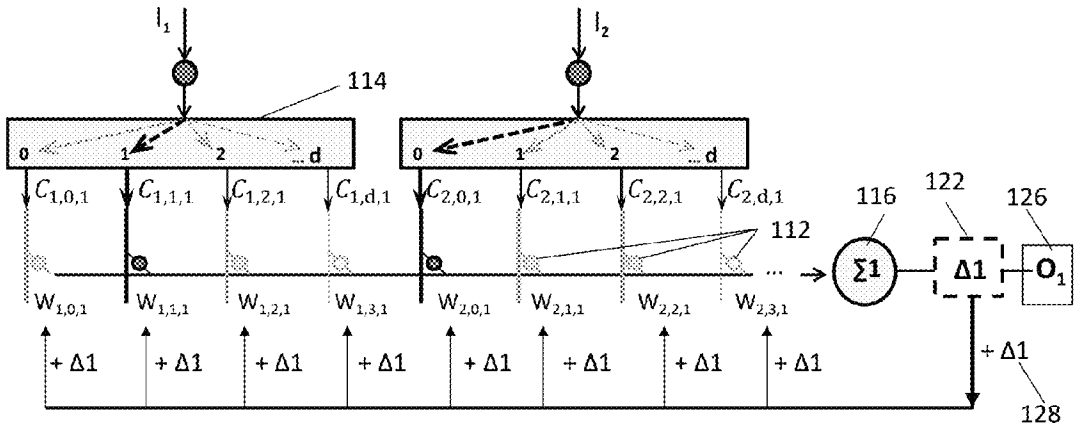

I1
I2
114
0
1
2
...d
C1,0,1
C1,1,1
C1,2,1
C1,d,1
C2,0,1
C2,1,1
C2,2,1
C2,d,1
112
116
122
126
Σ1
Δ1
O1
W1,0,1
W1,1,1
W1,2,1
W1,3,1
W2,0,1
W2,1,1
W2,2,1
W2,3,1
+ Δ1
128

Fig. 10

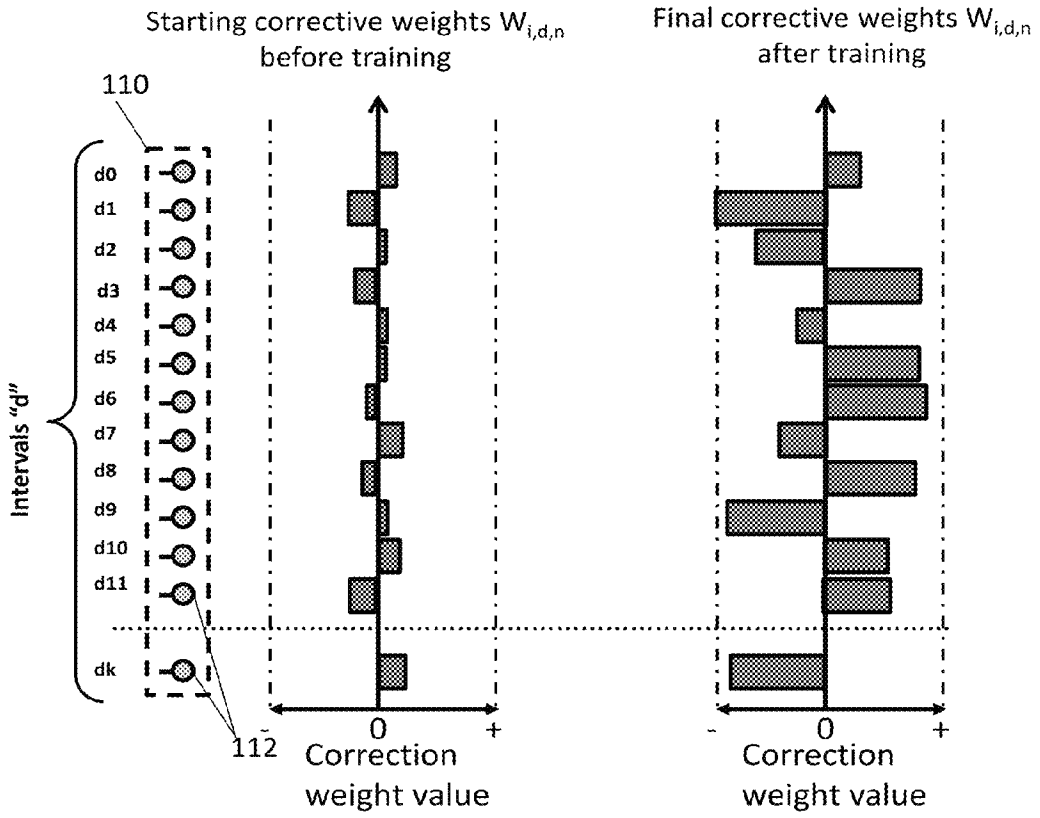

Starting corrective weights $W_{i,d,n}$
before training
Final corrective weights $W_{i,d,n}$
after training
110
d0
d1
d2
d3
d4
d5
d6
d7
d8
d9
d10
d11
dk
Intervals "d"
112
-
0
+
Correction
weight value
-
0
+
Correction
weight value

Fig. 11

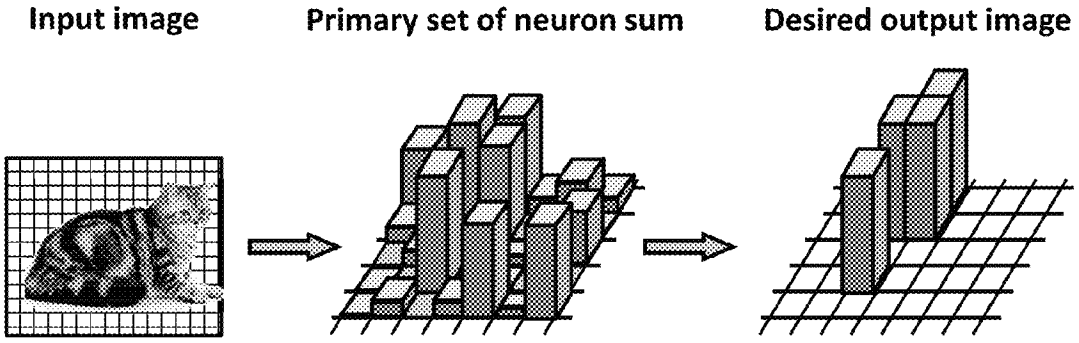

Input image
Primary set of neuron sum
Desired output image

Fig. 12

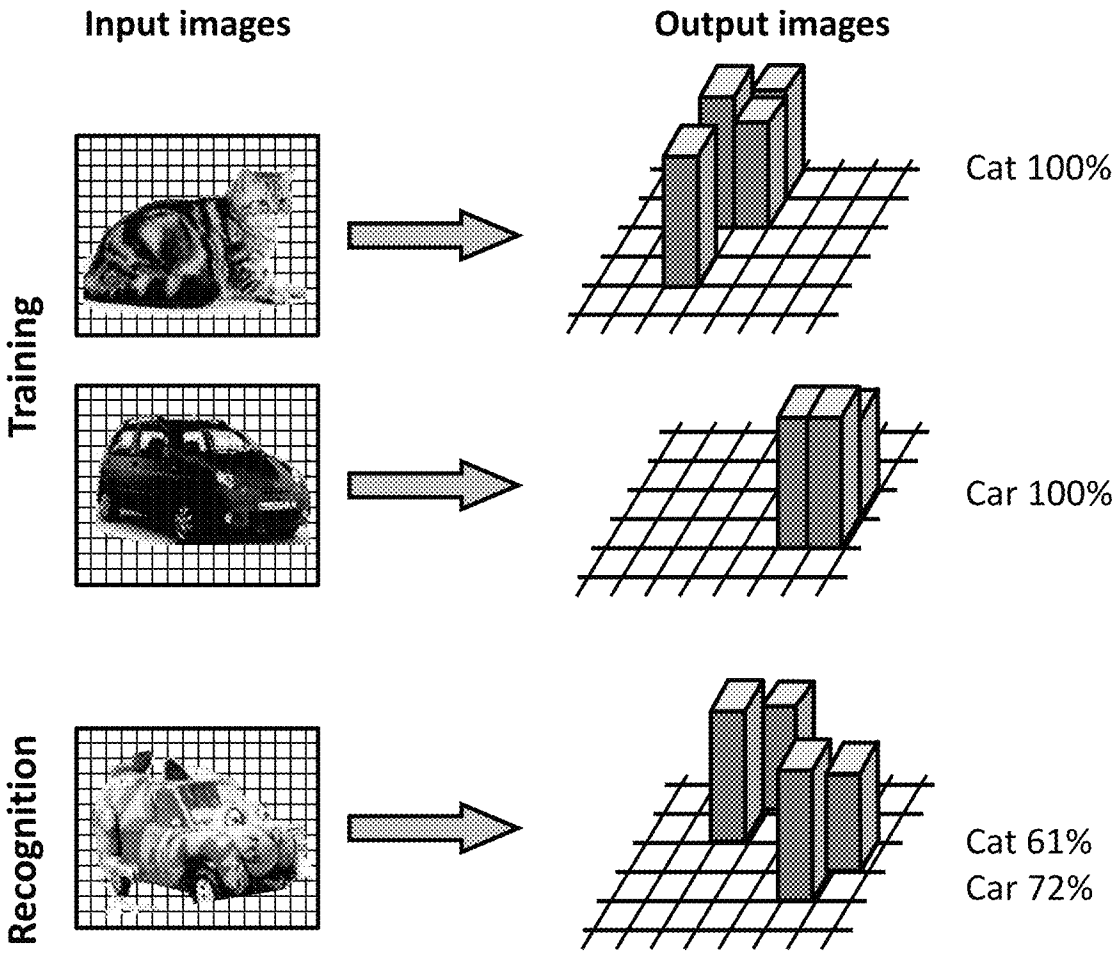

Input images
Output images
Training
Recognition
Cat 100%
Car 100%
Cat 61%
Car 72%

Fig. 13

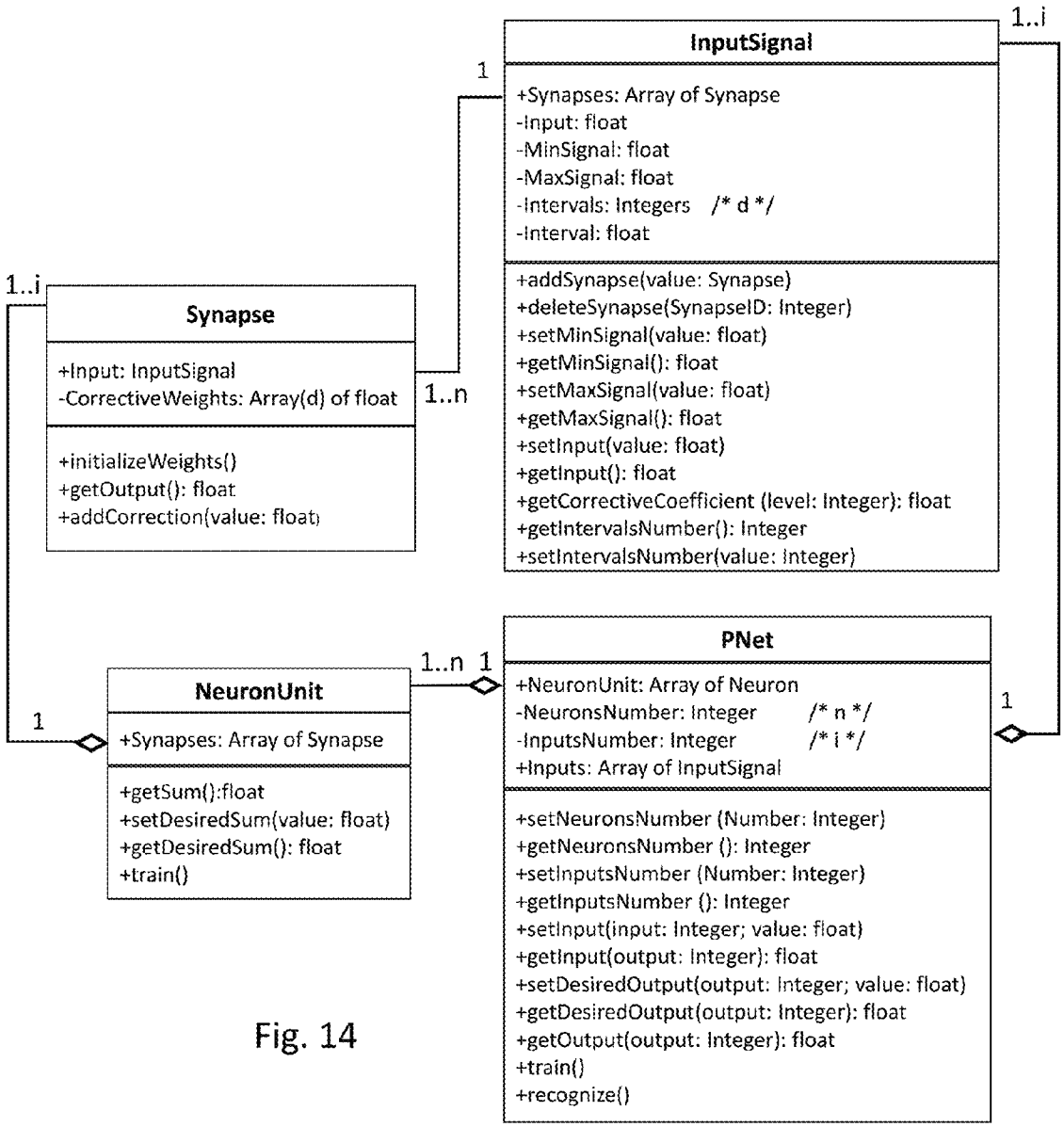

InputSignal
+Synapses: Array of Synapse
-Input: float
-MinSignal: float
-MaxSignal: float
-Intervals: Integers /* d */
-Interval: float
+addSynapse(value: Synapse)
+deleteSynapse(SynapseID: Integer)
+setMinSignal(value: float)
+getMinSignal(): float
+setMaxSignal(value: float)
+getMaxSignal(): float
+setInput(value: float)
+getInput(): float
+getCorrectiveCoefficient (level: Integer): float
+getIntervalsNumber(): Integer
+setIntervalsNumber(value: Integer)
Synapse
+Input: InputSignal
-CorrectiveWeights: Array(d) of float
+initializeWeights()
+getOutput(): float
+addCorrection(value: float)
NeuronUnit
+Synapses: Array of Synapse
+getSum():float
+setDesiredSum(value: float)
+getDesiredSum(): float
+train()
PNet
+NeuronUnit: Array of Neuron
-NeuronsNumber: Integer /* n */
-InputsNumber: Integer /* i */
+Inputs: Array of InputSignal
+setNeuronsNumber (Number: Integer)
+getNeuronsNumber (): Integer
+setInputsNumber (Number: Integer)
+getInputsNumber (): Integer
+setInput(input: Integer; value: float)
+getInput(output: Integer): float
+setDesiredOutput(output: Integer; value: float)
+getDesiredOutput(output: Integer): float
+getOutput(output: Integer): float
+train()
+recognize()
1..i
1
1..n
1..i
1
1..n
1
1

Fig. 14

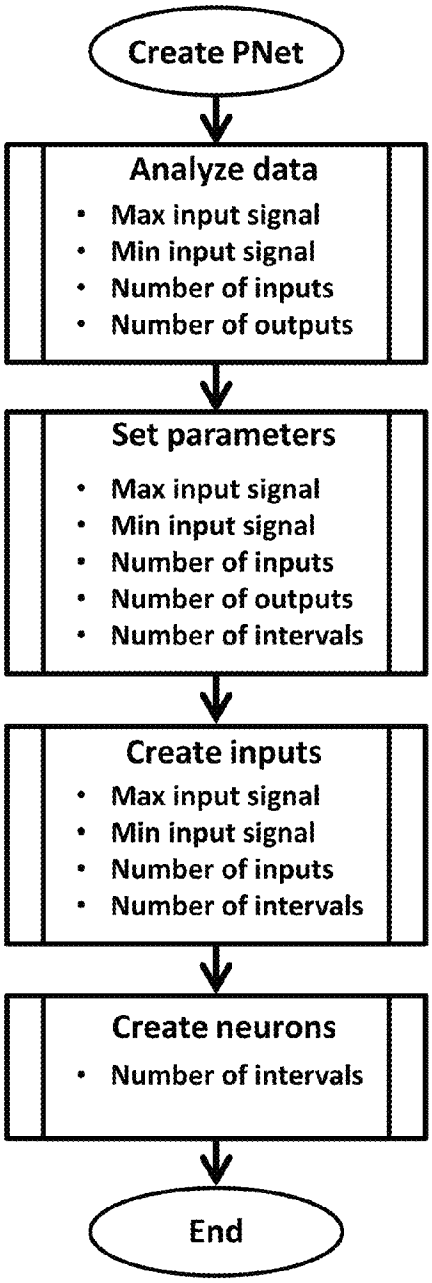

Create PNet
Analyze data
• Max input signal
• Min input signal
• Number of inputs
• Number of outputs
Set parameters
• Max input signal
• Min input signal
• Number of inputs
• Number of outputs
• Number of intervals
Create inputs
• Max input signal
• Min input signal
• Number of inputs
• Number of intervals
Create neurons
• Number of intervals
End

Fig. 15

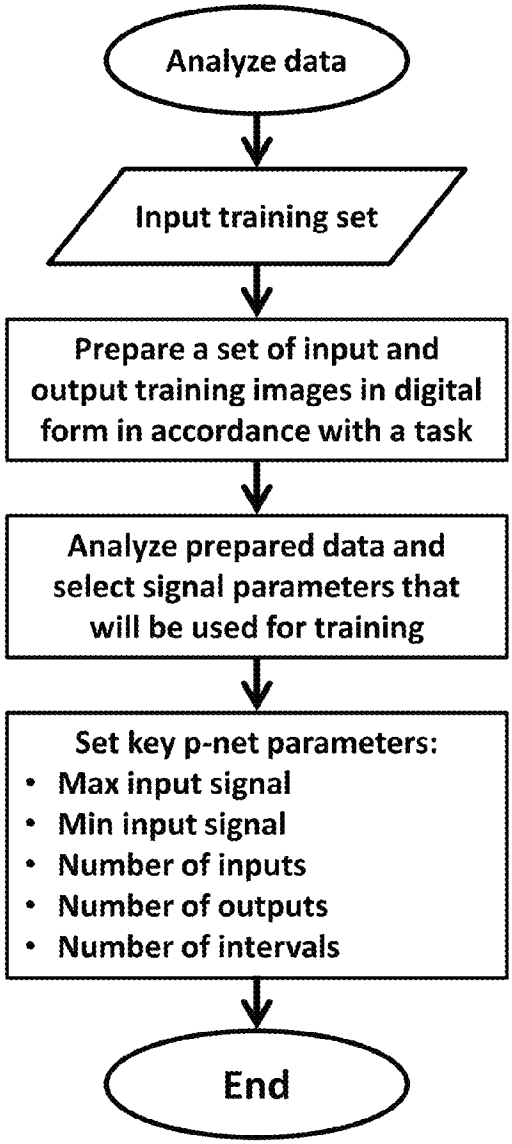

Analyze data
Input training set
Prepare a set of input and output training images in digital form in accordance with a task
Analyze prepared data and select signal parameters that will be used for training
Set key p-net parameters:
• Max input signal
• Min input signal
• Number of inputs
• Number of outputs
• Number of intervals
End

Fig. 16

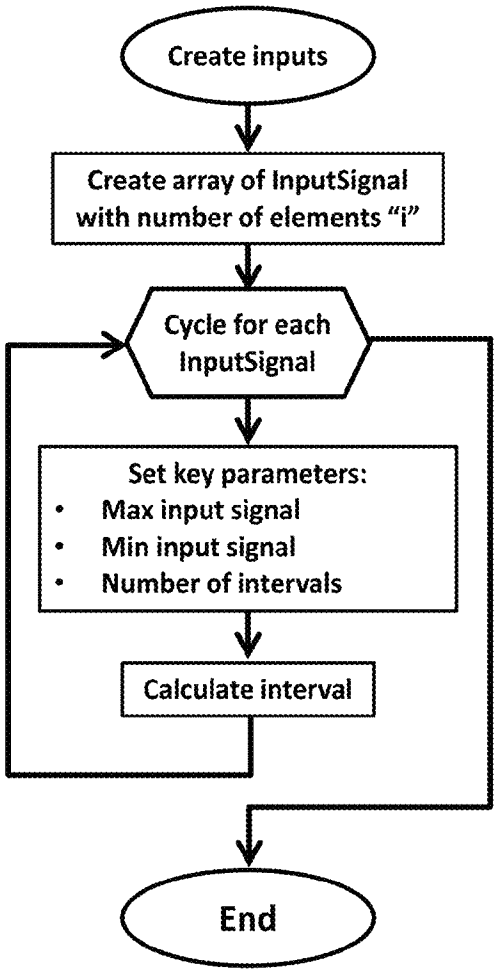

Create inputs
Create array of InputSignal with number of elements "i"
Cycle for each InputSignal
Set key parameters:
• Max input signal
• Min input signal
• Number of intervals
Calculate interval
End

Fig. 17

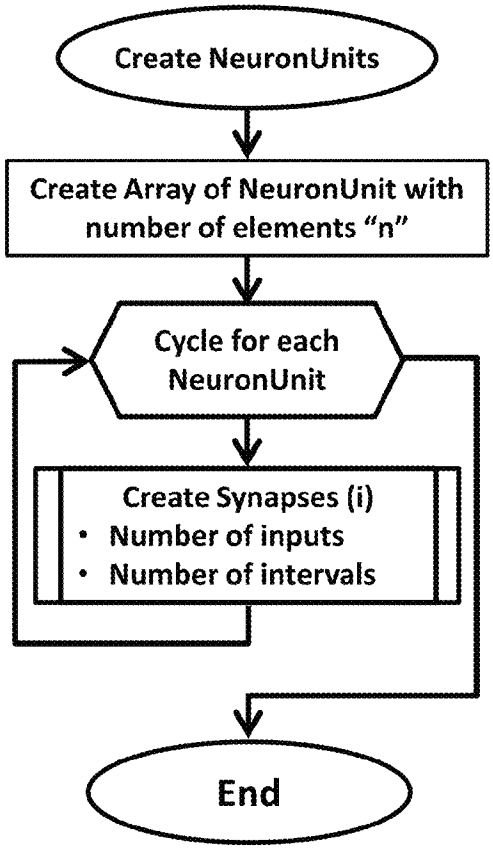

Create NeuronUnits
Create Array of NeuronUnit with number of elements "n"
Cycle for each NeuronUnit
Create Synapses (i)
• Number of inputs
• Number of intervals
End

Fig. 18

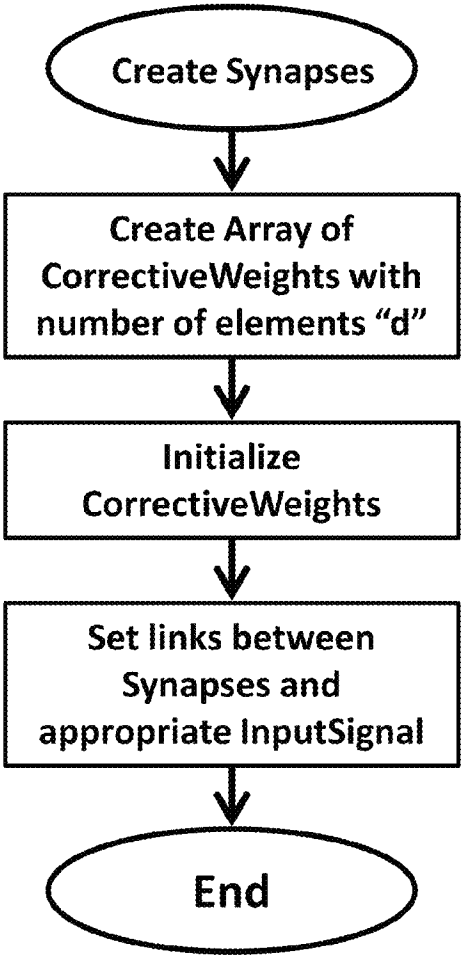

Create Synapses
Create Array of CorrectiveWeights with number of elements "d"
Initialize CorrectiveWeights
Set links between Synapses and appropriate InputSignal
End

Fig. 19

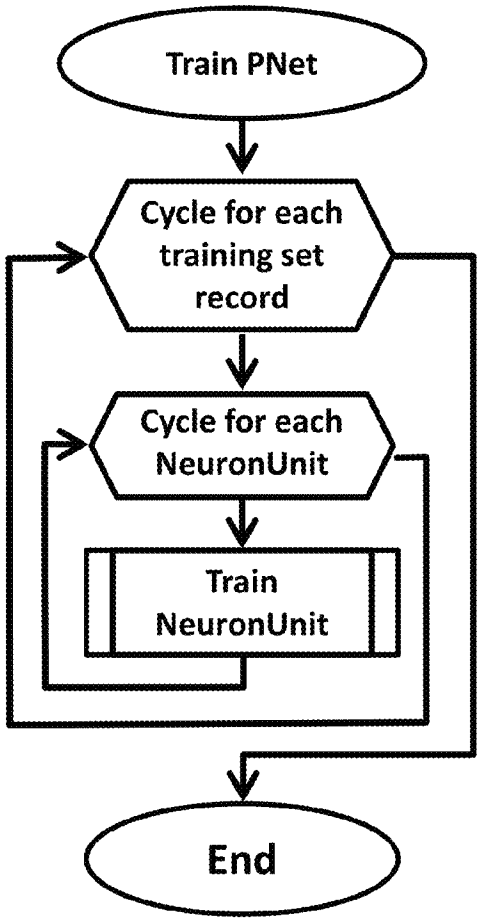

Train PNet
Cycle for each training set record
Cycle for each NeuronUnit
Train NeuronUnit
End

Fig. 20

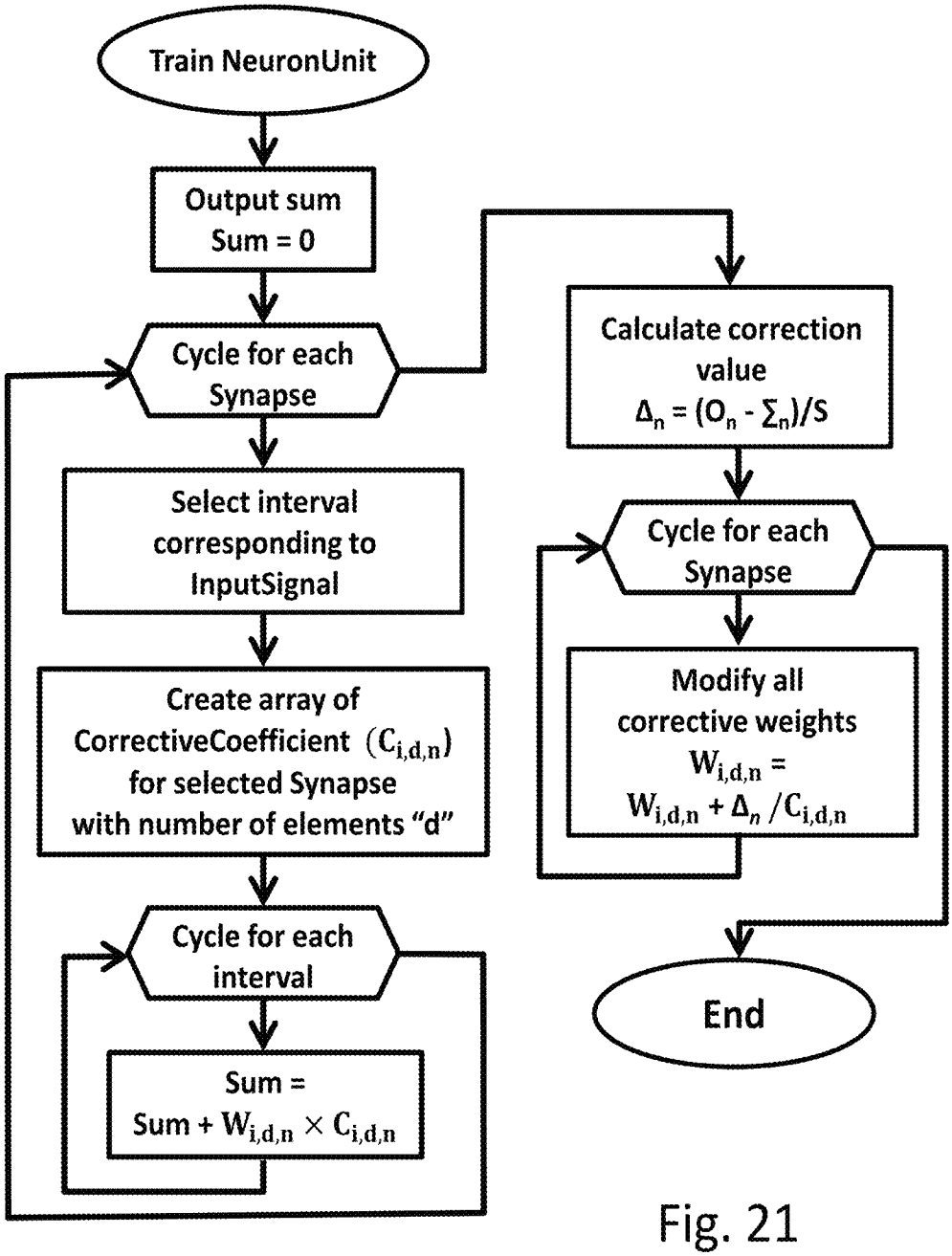

Train NeuronUnit
Output sum
Sum = 0
Cycle for each Synapse
Select interval corresponding to InputSignal
Create array of CorrectiveCoefficient ($C_{i,d,n}$) for selected Synapse with number of elements "d"
Cycle for each interval
Sum = Sum + $W_{i,d,n} \times C_{i,d,n}$
Calculate correction value $\Delta_n = (O_n - \sum_n)/S$
Cycle for each Synapse
Modify all corrective weights $W_{i,d,n} = W_{i,d,n} + \Delta_n / C_{i,d,n}$
End

Fig. 21

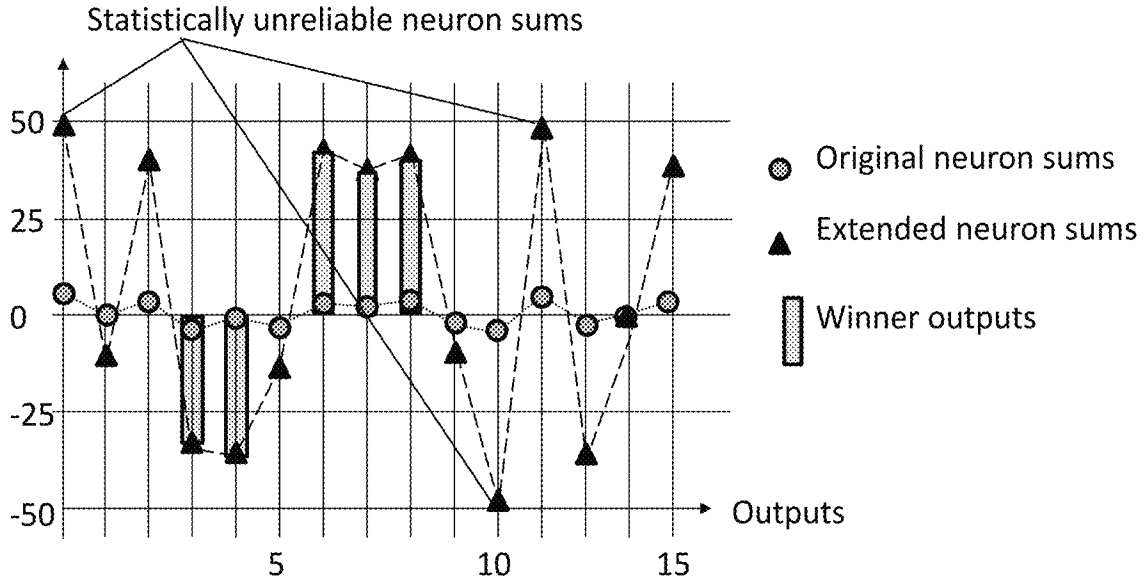

Statistically unreliable neuron sums
50
25
0
-25
-50
5
10
15
Outputs
Original neuron sums
Extended neuron sums
Winner outputs

Fig. 22

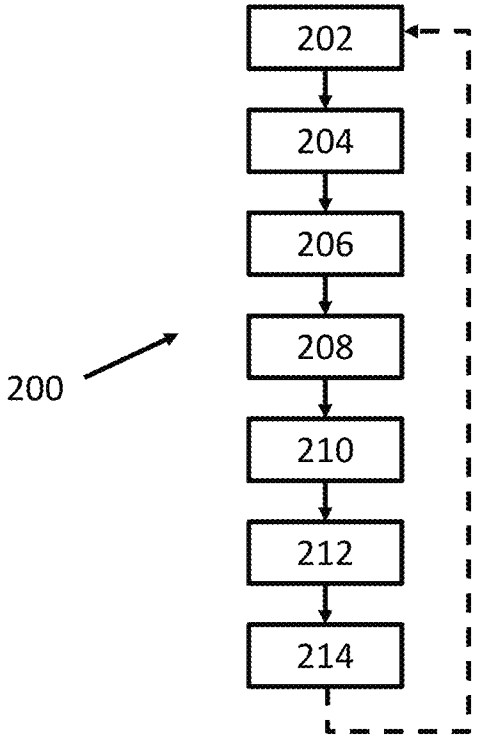

202
204
206
208
210
212
214
200

Fig. 23

NEURAL NETWORK AND METHOD OF NEURAL NETWORK TRAINING

CROSS-REFERENCE TO RELATED APPLICATION(S)

This application is a continuation of International Application Serial No. PCT/US 2015/19236 which claims the benefit of U.S. Provisional Application Ser. No. 61/949,210 filed Mar. 6, 2014, and U.S. Provisional Application Ser. No. 62/106,389 filed Jan. 22, 2015, the entire contents of which are hereby incorporated by reference.

TECHNICAL FIELD

The disclosure relates to an artificial neural network and a method of training the same.

BACKGROUND

In machine learning, artificial neural networks are a family of statistical learning algorithms inspired by biological neural networks, a.k.a., the central nervous systems of animals, in particular the brain. Artificial neural networks are primarily used to estimate or approximate generally unknown functions that can depend on a large number of inputs. Such neural networks have been used for a wide variety of tasks that are difficult to resolve using ordinary rule-based programming, including computer vision and speech recognition.

Artificial neural networks are generally presented as systems of "neurons" which can compute values from inputs, and, as a result of their adaptive nature, are capable of machine learning, as well as pattern recognition. Each neuron frequently connects with several inputs through synapses having synaptic weights.

Neural networks are not programmed as typical software, but are trained. Such training is typically accomplished via analysis of a sufficient number of representative examples and by statistical or algorithmic selection of synaptic weights, so that a given set of input images corresponds to a given set of output images. A common criticism of classical neural networks is that significant time and other resources are frequently required for their training.

Various artificial neural networks are described in the following U.S. Pat. Nos. 4,979,124; 5,479,575; 5,493,688; 5,566,273; 5,682,503; 5,870,729; 7,577,631; and 7,814,038.

SUMMARY

A neural network includes a plurality of network inputs, such that each input is configured to receive an input signal having an input value. The neural network also includes a plurality of synapses, wherein each synapse is connected to one of the plurality of inputs and includes a plurality of corrective weights, wherein each corrective weight is defined by a weight value. The neural network additionally includes a set of distributors. Each distributor is operatively connected to one of the plurality of inputs for receiving the respective input signal and is configured to select one or more corrective weights from the plurality of corrective weights in correlation with the input value. The neural network also includes a set of neurons. Each neuron has at least one output and is connected with at least one of the plurality of inputs via one of the plurality of synapses synapse and is configured to add up the weight values of the corrective weights selected from each synapse connected to the respective neuron and thereby generate a neuron sum. Furthermore, the neural network includes a weight correction calculator configured to receive a desired output signal having a value, determine a deviation of the neuron sum from the desired output signal value, and modify respective corrective weight values using the determined deviation. Adding up the modified corrective weight values to determine the neuron sum minimizes the deviation of the neuron sum from the desired output signal value in order to provide training the neural network.

The determination of the deviation of the neuron sum from the desired output signal may include division of the desired output signal value by the neuron sum to thereby generate a deviation coefficient. Additionally, the modification of the respective corrective weights may include multiplication of each corrective weight used to generate the neuron sum by the deviation coefficient.

The deviation of the neuron sum from the desired output signal may be a mathematical difference therebetween. In such a case, the generation of the respective modified corrective weights may include apportionment of the mathematical difference to each corrective weight used to generate the neuron sum. Such apportionment of the mathematical difference to each corrective weight is intended to converge each neuron sum on the desired signal value.

The apportionment of the mathematical difference may also include dividing the determined difference equally between each corrective weight used to generate the neuron sum.

The distributor may be additionally configured to assign a plurality of coefficients of impact to the plurality of corrective weights, such that each coefficient of impact is assigned to one of the plurality of corrective weights in a predetermined proportion to generate the neuron sum.

Each respective plurality of coefficients of impact may be defined by an impact distribution function. The plurality of input values my be received into a value range divided into intervals according to an interval distribution function, such that each input value is received within a respective interval, and each corrective weight corresponds to one of the intervals. Also, each distributor may use the respective received input value of the input signal to select the respective interval. Additionally, each distributor may assign the respective plurality of coefficients of impact to the corrective weight corresponding to the selected respective interval and to at least one corrective weight corresponding to an interval adjacent to the selected respective interval

Each neuron may be configured to add up a product of the corrective weight and the assigned coefficient of impact for all the synapses connected thereto.

The predetermined proportion of the coefficients of impact may be defined according to a statistical distribution, such as using a Gaussian function.

The weight correction calculator may be configured to apply a portion of the determined difference to each corrective weight used to generate the neuron sum according to the proportion established by the respective coefficient of impact.

Each corrective weight may additionally be defined by a set of indexes. Such indexes may include an input index configured to identify the corrective weight corresponding to the input, an interval index configured to specify the selected interval for the respective corrective weight, and a neuron index configured to specify the corrective weight corresponding to the neuron.

Each corrective weight may be further defined by an access index configured to tally a number of times the respective corrective weight is accessed by the input signal during training of the neural network.

A method of training such a neural network is also disclosed.

The above features and advantages, and other features and advantages of the present disclosure, will be readily apparent from the following detailed description of the embodiment(s) and best mode(s) for carrying out the described disclosure when taken in connection with the accompanying drawings and appended claims.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. **1** is an illustration of a prior art, classical artificial neural network.

FIG. **2** is an illustration of a "progressive neural network" (p-net) having a plurality of synapses, a set of distributors, and a plurality of corrective weights associated with each synapse.

FIG. **3**A is an illustration of a portion of the p-net shown in FIG. **2**, having a plurality of synapses and one synaptic weight positioned upstream of each distributor.

FIG. **3**B is an illustration of a portion of the p-net shown in FIG. **2**, having a plurality of synapses and a set of synaptic weights positioned downstream of the respective plurality of corrective weights.

FIG. **3**C is an illustration of a portion of the p-net shown in FIG. **2**, having a plurality of synapses and one synaptic weight positioned upstream of each distributor and a set of synaptic weights positioned downstream of the respective plurality of corrective weights.

FIG. **4**A is an illustration of a portion of the p-net shown in FIG. **2**, having a single distributor for all synapses of a given input and one synaptic weight positioned upstream of each distributor.

FIG. **4**B is an illustration of a portion of the p-net shown in FIG. **2**, having a single distributor for all synapses of a given input and a set of synaptic weights positioned downstream of the respective plurality of corrective weights.

FIG. **4**C is an illustration of a portion of the p-net shown in FIG. **2**, having a single distributor for all synapses of a given input, and having one synaptic weight positioned upstream of each distributor and a set of synaptic weights positioned downstream of the respective plurality of corrective weights.

FIG. **5** is an illustration of division of input signal value range into individual intervals in the p-net shown in FIG. **2**.

FIG. **6**A is an illustration of one embodiment of a distribution for values of coefficient of impact of corrective weights in the p-net shown in FIG. **2**.

FIG. **6**B is an illustration of another embodiment of the distribution for values of coefficient of impact of corrective weights in the p-net shown in FIG. **2**.

FIG. **6**C is an illustration of yet another embodiment of the distribution for values of coefficient of impact of corrective weights in the p-net shown in FIG. **2**.

FIG. **7** is an illustration of an input image for the p-net shown in FIG. **2**, as well as one corresponding table representing the image in the form of digital codes and another corresponding table representing the same image as a set of respective intervals.

FIG. **8** is an illustration of an embodiment of the p-net shown in FIG. **2** trained for recognition of two distinct images, wherein the p-net is configured to recognize a picture that includes some features of each image;

FIG. **9** is an illustration of an embodiment of the p-net shown in FIG. **2** with an example of distribution of synaptic weights around a "central" neuron.

FIG. **10** is an illustration of an embodiment of the p-net shown in FIG. **2**, depicting a uniform distribution of training deviation between corrective weights.

FIG. **11** is an illustration of an embodiment of the p-net shown in FIG. **2**, employing modification of the corrective weights during p-net training

FIG. **12** is an illustration of an embodiment of the p-net shown in FIG. **2**, wherein the basic algorithm generates a primary set of output neuron sums, and wherein the generated set is used to generate several "winner" sums with either retained or increased values and the contribution of remaining sums is negated.

FIG. **13** is an illustration of an embodiment of the p-net shown in FIG. **2** recognizing a complex image with elements of multiple images.

FIG. **14** is an illustration of a model for object oriented programming for the p-net shown in FIG. **2** using Unified Modeling Language (UML).

FIG. **15** is an illustration of a general formation sequence of the p-net shown in FIG. **2**.

FIG. **16** is an illustration of representative analysis and preparation of data for formation of the p-net shown in FIG. **2**.

FIG. **17** is an illustration of representative input creation permitting interaction of the p-net shown in FIG. **2** with input data during training and p-net application.

FIG. **18** is an illustration of representative creation of neuron units for the p-net shown in FIG. **2**.

FIG. **19** is an illustration of representative creation of each synapse connected with the neuron units.

FIG. **20** is an illustration of training the p-net shown in FIG. **2**.

FIG. **21** is an illustration of neuron unit training in the p-net shown in FIG. **2**.

FIG. **22** is an illustration of extending of neuron sums during training of the p-net shown in FIG. **2**.

FIG. **23** is a flow diagram of a method used to train the neural network shown in FIGS. **2-22**.

DETAILED DESCRIPTION

A classical artificial neural network **10**, as shown in FIG. **1**, typically includes input devices **12**, synapses **14** with synaptic weights **16**, neurons **18**, including an adder **20** and activation function device **22**, neuron outputs **24** and weight correction calculator **26**. Each neuron **18** is connected through synapses **14** to two or more input devices **12**. The values of synaptic weights **16** are commonly represented using electrical resistance, conductivity, voltage, electric charge, magnetic property, or other parameters.

Supervised training of the classical neural network **10** is generally based on an application of a set of training pairs **28**. Each training pair **28** commonly consists of an input image **28-1** and a desired output image **28-2**, a.k.a., a supervisory signal. Training of the classical neural network **10** is typically provided as follows. An input image in the form of a set of input signals (I_1-I_m) enters the input devices **12** and is transferred to the synaptic weights **16** with initial weights (W_1). The value of the input signal is modified by the weights, typically by multiplying or dividing each signal (I_1-I_m) value by the respective weight. From the synaptic weights **16**, modified input signals are transferred either to the respective neurons **18**. Each neuron **18** receives a set of signals from a group of synapses **14** related to the subject neuron **18**. The adder **20** included in the neuron **18** sums up all the input signals modified by the weights and received by the subject neuron. Activation function devices **22** receive the respective resultant neuron sums and modify the sums according to

mathematical function(s), thus forming respective output images as sets of neuron output signals ($\Sigma F_1 \ldots \Sigma F_n$).

The obtained neuron output image defined by the neuron output signals ($\Sigma F_1 \ldots \Sigma F_n$) is compared by a weight correction calculator **26** with pre-determined desired output images (O_1-O_n). Based on the determined difference between the obtained neuron output image ΣF_n and the desired output image O_n, correction signals for changing the synaptic weights **16** are formed using a pre-programmed algorithm. After corrections are made to all the synaptic weights **16**, the set of input signals (I_1-I_m) is reintroduced to the neural network **10** and new corrections are made. The above cycle is repeated until the difference between the obtained neuron output image ΣF_n and the desired output image O_n is determined to be less than some predetermined error. One cycle of network training with all the individual images is typically identified as a "training epoch". Generally, with each training epoch, the magnitude of error is reduced. However, depending on the number of individual inputs (I_1-I_m), as well as the number of inputs and outputs, training of the classical neural network **10** may require a significant number of training epochs, which, in some cases, may be as great as hundreds of thousands.

A variety of classical neural networks exist, including Hopfield network, Restricted Boltzmann Machine, Radial basis function network, and recurrent neural network. Specific tasks of classification and clustering require a specific type of neural network, the Self-Organizing Maps that use only input images as network input training information, whereas the desired output image, corresponding to a certain input image is formed directly during the training process based on a single winning neuron having an output signal with the maximum value.

As noted above, one of the main concerns with existing, classical neural networks, such as the neural network **10**, is that successful training thereof may require a significant duration of time. Some additional concerns with classical networks may be a large consumption of computing resources, which would in turn drive the need for powerful computers. Additional concerns are an inability to increase the size of the network without full retraining of the network, a predisposition to such phenomena as "network paralysis" and "freezing at a local minimum", which make it impossible to predict if a specific neural network would be capable of being trained with a given set of images in a given sequence. Also there may be limitations related to specific sequencing of images being introduced during training, where changing the order of introduction of training images may lead to network freezes, as well as an inability to perform additional training of an already trained network.

Referring to the remaining drawings, wherein like reference numbers refer to like components, FIG. **2** shows a schematic view of a progressive neural network, thereafter "progressive network", or "p-net" **100**. The p-net **100** includes a plurality or a set of inputs **102** of the p-net. Each input **102** is configured to receive an input signal **104**, wherein the input signals are represented as $I_1, I_2 \ldots I_m$ in FIG. **2**. Each input signal $I_1, I_2 \ldots I_m$ represents a value of some characteristic(s) of an input image **106**, for example, a magnitude, frequency, phase, signal polarization angle, or association with different parts of the input image **106**. Each input signal **104** has an input value, wherein together the plurality of input signals **104** generally describes the input image **106**.

Each input value may be within a value range that lies between $-\infty$ and $+\infty$ and can be set in digital and/or analog forms. The range of the input values may depend on a set of training images. In the simplest case, the range input values could be the difference between the smallest and largest values of input signals for all training images. For practical reasons, the range of the input values may be limited by eliminating input values that are deemed too high. For example, such limiting of the range of the input values may be accomplished via known statistical methods for variance reduction, such as importance sampling. Another example of limiting the range of the input values may be designation of all signals that are lower than a predetermined minimum level to a specific minimum value and designation of all signals exceeding a predetermined maximum level to a specific maximum value.

The p-net **100** also includes a plurality or a set of synapses **118**. Each synapse **118** is connected to one of the plurality of inputs **102**, includes a plurality of corrective weights **112**, and may also include a synaptic weight **108**, as shown in FIG. **2**. Each corrective weight **112** is defined by a respective weight value **112**. The p-net **100** also includes a set of distributors **114**. Each distributor **114** is operatively connected to one of the plurality of inputs **102** for receiving the respective input signal **104**. Additionally, each distributor **114** is configured to select one or more corrective weights from the plurality of corrective weights **112** in correlation with the input value.

The p-net **100** additionally includes a set of neurons **116**. Each neuron **116** has at least one output **117** and is connected with at least one of the plurality of inputs **102** via one synapse **118**. Each neuron **116** is configured to add up or sum the corrective weight values of the corrective weights **112** selected from each synapse **118** connected to the respective neuron **116** and thereby generate and output a neuron sum **120**, otherwise designated as In. A separate distributor **114** can be used for each synapse **118** of a given input **102**, as shown in FIGS. **3**A, **3**B, and **3**C, or a single distributor can be used for all such synapses, as shown in FIGS. **4**A, **4**B, and **4**C. During formation or setup of the p-net **100**, all corrective weights **112** are assigned initial values, which can change during the process of p-net training The initial value of the corrective weight **112** may be assigned as in the classical neural network **10**, for example, the weights may be selected randomly, calculated with the help of a pre-determined mathematical function, selected from a predetermined template, etc.

The p-net **100** also includes a weight correction calculator **122**. The weight correction calculator **122** is configured to receive a desired, i.e., predetermined, output signal **124** having a signal value and representing a portion of an output image **126**. The weight correction calculator **122** is also configured to determine a deviation **128** of the neuron sum **120** from the value of the desired output signal **124**, a.k.a., training error, and modify respective corrective weight values using the determined deviation **128**. Thereafter, summing the modified corrective weight values to determine the neuron sum **120** minimizes the deviation of the subject neuron sum from the value of the desired output signal **124** and, as a result, is effective for training the p-net **100**.

For analogy with the classical network **10** discussed with respect to FIG. **1**, the deviation **128** may also be described as the training error between the determined neuron sum **120** and the value of the desired output signal **124**. In comparison with the classical neural network **10** discussed with respect to FIG. **1**, in the p-net **100** the input values of the input signal **104** only change in the process of general network setup, and are not changed during training of the p-net. Instead of changing the input value, training of the p-net **100** is provided by changing the values **112** of the corrective weights **112**. Additionally, although each neuron **116** includes a summing function, where the neuron adds up the corrective weight values,

the neuron **116** does not require, and, in fact, is characterized by absence of an activation function, such as provided by the activation function device **22** in the classical neural network **10**.

In the classical neural network **10**, weight correction during training is accomplished by changing synaptic weights **16**, while in the p-net **100** corresponding weight correction is provided by changing corrective weights values **112**, as shown in FIG. **2**. The respective corrective weights **112** may be included in weight correction blocks **110** positioned on all or some of the synapses **118**. In neural network computer emulations, each synaptic and corrective weight may be represented either by a digital device, such as a memory cell, and/or by an analog device. In neural network software emulations, the values of the corrective weights **112** may be provided via an appropriate programmed algorithm, while in hardware emulations, known methods for memory control could be used.

In the p-net **100**, the deviation **128** of the neuron sum **120** from the desired output signal **124** may be represented as a mathematically computed difference therebetween. Additionally, the generation of the respective modified corrective weights **112** may include apportionment of the computed difference to each corrective weight used to generate the neuron sum **120**. In such an embodiment, the generation of the respective modified corrective weights **112** will permit the neuron sum **120** to be converged on the desired output signal value within a small number of epochs, in some cases needing only a single epoch, to rapidly train the p-net **100**. In a specific case, the apportionment of the mathematical difference among the corrective weights **112** used to generate the neuron sum **120** may include dividing the determined difference equally between each corrective weight used to generate the respective neuron sum **120**.

In a separate embodiment, the determination of the deviation **128** of the neuron sum **120** from the desired output signal value may include division of the desired output signal value by the neuron sum to thereby generate a deviation coefficient. In such a specific case, the modification of the respective modified corrective weights **112** includes multiplication of each corrective weight used to generate the neuron sum **120** by the deviation coefficient. Each distributor **114** may additionally be configured to assign a plurality of coefficients of impact **134** to the plurality of corrective weights **112**. In the present embodiment, each coefficient of impact **134** may be assigned to one of the plurality of corrective weights **112** in some predetermined proportion to generate the respective neuron sum **120**. For correspondence with each respective corrective weight **112**, each coefficient of impact **134** may be assigned a "$C_{i,d,n}$" nomenclature, as shown in the Figures.

Each of the plurality of coefficients of impact **134** corresponding to the specific synapse **118** is defined by a respective impact distribution function **136**. The impact distribution function **136** may be same either for all coefficients of impact **134** or only for the plurality of coefficients of impact **134** corresponding a specific synapse **118**. Each of the plurality of input values may be received into a value range **138** divided into intervals or sub-divisions "d" according to an interval distribution function **140**, such that each input value is received within a respective interval "d" and each corrective weight corresponds to one of such intervals. Each distributor **114** may use the respective received input value to select the respective interval "d", and to assign the respective plurality of coefficients of impact **134** to the corrective weight **112** corresponding to the selected respective interval "d" and to at least one corrective weight corresponding to an interval adjacent to the selected respective interval, such as $w_{i,d+1,n}$ or $W_{i,d-1,n}$. In another non-limiting example, the predetermined proportion of the coefficients of impact **134** may be defined according to a statistical distribution.

Generating the neuron sum **120** may include initially assigning respective coefficients of impact **134** to each corrective weight **112** according to the input value **102** and then multiplying the subject coefficients of impact by values of the respective employed corrective weights **112**. Then, summing via the each neuron **116** the individual products of the corrective weight **112** and the assigned coefficient of impact **134** for all the synapses **118** connected thereto.

The weight correction calculator **122** may be configured to apply the respective coefficients of impact **134** to generate the respective modified corrective weights **112**. Specifically, the weight correction calculator **122** may apply a portion of the computed mathematical difference between the neuron sum **120** and the desired output signal **124** to each corrective weight **112** used to generate the neuron sum **120** according to the proportion established by the respective coefficients of impact **134**. Additionally, the mathematical difference divided among the corrective weights **112** used to generate the neuron sum **120** can be further divided by the respective coefficient of impact **134**. Subsequently, the result of the division of the neuron sum **120** by the respective coefficient of impact **134** can be added to the corrective weight **112** in order to converge the neuron sum **120** on the desired output signal value.

Typically formation of the p-net **100** will take place before the training of the p-net commences. However, in a separate embodiment, if during training the p-net **100** receives an input signal **104** for which initial corrective weights are absent, appropriate corrective weights **112** may be generated. In such a case, the specific distributor **114** will determine the appropriate interval "d" for the particular input signal **104**, and a group of corrective weights **112** with initial values will be generated for the given input **102**, the given interval "d", and all the respective neurons **116**. Additionally, a corresponding coefficient of impact **134** can be assigned to each newly generated corrective weight **112**.

Each corrective weight **112** may be defined by a set of indexes configured to identify a position of each respective corrective weight on the p-net **100**. The set of indexes may specifically include an input index "i" configured to identify the corrective weight **112** corresponding to the specific input **102**, an interval index "d" configured to specify the discussed-above selected interval for the respective corrective weight, and a neuron index "n" configured to specify the corrective weight **112** corresponding to the specific neuron **116** with nomenclature "$W_{i,d,n}$". Thus, each corrective weight **112** corresponding to a specific input **102** is assigned the specific index "i" in the subscript to denote the subject position. Similarly, each corrective weight "W" corresponding to a specific neuron **116** and a respective synapse **118** is assigned the specific indexes "n" and "d" in the subscript to denote the subject position of the corrective weight on the p-net **100**. The set of indexes may also include an access index "a" configured to tally a number of times the respective corrective weight **112** is accessed by the input signal **104** during training of the p-net **100**. In other words, each time a specific interval "d" and the respective corrective weight **112** is selected for training from the plurality of corrective weights in correlation with the input value, the access index "a" is incremented to count the input signal. The access index "a" may be used to further specify or define a present status of each corrective weight by adopting a nomenclature "$W_{i,d,n,a}$". Each of the indexes "i", "d", "n", and "a" can be numerical values in the range of 0 to $+\infty$.

Various possibilities of dividing the range of input signals **104** into intervals d_0, d_1 . . . d_m are shown in FIG. **5**. The specific interval distribution can be uniform or linear, which, for example, can be achieved by specifying all intervals "d" with the same size. All input signals **104** having their respective input signal value lower than a predetermined lowest level can be considered to have zero value, while all input signals having their respective input signal value greater than a predetermined highest level can be assigned to such highest level, as also shown in FIG. **5**. The specific interval distribution can also be non-uniform or nonlinear, such as symmetrical, asymmetrical, or unlimited. Nonlinear distribution of intervals "d" may be useful when the range of the input signals **104** is considered to be impractically large, and a certain part of the range could include input signals considered to be most critical, such as in the beginning, in the middle, or at end of the range. The specific interval distribution can also be described by a random function. All the preceding examples are of the non-limiting nature, as other variants of intervals distribution are also possible.

The number of intervals "d" within the selected range of input signals **104** may be increased to optimize the p-net **100**. Such optimization of the p-net **100** may be desirable, for example, with the increase in complexity of training the input images **106**. For example, a greater number of intervals may be needed for multi-color images as compared with mono-color images, and a greater number of intervals may be needed for complex ornaments than for simple graphics. An increased number of intervals may be needed for precise recognition of images with complex color gradients as compared with images described by contours, as well for a larger overall number of training images. A reduction in the number of intervals "d" may also be needed in cases with a high magnitude of noise, a high variance in training images, and excessive consumption of computing resources.

Depending on the task or type of information handled by the p-net **100**, for example, visual or textual data, data from sensors of various nature, different number of intervals and the type of distribution thereof can be assigned. For each input signal value interval "d", a corresponding corrective weight of the given synapse with the index "d" may be assigned. Thus, a certain interval "d" will include all corrective weights **112** with the index "i" relevant to the given input, the index "d" relevant to the given interval; and all values for the index "n" from 0 to n. In the process of training the p-net **100**, the distributor **114** defines each input signal value and thus relates the subject input signal **104** to the corresponding interval "d". For example, if there are 10 equal intervals "d" within the range of input signals from 0 to 100, the input signal having a value between 30 and 40 will be related to the interval 3, i.e., "d"=3.

For all corrective weights **112** of each synapse **118** connected with the given input **102**, the distributor **114** can assign values of the coefficient of impact **134** in accordance with the interval "d" related to the particular input signal. The distributor **114** can also assign values of the coefficient of impact **134** in accordance with a pre-determined distribution of values of the coefficient of impact **134** (shown in FIG. **6**), such as a sinusoidal, normal, logarithmic distribution curve, or a random distribution function. In many cases, the sum or integral of coefficient of impact **134** or $C_{i,d,n}$ for a specific input signal **102** related to each synapse **118** will have a value of 1 (one).

$$\Sigma_{synapse} C_{i,d,n}=1 \text{ or } \int_{synapse} C_{i,d,n}=1 \quad [1]$$

In the simplest case, the corrective weight **112** that corresponds most closely to the input signal value may be assigned a value of 1 (one) to the coefficient of impact **134** ($C_{i,d,n}$), while corrective weights for other intervals may receive a value of 0 (zero).

The p-net **100** is focused on reduction of time duration and usage of other resources during training of the p-net, as compared with classical neuron network **10**. Although some of the elements disclosed herein as part of the p-net **100** are designated by certain names or identifiers known to those familiar with classical neural networks, the specific names are used for simplicity and may be employed differently from their counterparts in classical neural networks. For example, synaptic weights **16** controlling magnitudes of the input signals (I_1-I_m) are instituted during the process of general setup of the classical neural network **10** and are changed during training of the classical network. On the other hand, training of the p-net **100** is accomplished by changing the corrective weights **112**, while the synaptic weights **108** do not change during training Additionally, as discussed above, each of the neurons **116** includes a summing or adding component, but does not include an activation function device **22** that is typical to the classical neural network **10**.

In general, the p-net **100** is trained by training each neuron unit **119** that includes a respective neuron **116** and all the connecting synapses **118**, including the particular neuron and all the respective synapses **118** and correction weights **112** connected with the subject neuron. Accordingly, training of the p-net **100** includes changing corrective weights **112** contributing to the respective neuron **116**. Changes to the corrective weights **112** take place based on a group-training algorithm included in a method **200** disclosed in detail below. In the disclosed algorithm, training error, i.e., deviation **128**, is determined for each neuron, based on which correction values are determined and assigned to each of the weights **112** used in determining the sum obtained by each respective neuron **116**. Introduction of such correction values during training is intended to reduce the deviations **128** for the subject neuron **116** to zero. During training with additional images, new errors related to images utilized earlier may again appear. To eliminate such additional errors, after completion of one training epoch, errors for all training images of the entire p-net **100** may be calculated, and if such errors are greater than pre-determined values, one or more additional training epochs may be conducted until the errors become less than a target or predetermined value.

FIG. **23** depicts the method **200** of training the p-net **100**, as described above with respect to FIGS. **2-22**. The method **200** commences in frame **202** where the method includes receiving, via the input **102**, the input signal **104** having the input value. Following frame **202**, the method advances to frame **204**. In frame **204**, the method includes communicating the input signal **104** to the distributor **114** operatively connected to the input **102**. Either in frame **202** or frame **204**, the method **200** may include defining each corrective weight **112** by the set of indexes. As described above with respect to the structure of the p-net **100**, the set of indexes may include the input index "i" configured to identify the corrective weight **112** corresponding to the input **102**. The set of indexes may also include the interval index "d" configured to specify the selected interval for the respective corrective weight **112**, and the neuron index "n" configured to specify the corrective weight **112** corresponding to the specific neuron **116** as "$W_{i,d,n}$". The set of indexes may additionally include the access index "a" configured to tally a number of times the respective corrective weight **112** is accessed by the input signal **104** during training of the p-net **100**. Accordingly, the present status of each corrective weight may adopt the nomenclature "$W_{i,d,n,a}$".

After frame **204**, the method proceeds to frame **206**, in which the method includes selecting, via the distributor **114**, in correlation with the input value, one or more corrective weights **112** from the plurality of corrective weights located on the synapse **118** connected to the subject input **102**. As described above, each corrective weight **112** is defined by its respective weight value. In frame **206** the method may additionally include assigning, via the distributor **114**, the plurality of coefficients of impact **134** to the plurality of corrective weights **112**. In frame **206** the method may also include assigning each coefficient of impact **134** to one of the plurality of corrective weights **112** in a predetermined proportion to generate the neuron sum **120**. Also, in frame **206** the method may include adding up, via the neuron **116**, a product of the corrective weight **112** and the assigned coefficient of impact **134** for all the synapses **118** connected thereto. Additionally, in frame **206** the method may include applying, via the weight correction calculator **122**, a portion of the determined difference to each corrective weight **112** used to generate the neuron sum **120** according to the proportion established by the respective coefficient of impact **134**.

As described above with respect to the structure of the p-net **100**, the plurality of coefficients of impact **134** may be defined by an impact distribution function **136**. In such a case, the method may additionally include receiving the input value into the value range **138** divided into intervals "d" according to the interval distribution function **140**, such that the input value is received within a respective interval, and each corrective weight **112** corresponds to one of the intervals. Also, the method may include using, via the distributor **114**, the received input value to select the respective interval "d" and assign the plurality of coefficients of impact **134** to the corrective weight **112** corresponding to the selected respective interval "d" and to at least one corrective weight corresponding to an interval adjacent to the selected respective interval "d". As described above with respect to the structure of the p-net **100**, corrective weights **112** corresponding to an interval adjacent to the selected respective interval "d" may be identified, for example, as $W_{i,d+1,n}$ or $W_{i,d-1,n}$.

Following frame **206**, the method advances to frame **208**. In frame **208**, the method includes adding up the weight values of the selected corrective weights **112** by the specific neuron **116** connected with the input **102** via the synapse **118** to generate the neuron sum **120**. As described above with respect to the structure of the p-net **100**, each neuron **116** includes at least one output **117**. After frame **208**, the method proceeds to frame **210**, in which the method includes receiving, via the weight correction calculator **122**, the desired output signal **124** having the signal value. Following frame **210**, the method advances to frame **212** in which the method includes determining, via the weight correction calculator **122**, the deviation **128** of the neuron sum **120** from the value of the desired output signal **124**.

As disclosed above in the description of the p-net **100**, the determination of the deviation **128** of the neuron sum **120** from the desired output signal value may include determining the mathematical difference therebetween. Additionally, the modification of the respective corrective weights **112** may include apportioning the mathematical difference to each corrective weight used to generate the neuron sum **120**. Alternatively, the apportionment of the mathematical difference may include dividing the determined difference equally between each corrective weight **112** used to generate the neuron sum **120**. In a yet separate embodiment, the determination of the deviation **128** may also include dividing the value of the desired output signal **124** by the neuron sum **120** to thereby generate the deviation coefficient. Furthermore, in such a case, the modification of the respective corrective weights **112** may include multiplying each corrective weight **112** used to generate the neuron sum **120** by the generated deviation coefficient.

After frame **212**, the method proceeds to frame **214**. In frame **214** the method includes modifying, via the weight correction calculator **122**, respective corrective weight values using the determined deviation **128**. The modified corrective weight values can subsequently be added or summed up and then used to determine a new neuron sum **120**. The summed modified corrective weight values can then serve to minimize the deviation of the neuron sum **120** from the value of the desired output signal **124** and thereby train the p-net **100**. Following frame **214**, method **200** can include returning to frame **202** to perform additional training epochs until the deviation of the neuron sum **120** from the value of the desired output signal **124** is sufficiently minimized. In other words, additional training epochs can be performed to converge the neuron sum **120** on the desired output signal **124** to within the predetermined deviation or error value, such that the p-net **100** can be considered trained and ready for operation with new images.

Generally, the input images **106** need to be prepared for training of the p-net **100**. Preparation of the p-net **100** for training generally begins with formation of a set of training images, including the input images **106** and, in the majority of cases, desired output images **126** corresponding to the subject input images. The input images **106** (shown in FIG. **2**) defined by the input signals $I_1, I_2 \ldots I_m$ for training of the p-net **100** are selected in accordance with tasks that the p-net is assigned to handle, for example recognition of human images or other objects, recognition of certain activities, clustering or data classification, analysis of statistical data, pattern recognition, forecasting, or controlling certain processes. Accordingly, the input images **106** can be presented in any format suitable for introduction into a computer, for example, using formats jpeg, gif, or pptx, in the form of tables, charts, diagrams and graphics, various document formats, or a set of symbols.

Preparation for training of the p-net **100** may also include conversion of the selected input images **106** for their unification that is convenient for the processing of the subject images by the p-net **100**, for example, transforming all images to a format having the same number of signals, or, in the case of pictures, same number of pixels. Color images could be, for example, presented as a combination of three basic colors. Image conversion could also include modification of characteristics, for example, shifting an image in space, changing visual characteristics of the image, such as resolution, brightness, contrast, colors, viewpoint, perspective, focal length and focal point, as well as adding symbols, numbers, or notes.

After selection of the number of intervals, a specific input image may be converted into an input image in interval format, that is, real signal values may be recorded as numbers of intervals to which the subject respective signals belong. This procedure can be carried out in each training epoch for the given image. However, the image may also be formed once as a set of interval numbers. For example, in FIG. **7** the initial image is presented as a picture, while in the table "Image in digital format" the same image is presented in the form of digital codes, and in the table "Image in interval format" then image is presented as a set of interval numbers, where a separate interval is assigned for each **10** values of digital codes.

The described structure of the p-net **100** and the training algorithm or method **200** as described permit continued or iterative training of the p-net, thus there is no requirement to form a complete set of training input images **106** at the start of

the training process. It is possible to form a relatively small starting set of training images, and such a starting set could be expanded as necessary. The input images **106** may be divided into distinct categories, for example, a set of pictures of one person, a set of photos of cats, or a set of photographs of cars, such that each category corresponds to a single output image, such a person's name or a specific label. Desired output images **126** represent a field or table of digital, where each point corresponds to a specific numeric value from $-\infty$ to $+\infty$, or analog values. Each point of the desired output image **126** may correspond to the output of one of the neurons of the p-net **100**. Desired output images **126** can be encoded with digital or analog codes of images, tables, text, formulas, sets of symbols, such as barcodes, or sounds.

In the simplest case, each input image **106** may correspond to an output image, encoding the subject input image. One of the points of such output image may be assigned a maximum possible value, for example 100%, whereas all other points may be assigned a minimum possible value, for example, zero. In such a case, following training, probabilistic recognition of various images in the form of a percentage of similarity with training images will be enabled. FIG. **8** shows an example of how the p-net **100** trained for recognition of two images, a square and a circle, may recognize a picture that contains some features of each figure being expressed in percentages, with the sum not necessarily equal 100%. Such a process of pattern recognition by defining the percentage of similarity between different images used for training can be used to classify specific images.

To improve the accuracy and exclude errors, coding can be accomplished using a set of several neural outputs rather than one output (see below). In the simplest case, output images may be prepared in advance of training However, it is also possible to have the output images formed by the p-net **100** during training.

In the p-net **100**, there is also a possibility of inverting the input and output images. In other words, input images **106** can be in the form of a field or table of digital or analog values, where each point corresponds to one input of the p-net, while output images can be presented in any format suitable for introduction into the computer, for example using formats jpeg, gif, pptx, in the form of tables, charts, diagrams and graphics, various document formats, or a set of symbols. The resultant p-net **100** can be quite suitable for archiving systems, as well as an associative search of images, musical expressions, equations, or data sets.

Following preparation of the input images **106**, typically the p-net **100** needs to be formed and/or parameters of an existing p-net must be set for handling given task(s). Formation of the p-net **100** may include the following designations:

- dimensions of the p-net **100**, as defined by the number of inputs and outputs;
- synaptic weights **108** for all inputs;
- number of corrective weights **112**;
- distribution of coefficients of corrective weight impact ($C_{i,d,n}$) for different values of input signals **104**; and
- desired accuracy of training

The number of inputs is determined based on the sizes of input images **106**. For example, a number of pixels can be used for pictures, while the selected number of outputs can depend on the size of desired output images **126**. In some cases, the selected number of outputs may depend on the number of categories of training images.

Values of individual synaptic weights **108** can be in the range of $-\infty$ to $+\infty$. Values of synaptic weights **108** that are less than 0 (zero) can denote signal amplification, which can be used to enhance the impact of signals from specific inputs, or from specific images, for example, for a more effective recognition of human faces in photos containing a large number of different individuals or objects. On the other hand, values of synaptic weights **108** that are greater than 0 (zero) can be used to denote signal attenuation, which can be used to reduce the number of required calculations and increase operational speed of the p-net **100**. Generally, the greater the value of the synaptic weight, the more attenuated is the signal transmitted to the corresponding neuron. If all synaptic weights **108** corresponding to all inputs are equal and all neurons are equally connected with all inputs, the neural network will become universal and will be most effective for common tasks, such as when very little is known about the nature of the images in advance. However, such a structure will generally increase the number of required calculations during training and operation.

FIG. **9** shows an embodiment of the p-net **100** in which the relationship between an input and respective neurons is reduced in accordance with statistical normal distribution. Uneven distribution of synaptic weights **108** can result in the entire input signal being communicated to a target or "central" neuron for the given input, thus assigning a value of zero to the subject synaptic weight. Additionally, uneven distribution of synaptic weights can result in other neurons receiving reduced input signal values, for example, using normal, log-normal, sinusoidal, or other distribution. Values of the synaptic weights **108** for the neurons **116** receiving reduced input signal values can increase along with the increase of their distance from the "central" neuron. In such a case, the number of calculations can be reduced and operation of the p-net can speed up. Such networks, which are a combination of known fully connected and non-fully connected neural networks may be the exceedingly effective for analysis of images with strong internal patterns, for example, human faces or consecutive frames of a movie film.

FIG. **9** shows an embodiment of the p-net **100** that is effective for recognition of local patterns. In order to improve the identification of common patterns, 10-20% of strong connections, where the values of the synaptic weights **108** are small or zero, can be distributed throughout the entire p-net **100**, in a deterministic, such as in the form of a grid, or a random approach. The actual formation of the p-net **100** intended for handling a particular task is performed using a program, for example, written in an object-oriented programming language, that generates main elements of the p-net, such as synapses, synaptic weights, distributors, corrective weights, neurons, etc., as software objects. Such a program can assign relationships between the noted objects and algorithms specifying their actions. In particular, synaptic and corrective weights can be formed in the beginning of formation of the p-net **100**, along with setting their initial values. The p-net **100** can be fully formed before the start of its training, and be modified or added-on at a later frame, as necessary, for example, when information capacity of the network becomes exhausted, or in case of a fatal error. Completion of the p-net **100** is also possible while training continues.

If the p-net **100** is formed in advance, the number of selected corrective weights on a particular synapse may be equal to the number of intervals within the range of input signals. Additionally, corrective weights may be generated after the formation of the p-net **100**, as signals in response to appearance of individual intervals. Similar to the classical neural network **10**, selection of parameters and settings of the p-net **100** is provided with a series of targeted experiments. Such experiments can include (1) formation of the p-net with the same synaptic weights **108** at all inputs, and (2) assess-

ment of input signal values for the selected images and initial selection of the number of intervals. For example, for recognition of binary (one-color) images, it may be sufficient to have only 2 intervals; for qualitative recognition of 8 bit images, up to 256 intervals can be used; approximation of complex statistical dependencies may require dozens or even hundreds of intervals; for large databases, the number of intervals could be in the thousands.

In the process of training the p-net **100**, the values of input signals may be rounded as they are distributed between the specific intervals. Thus, accuracy of input signals greater than the width of the range divided by the number of intervals may not be required. For example, if the input value range is set for 100 units and the number of intervals is 10, the accuracy better than ±5 will not be required. Such experiments can also include (3) selection of uniform distribution of intervals throughout the entire range of values of the input signals and the simplest distribution for coefficients of corrective weight impact $C_{i,d,n}$ can be set equal to 1 for corrective weight corresponding to the interval for the particular input signal, while the corrective weight impact for all remaining corrective weights can be set to 0 (zero). Such experiments can additionally include (4) training p-net **100** with one, more, or all prepared training images with pre-determined accuracy.

Training time of the p-net **100** for predetermined accuracy can be established by experimentation. If accuracy and training time of the p-net **100** are satisfactory, selected settings could be either maintained or changed, while a search is continued for a more effective variant. If the required accuracy is not achieved, for optimization purposes influence of specific modification may be evaluated, which can be performed either one at the time, or in groups. Such evaluation of modifications may include changing, either increasing or reducing, the number of intervals; changing the type of distribution of the coefficients of corrective weight impact ($C_{i,d,n}$), testing variants with non-uniform distribution of intervals, such as using normal, power, logarithmic, or log-normal distribution; and changing values of synaptic weights **108**, for example their transition to non-uniform distribution.

If the required training time for an accurate result is deemed excessive, training with an increased number of intervals, can be evaluated for its effect on training time. If, as a result, the training time was reduced, the increase in the number of intervals can be repeated until desired training time is obtained without a loss of required accuracy. If the training time grows with increasing number of intervals instead of being reduced, additional training can be performed with reduced number of intervals. If the reduced number of intervals results in reduced training time, the number of intervals could be further reduced until desired training time is obtained.

Formation of the p-net **100** settings can be via training with pre-determined training time and experimental determination of training accuracy. Parameters could be improved via experimental changes similar to those described above. Actual practice with various p-nets has shown that the procedure of setting selection is generally straight-forward and not time-consuming.

Actual training of the p-net **100** as part of the method **200**, shown in FIG. **23**, starts with feeding the input image signals $I_1, I_2 \ldots I_m$ to the network input devices **102**, from where they are transmitted to synapses **118**, pass through the synaptic weight **108** and enter the distributor (or a group of distributors) **114**. Based on the input signal value, the distributor **114** sets the number of the interval "d" that the given input signal **104** corresponds to, and assigns coefficients of corrective weight impact $C_{i,d,n}$ for all the corrective weights **112** of the weight correction blocks **110** of all the synapses **118** connected with the respective input **102**. For example, if the interval "d" may be set to 3 for the first input, for all weights $W_{1,3,n}$, $C_{1,3,n}$=1 is set to 1, while for all other weights with i#1 and d#3, $C_{i,d,n}$ can be set to 0 (zero).

For each neuron **116**, identified as "n" in the relationship below, neuron output sums Σ1, Σ2 . . . Σn are formed by multiplying each corrective weight **112**, identified as $W_{i,d,n}$ in the relationship below, by a corresponding coefficient of corrective weight impact $C_{i,d,n}$ for all synapses **118** contributing into the particular neuron and by adding all the obtained values:

$$\Sigma_n=\Sigma_{i,d,n}W_{i,d,n}\times C_{i,d,n} \quad [2]$$

Multiplication of $W_{i,d,n}\times C_{i,d,n}$ can be performed by various devices, for example by distributors **114**, devices with stored weights or directly by neurons **116**. The sums are transferred via neuron output **117** to the weight correction calculator **122**. The desired output signals $O_1, O_2 \ldots O_n$ describing the desired output image **126** are also fed to the calculator **122**.

As discussed above, the weight correction calculator **122** is a computation device for calculating the modified value for corrective weights by comparison of the neuron output sums Σ1, Σ2 . . . Σn with desired output signals $O_1, O_2 \ldots O_n$. FIG. **11** shows a set of corrective weights $W_{i,d,1}$, contributing into the neuron output sum Σ1, which are multiplied by corresponding coefficient of corrective weight impact $C_{i,d,1}$, and these products are subsequently added by the neuron output sum Σ1:

$$\Sigma 1=W_{1,0,1}\times C_{1,0,1}+W_{1,1,1}\times C_{1,1,1}+W_{1,2,1}\times C_{1,2,1}+ \quad [3]$$

As the training commences, i.e., during the first epoch, corrective weights $W_{i,d,1}$ do not correspond to the input image **106** used for training, thus, neuron output sums Σ1 are not equal to the corresponding desired output image **126**. Based on the initial corrective weights $W_{i,d,1}$, the weight correction system calculates the correction value Δ1, which is used for changing all the corrective weights contributing to the neuron output sum Σ1 ($W_{i,d,i}$). The p-net **100** permits various options or variants for its formation and utilization of collective corrective signals for all corrective weights contributing to a specified neuron **116**.

Below are two exemplary and non-limiting variants for the formation and utilization of the collective corrective signals.

Variant 1—formation and utilization of corrective signals based on the difference between desired output signals and obtained output sums as follows:

calculation of the equal correction value Δn for all corrective weights contributing into the neuron "n" according to the equation:

$$\Delta_n=(O_n-\Sigma_n)/S \quad [4],$$

Where:

O_n—desirable output signal corresponding to the neuron output sum Σn;

S—number of synapses connected to the neuron "n".

modification of all corrective weights $W_{i,d,n}$ contributing into the neuron "n" according to the equation:

$$W_{i,d,n}\text{ modified}=W_{i,d,n}+\Delta_n/C_{i,d,n} \quad [5],$$

Variant 2—formation and utilization of corrective signals based on ratio of desired output signals versus obtained output sums as follows:

calculation of the equal correction value Δn for all corrective weights contributing into the neuron "n" according to the equation:

$$\Delta_n=O_n/\Sigma_n \quad [6],$$

modification of all corrective weights $W_{i,d,n}$ contributing into the neuron "n" according to the equation:

$$W_{i,d,n}, \text{modified} = W_{i,d,n} \times \Delta_n \quad [7],$$

Modification of corrective weights $W_{i,d,n}$ by any available variant is intended to reduce the training error for each neuron **116** by converging its output sum Σ_n on the value of the desired output signal. In such a way, the training error for a given image can be reduced until such becomes equal, or close to zero.

An example of modification of corrective weights $W_{i,d,n}$ during training is shown in FIG. **11**. The values of corrective weights $W_{i,d,n}$ are set before the training starts in the form of random weight distribution with the weight values being set to 0±10% from the correction weight range and reach final weight distribution after training The described calculation of collective signals is conducted for all neurons **116** in the p-net **100**. The described training procedure for one training image can be repeated for all other training images. Such procedure can lead to appearance of training errors for some of the previously trained images, as some corrective weights $W_{i,d,n}$ may participate in several images. Accordingly, training with another image may partially disrupt the distribution of corrective weights $W_{i,d,n}$ formed for the previous images. However, due to the fact that each synapse **118** includes a set of corrective weights $W_{i,d,n}$, training with new images while possibly increasing training error, does not delete the images, for which the p-net **100** was previously trained. Moreover, the more synapses **118** contribute to each neuron **116** and the greater the number of corrective weights $W_{i,d,n}$ at each synapse, the less training for a specific image affects the training for other images.

Each training epoch generally ends with the substantial convergence of the total training error and/or local training errors for all training images. Errors can be evaluated using known statistical methods, such as, for example, the Mean Squared Error (MSE), the Mean Absolute Error (MAE), or the Standard Error Mean (SEM). If the total error or some of the local errors are too high, additional training epoch can be conducted until the error is reduced to less than a predetermined error value. Earlier described process of image recognition with defining the percentage of similarity between different images used for training (shown in FIG. **8**) is by itself a process of classification of images along previously defined categories.

For clustering, i.e., dividing images into natural classes or groups that were not previously specified, the basic training algorithm of the method **200** can be modified with the modified Self-Organizing Maps (SOM) approach. The desired output image **126** corresponding to a given input image can be formed directly in the process of training the p-net **100** based on a set of winning neurons with a maximum value of the output neuron sums **120**. FIG. **22** shows how the use of the basic algorithm of the method **200** can generate a primary set of the output neuron sums, where the set further is converted such that several greater sums retain their value, or increase, while all other sums are considered equal to zero. This transformed set of output neuron sums can be accepted as the desired output image **126**.

Formed as described above, the set of desired output images **126** includes clusters or groups. As such, the set of desired output images **126** allows for clustering of linearly inseparable images, which is distinct from the classical network **10**. FIG. **13** shows how the described approach can assist with clustering a complex hypothetical image "cat-car", where different features of the image are assigned to different clusters—cats and cars. A set of desired output images **126** created as described can be used, for example, for creating different classifications, statistical analysis, images selection based on criteria formed as a result of clustering. Also, the desired output images **126** generated by the p-net **100** can be used as input images for another or additional p-net, which can also be formed along the lines described for the subject p-net **100**. Thus formed, the desired output images **126** may be used for a subsequent layer of a multi-layer p-net.

Classical neural network **10** training is generally provided via a supervised training method that is based on preliminary prepared pairs of an input image and a desired output image. The same general method is also used for training of the p-net **100**, however, the increased training speed of the p-net **100** also allows for training with an external trainer. The role of the external trainer can be performed, for example, by an individual or by a computer program. Acting as an external trainer, the individual may be involved in performing a physical task or operate in a gaming environment. The p-net **100** receives input signals in the form of data regarding a particular situation and changes thereto. The signals reflecting actions of the trainer can be introduced as desired output images **126** and permit the p-net **100** to be trained according to the basic algorithm. In such a way, modeling of various processes can be generated by the p-net **100** in real-time.

For example, the p-net **100** can be trained to drive a vehicle by receiving information regarding road conditions and actions of the driver. Through modeling a large variety of critical situations, the same p-net **100** can be trained by many different drivers and accumulate more driving skills than is generally possible by any single driver. The p-net **100** is capable of evaluating a specific road condition in 0.1 seconds or faster and amassing substantial "driving experience" that can enhance traffic safety in a variety of situations. The p-net **100** can also be trained to cooperate with a computer, for example, with a chess-playing machine. The ability of the p-net **100** to easily shift from training mode to the recognition mode and vice versa allows for realization of a "learn from mistakes" mode, when the p-net **100** is trained by an external trainer. In such a case, the partially trained p-net **100** can generate its own actions, for example, to control a technological process. The trainer could control the actions of the p-net **100** and correct those actions when necessary. Thus, additional training of the p-net **100** could be provided.

Informational capacity of the p-net **100** is very large, but is not unlimited. With the set dimensions, such as the number of inputs, outputs, and intervals, of the p-net **100**, and with an increase in the number of images that the p-net is trained with, after a certain number of images, the number and magnitude of training errors can also increase. When such an increase in error generation is detected, the number and/or magnitude of errors can be reduced by increasing the size of p-net **100**, since the p-net permits increasing the number of neurons **116** and/or the number of the signal intervals "d" across the p-net or in its components between training epochs. P-net **100** expansion can be provided by adding new neurons **116**, adding new inputs **102** and synapses **118**, changing distribution of the coefficients of corrective weight impact $C_{i,d,n}$, and dividing existing intervals "d".

In most cases p-net **100** will be trained to ensure its ability to recognize images, patterns, and correlations inherent to the image, or to a sets of images. The recognition process in the simplest case repeats the first steps of the training process according to the basic algorithm disclosed as part of the method **200**. In particular:

direct recognition starts with formatting of the image according to the same rules that are used to format images for training;

the image is sent to the inputs of the trained p-net **100**, distributors assign the corrective weights $W_{i,d,n}$ corresponding to the values of input signals that were set during training, and the neurons generate the respective neuron sums, as shown in FIG. **8**;

if the resulting output sums representing the output image **126** fully complies with one of the images that the p-net **100** is being trained with, there is an exact recognition of the object; and

if the output image **126** partially complies with several images the p-net **100** is being trained with, the result shows the matching rate with different images as a percentage. FIG. **13** demonstrates that during recognition of the complex image that is made based on a combination of images of a cat and a vehicle, the output image **126** represents the given image combination and indicates the percentage of each initial image's contribution into the combination.

For example, if several pictures of a specific person were used for training, the recognized image may correspond 90% to the first picture, 60% to the second picture, and 35% to the third picture. It may be that the recognized image corresponds with a certain probability to the pictures of other people or even of animals, which means that there is some resemblance between the pictures. However, the probability of such resemblance is likely to be lower. Based on such probabilities, the reliability of recognition can be determined, for example, based on Bayes' theorem.

With the p-net **100** it is also possible to implement multistage recognition that combines the advantages of algorithmic and neural network recognition methods. Such multistage recognition can include:

initial recognition of an image by a pre-trained network via using not all, but only 1%-10% of inputs, which are herein designated as "basic inputs". Such a portion of the inputs can be distributed within the p-net **100** either uniformly, randomly, or by any other distribution function. For example, the recognition of a person in the photograph that includes a plurality of other objects;

selecting the most informative objects or parts of objects for further detailed recognition. Such selection can be provided according to structures of specific objects that are pre-set in memory, as in the algorithmic method, or according to a gradient of colors, brightness, and/or depth of the image. For example, in recognition of portraits the following recognition zones can be selected: eyes, corners of the mouth, nose shape, as well as certain specific features, such as tattoos, vehicle plate numbers, or house numbers can also be selected and recognized using a similar approach; and

detailed recognition of selected images, if necessary, is also possible.

Formation of a computer emulation of the p-net **100** and its training can be provided based of the above description by using any programming language. For example, an object-oriented programming can be used, wherein the synaptic weights **108**, corrective weights **112**, distributors **114**, and neurons **116** represent programming objects or classes of objects, relations are established between object classes via links or messages, and algorithms of interaction are set between objects and between object classes.

Formation and training of the p-net **100** software emulation can include the following:

1. Preparation for the formation and training of the p-net **100**, in particular:

conversion of sets of training input images into digital form in accordance with a given task;

analysis of the resulting digital images, including selection of parameters of the input signals to be used for training, for example, frequencies, magnitudes, phases, or coordinates; and

setting a range for the training signals, a number of intervals within the subject range, and a distribution of coefficients of corrective weight impact $C_{i,d,n}$.

2. Formation of the p-net software emulation, including:

formation of a set of inputs to the p-net **100**. For example, the number of inputs may be equal to the number of signals in the training input image;

formation of a set of neurons, where each neuron represents an adding device;

formation of a set of synapses with synaptic weights, where each synapse is connected to one p-net input and one neuron;

formation of weight correction blocks in each synapse, where the weight correction blocks include distributors and corrective weights, and where each corrective weight has the following characteristics:

Corrective weight input index (i);

Corrective weight neuron index (n);

Corrective weight interval index (d); and

Corrective weight initial value ($W_{i,d,n}$).

designating a correlation between intervals and corrective weights.

3. Training each neuron with one input image, including:

designating coefficients of corrective weight impact $C_{i,d,n}$, including:

determining an interval corresponding to the input signal of the training input image received by each input; and

designating magnitudes of the coefficients of corrective weight impact $C_{i,d,n}$ to all corrective weights for all synapses.

calculating neuron output sum (Σn) for each neuron "n" by adding corrective weight value $W_{i,d,n}$ of all synaptic weights contributing to the neuron multiplied by the corresponding coefficients of corrective weight impact $C_{i,d,n}$:

$$\Sigma_n=\Sigma_{i,d,n}W_{i,d,n}\times C_{i,d,n}$$

calculating the deviation or training error (T_n) via subtraction of the neuron output sum Σn from the corresponding desired output signal O_n:

$$T_nO_n-\Sigma_n;$$

calculating the equal correction value (Δ_n) for all corrective weights contributing to the neuron "n" via dividing the training error by the number of synapses "S" connected to the neuron "n":

$$\Delta_n=T_n/S$$

modifying all corrective weights $W_{i,d,n}$ contributing to the respective neuron by adding to each corrective weight the correction value An divided by the corresponding coefficients of corrective weight impact $C_{i,d,n}$:

$$W_{i,d,n}\text{ modified}=W_{i,n,d}+_n/C_{i,d,n}.$$

Another method of calculating the equal correction value (Δ_n) and modifying the corrective weights $W_{i,d,n}$ for all corrective weight contributing to the neuron "n" can include the following:

dividing the signal of desired output image O_n by a neuron output sum Σ_n:

$\Delta_n=O_n/\Sigma_n$

modifying the corrective weights $W_{i,d,n}$ contributing to the neuron by multiplying the corrective weights by the correction value Δ_n:

$$W_{i,d,n} \text{ modified} = W_{i,d,n} \times \Delta_n$$

4. Training the p-net **100** using all training images, including:
repeating the process described above for all selected training images that are included in one training epoch; and
determining an error or errors of the specific training epoch, comparing those error(s) with a predetermined acceptable error level, and repeating training epochs until the training errors become less than the predetermined acceptable error level.

An actual example of software emulation of the p-net **100** using object-oriented programming is described below and shown in FIGS. **14-21**.

Formation of a NeuronUnit object class can include formation of:
set of objects of the Synapse class;
neuron **116** presenting a variable, wherein adding is performed during training; and
calculator **122** presenting a variable, wherein the value of desired neuron sum **120** is stored and calculation of correction values An is performed during the training process.

Class NeuronUnit provides p-net **100** training can include:
formation of neuron sums **120**;
setting desired sums;
calculation of correction value Δn; and
adding the calculated correction value Δn to the corrective weights $W_{i,n,d}$.

Formation of the object class Synapse can include:
set of corrective weights $W_{i,n,d}$; and
pointer indicating the input connected to synapse **118**.

Class Synapse can perform the following functions:
initialization of corrective weights $W_{i,n,d}$;
multiplying the weights $W_{i,n,d}$ by the coefficients $C_{i,d,n}$; and
correction of weights $W_{i,n,d}$.

Formation of the object class InputSignal can include:
set of indexes on synapses **118** connected to a given input **102**;
variable that includes the value of the input signal **104**;
values of possible minimum and maximum input signal;
number of intervals "d"; and
interval length.

Class InputSignal can provide the following functions:
formation of the p-net **100** structure, including:
Adding and removal of links between an input **102** and synapses **118**; and
Setting the number of intervals "d" for synapses **118** of a particular input **102**.
setting parameters of minimum and maximum input signals **104**;
contribution into the operation of p-net **100**:
setting an input signal **104**; and
setting coefficients of corrective weight impact $C_{i,d,n}$.

Formation of the object class PNet includes a set of object classes:
NeuronUnit; and
InputSignal.

Class PNet provides the following functions:
setting the number of objects of the InputSignal class;
setting the number of objects of the NeuronUnit class; and
group request of functions of the objects NeuronUnit and InputSignal.

During the training process the cycles can be formed, where:
neuron output sum that is equal to zero is formed before the cycle starts;
all synapses contributing to the given NeuronUnit are reviewed. For each synapse **118**:
Based on the input signal **102**, the distributor forms a set of coefficients of corrective weight impact $C_{i,d,n}$;
All weights $W_{i,n,d}$ of the said synapse **118** are reviewed, and for each weight:
The value of weight $W_{i,n,d}$ is multiplied by the corresponding coefficient of corrective weight impact $C_{i,d,n}$;
The result of multiplication is added to the forming neuron output sum;
correction value Δ_n is calculated;
correction value Δ_n is divided by the coefficient of corrective weight impact $C_{i,d,n}$, i.e., $\Delta_n/C_{i,d,n}$; and
all synapses **118** contributing to the given NeuronUnit are reviewed. For each synapse **118**, all weights $W_{i,n,d}$ of the subject synapse are reviewed, and for each weight its value is modified to the corresponding correction value Δ_n.

The previously noted possibility of additional training of the p-net **100** allows a combination of training with the recognition of the image that enables the training process to be sped up and its accuracy to be improved. When training the p-net **100** on a set of sequentially changing images, such as training on consecutive frames of the film that are slightly different from each other, additional training can include:
training with the first image;
recognition of the next image and identifying a percentage of similarity between the new image and the image the network was initially trained with. Additional training is not required if the recognition error is less than its predetermined value; and
if the recognition error exceeds the predetermined value, additional training is provided.

Training of the p-net **100** by the above basic training algorithm is effective for solving problems of image recognition, but does not exclude the loss or corruption of data due to overlapping images. Therefore, the use of the p-net **100** for memory purposes, though possible, may not be entirely reliable. The present embodiment describes training of the p-net **100** that provides protection against loss or corruption of information. An additional restriction can be introduced into the basic network training algorithm which requires that every corrective weight $W_{i,n,d}$ can be trained only once. After the first training cycle, the value of the weight $W_{i,n,d}$ remains fixed or constant. This can be achieved by entering an additional access index "a" for each corrective weight, which is the above-described index representing the number of accesses to the subject corrective weight $W_{i,n,d}$ during the training process.

As described above, each corrective weight can take on the nomenclature of $W_{i,n,d,a}$, wherein "a" is the number of accesses to the subject weight during the training process. In the simplest case, for the non-modified, i.e., not fixed, weights, a=0, while for the weights that have been modified or fixed by the described basic algorithm, a=1. Moreover, while applying the basic algorithm, the corrective weights $W_{i,n,d,a}$ with the fixed value a=1 can be excluded from the weights to which corrections are being made.

In such a case, equations [5], [6], and [7] can be transformed as follows:

Value	Basic algorithm	Training algorithm with fixed weights
Equal correction value - Variant 1	$\Delta_n = (O_n - \Sigma_n)/S$ [4],	$\Delta_n = (O_n - \Sigma_n)/S_0$ [8], where S_0 – sum $C_{i,d,n,a}$ of all corrective weights $W_{i,n,d,a}$ contributing to the subject neuron and having the index a = 0
Modified corrective weight - Variant 1	$W_{i,n,d}$ modified = $W_{i,n,d} + \Delta_n / C_{i,d,n}$ [5],	$W_{i,n,d,0}$ modified = $W_{i,n,d,0} + \Delta_n / C_{i,d,n,0}$ [9], wherein $W_{i,n,d,0}$ are weights contributing to the subject neuron and having the index a = 0, and $C_{i,d,n,0}$ are coefficients of corrective weight impact for the corrective weights contributing to subject the neuron and having the index a = 0
Modified corrective weight - Variant 2	$W_{i,n,d}$ modified = $W_{i,n,d} \times \Delta_n$ [7]	$W_{i,n,d,0}$ modified = $W_{i,n,d,0} \times \Delta_n$ [10]

The above restriction can be partially applied to the correction of the previously trained corrective weights $W_{i,n,d,a}$, but only to the weights that form the most important images. For example, within the training on a set of portraits of a single person, one specific image can be declared primary and be assigned priority. After training on such a priority image, all corrective weights $W_{i,n,d,a}$ that are changed in the process of training can be fixed, i.e., where the index a=1, thus designating the weight as and other images of the same person may remain changeable. Such priority may include other images, for example those that are used as encryption keys and/or contain critical numeric data.

The changes to the corrective weights $W_{i,n,d,a}$ may also not be completely prohibited, but limited to the growth of the index "a". That is, each subsequent use of the weight $W_{i,n,d,a}$ can be used to reduce its ability to change. The more often a particular corrective weight $W_{i,n,d,a}$ is used, the less the weight changes with each access, and thus, during training on subsequent images, the previous, stored images are changed less and experience reduced corruption. For example, if a=0, any change in the weight $W_{i,n,d,a}$ is possible; when a=1 the possibility of change for the weight can be decreased to ±50% of the weight's value; with a=2 the possibility of change can be reduced to ±25% of the weight's value.

After reaching the predetermined number of accesses, as signified by the index "a", for example, when a=5, further change of the weight $W_{i,n,d,a}$ may be prohibited. Such an approach can provide a combination of high intelligence and information safety within a single p-net **100**. Using the network error calculating mechanism, levels of permissible errors can be set such that information with losses within a predetermined accuracy range may be saved, wherein the accuracy range can be assigned according to a particular task. In other words, for the p-net **100** operating with visual images, the error can be set at the level of that cannot be captured by the naked eye, which would provide a significant, "factor of" increase in storage capacity. The above can enable creation of highly effective storage of visual information, for example movies.

The ability to selectively clean computer memory can be valuable for continued high-level functioning of the p-net **100**. Such selective cleaning of memory may be done by removing certain images without loss of or corruption of the rest of the stored information. Such cleaning can be provided as follows:

- identification of all corrective weights $W_{i,n,d,a}$ that participate in the image formation, for example, by introducing the image to the network or by compiling the list of used corrective weights for each image;
- reduction of index "a" for the respective corrective weights $W_{i,n,d,a}$; and
- replacement of corrective weights $W_{i,n,d,a}$ either with zero or with a random value close to the middle of the range of possible values for the subject weight when the index "a" is reduced to zero.

An appropriate order and succession of reduction of the index "a" can be experimentally selected to identify strong patterns hidden in the sequence of images. For example, for every 100 images introduced into the p-net **100** during training, there can be a reduction of the index "a" by a count of one, until "a" reaches the zero value. In such a case, the value of "a" can grow correspondingly with the introduction of new images. The competition between growth and reduction of "a" can lead to a situation where random changes are gradually removed from memory, while the corrective weights $W_{i,n,d,a}$ that have been used and confirmed many times can be saved. When the p-net **100** is trained on a large number of images with similar attributes, for example, of the same subject or similar environment, the often-used corrective weights $W_{i,n,d,a}$ constantly confirm their value and information in these areas becomes very stable. Furthermore, random noise will gradually disappear. In other words, the p-net **100** with a gradual decrease in the index "a" can serve as an effective noise filter.

The described embodiments of the p-net **100** training without loss of information allow creating a p-net memory with high capacity and reliability. Such memory can be used as a high-speed computer memory of large capacity providing greater speed than even the "cash memory" system, but will not increase computer cost and complexity as is typical with the "cash memory" system. According to published data, in general, while recording a movie with neural networks, memory can be compressed tens or hundreds of times without significant loss of recording quality. In other words, a neural network is able to operate as a very effective archiving program. Combining this ability of neural networks with the high-speed training ability of the p-net **100** may permit a creation of high-speed data transmission system, a memory with high storage capacity, and high-speed decryption program multimedia files, i.e., a codex.

Due to the fact that in the p-net **100** data is stored as a set of corrective weights $W_{i,n,d,a}$, which is a type of code recording, decoding or unauthorized access to the p-net via existing methods and without the use of an identical network and key is unlikely. Thus, p-net **100** can offer a considerable degree of data protection. Also, unlike conventional computer memory, damage to individual storage elements of the p-net **100** presents an insignificant detrimental effect, since other elements significantly compensate lost functions. In the image recognition process, inherent patterns of the image being used are practically not distorted as a result of damage to one or more elements. The above can dramatically improve the reliability of computers and allow using certain memory blocks, which under normal conditions would be considered defective. In

addition, this type of memory is less vulnerable to hacker attacks due to the absence of permanent address(s) for critical bytes in the p-net **100**, making it impervious to attack of such a system by a variety of computer viruses.

The previously-noted process of image recognition with determination of the percentage of similarity between different images used in training can also be employed as a process of image classification according to the previously defined categories, as noted above. For clustering, which is a division of the images into not predefined natural classes or groups, the basic training process can be modified. The present embodiment can include:

- preparation of a set of input images for training, without including prepared output images;
- formation and training the network with the formation of the neuron output sums as it is done according to the basic algorithm;
- selection in the resulting output image of the output with maximum output sum, i.e., the winner output, or a group of winner outputs, which can be organized similar to Kohonen network;
- creation of a desired output image, in which the winner output or the group of winner outputs receive maximum values. At the same time:
  - The number of selected winner outputs can be predetermined, for example, in a range of 1 to 10, or winner outputs can be selected according to the rule "no less than N % of the maximum neuron sum", where "N" may be, for example, within 90-100%; and
  - All other outputs can be set equal to zero.
- training according to the basic algorithm with using the created desired output image, FIG. **13**; and
- repeating all procedures for other images with formation for each image of different winners or winner groups.

The set of desired output images formed in the above manner can be used to describe clusters or groups into which the plurality of input images can naturally separate. Such a set of desired output images can be used to produce different classifications, such as for selection of images according to the established criteria and in statistical analysis. The above can also be used for the aforementioned inversion of input and output images. In other words, the desired output images can be used as the input images for another, i.e., additional, network, and the output of the additional network can be images presented in any form suitable for computer input.

In the p-net **100**, after a single cycle of training with the described-above algorithm, desired output images can be generated with small output sum variation, which can slow down the training process and can also reduce its accuracy. To improve training of the p-net **100**, the initial variation of points can be artificially increased or extended, so that the variation of the magnitude of the points would cover the entire range of possible output values, for example −50 to +50, as shown in FIG. **21**. Such an extension of the initial variation of points may be either linear or nonlinear.

A situation may develop where the maximum value of a certain output is an outlier or a mistake, for example, a manifestation of noise. Such can be manifested by the appearance of a maximum value surrounded by a multitude of small signals. When winning outputs are selected, the small signal values can be disregarded through selection the greatest signals surrounded by other large signals as the winners. For this purpose, known statistical techniques of variance reduction may be used, such as importance sampling. Such an approach can permit removing noise while maintaining basic valuable patterns. Creation of winner groups enables clustering of linearly inseparable images, i.e., images that relate to more than one cluster, as shown in FIG. **13**. The above can provide a significant improvement in accuracy and decrease the number of clustering errors.

In the process of p-net **100** training, typical errors being subjected to correction are:

Typical error of neural network	Method of p-net 100 correction
Errors in selection of training images. For example, the set of human images includes an image of a cat	Erasing the corresponding desired output image or restriction of its demonstration
Network errors that were not corrected during training. For example, a certain image is recognized incorrectly because the network cannot divide some features of the object (the effect of linear inseparability).	Additional training of the p-net 100 after the error is detected; introduction of additional desired output image
Decline in accuracy due to reaching the limit of network information capacity	P-net 100 expansion

Error correction is also possible with the help of the above-described algorithm in training with an outside trainer.

The detailed description and the drawings or figures are supportive and descriptive of the disclosure, but the scope of the disclosure is defined solely by the claims. While some of the best modes and other embodiments for carrying out the claimed disclosure have been described in detail, various alternative designs and embodiments exist for practicing the disclosure defined in the appended claims. Furthermore, the embodiments shown in the drawings or the characteristics of various embodiments mentioned in the present description are not necessarily to be understood as embodiments independent of each other. Rather, it is possible that each of the characteristics described in one of the examples of an embodiment can be combined with one or a plurality of other desired characteristics from other embodiments, resulting in other embodiments not described in words or by reference to the drawings. Accordingly, such other embodiments fall within the framework of the scope of the appended claims.

The invention claimed is:

1. A neural network comprising:

- a plurality of inputs of the neural network, each input configured to receive an input signal having an input value;
- a plurality of synapses, wherein each synapse is connected to one of the plurality of inputs and includes a plurality of corrective weights, wherein each corrective weight is defined by a weight value;
- a set of distributors, wherein each distributor is operatively connected to one of the plurality of inputs for receiving the respective input signal and is configured to select one or more corrective weights from the plurality of corrective weights in correlation with the input value;
- a set of neurons, wherein each neuron has at least one output and is connected with at least one of the plurality of inputs via one of the plurality of synapses, and wherein each neuron is configured to add up the weight values of the corrective weights selected from each synapse connected to the respective neuron and thereby generate a neuron sum; and
- a weight correction calculator configured to receive a desired output signal having a value, determine a deviation of the neuron sum from the desired output signal value, and modify respective corrective weight values using the determined deviation, such that adding up the modified corrective weight values to determine the neu-

ron sum minimizes the deviation of the neuron sum from the desired output signal value to thereby train the neural network.

2. The neural network of claim **1**, wherein:

the determination of the deviation of the neuron sum from the desired output signal includes division of the desired output signal value by the neuron sum to thereby generate a deviation coefficient; and

the modification of the respective corrective weight values includes multiplication of each corrective weight used to generate the neuron sum by the deviation coefficient.

3. The neural network of claim **1**, wherein the deviation of the neuron sum from the desired output signal is a mathematical difference therebetween, and wherein the generation of the respective modified corrective weights includes apportionment of the mathematical difference to each corrective weight used to generate the neuron sum.

4. The neural network of claim **3**, wherein the apportionment of the mathematical difference includes dividing the determined difference equally between each corrective weight used to generate the neuron sum.

5. The neural network of claim **3**, wherein:

each distributor is additionally configured to assign a plurality of coefficients of impact to the respective plurality of corrective weights, such that each coefficient of impact is assigned to one of the plurality of corrective weights in a predetermined proportion to generate the respective neuron sum;

each neuron is configured to add up a product of the corrective weight and the assigned coefficient of impact for all the synapses connected thereto; and

the weight correction calculator is configured to apply a portion of the determined difference to each corrective weight used to generate the neuron sum according to the proportion established by the respective coefficient of impact.

6. The neural network of claim **5**, wherein:

each respective plurality of coefficients of impact is defined by an impact distribution function;

the plurality of input values is received into a value range divided into intervals according to an interval distribution function, such that each input value is received within a respective interval, and each corrective weight corresponds to one of the intervals; and

each distributor uses the respective received input value to select the respective interval, and to assign the respective plurality of coefficients of impact to the corrective weight corresponding to the selected respective interval and to at least one corrective weight corresponding to an interval adjacent to the selected respective interval.

7. The neural network of claim **6**, wherein each corrective weight is additionally defined by a set of indexes including:

an input index configured to identify the corrective weight corresponding to the input;

an interval index configured to specify the selected interval for the respective corrective weight; and

a neuron index configured to specify the corrective weight corresponding to the neuron.

8. The neural network of claim **7**, wherein each corrective weight is further defined by an access index configured to tally a number of times the respective corrective weight is accessed by the input signal during training of the neural network.

9. A method of training a neural network, comprising:

receiving, via an input to the neural network, an input signal having an input value;

communicating the input signal to a distributor operatively connected to the input;

selecting, via the distributor, in correlation with the input value, one or more corrective weights from a plurality of corrective weights, wherein each corrective weight is defined by a weight value and is positioned on a synapse connected to the input;

adding up the weight values of the selected corrective weights, via a neuron connected with the input via the synapse and having at least one output, to generate a neuron sum;

receiving, via a weight correction calculator, a desired output signal having a value;

determining, via the weight correction calculator, a deviation of the neuron sum from the desired output signal value; and

modifying, via the weight correction calculator, respective corrective weight values using the determined deviation, such that adding up the modified corrective weight values to determine the neuron sum minimizes the deviation of the neuron sum from the desired output signal value to thereby train the neural network.

10. The method of claim **9**, wherein:

said determining the deviation of the neuron sum from the desired output signal value includes dividing the desired output signal value by the neuron sum to thereby generate a deviation coefficient; and

said modifying the respective corrective weights includes multiplying each corrective weight used to generate the neuron sum by the deviation coefficient.

11. The method of claim **9**, wherein said determining the deviation of the neuron sum from the desired output signal value includes determining a mathematical difference therebetween, and wherein said modifying of the respective corrective weights includes apportioning the mathematical difference to each corrective weight used to generate the neuron sum.

12. The method of claim **11**, wherein said apportioning of the mathematical difference includes dividing the determined difference equally between each corrective weight used to generate the neuron sum.

13. The method of claim **9**, further comprising:

assigning, via the distributor, a plurality of coefficients of impact to the plurality of corrective weights, and includes assigning each coefficient of impact to one of the plurality of corrective weights in a predetermined proportion to generate the neuron sum;

adding up, via the neuron, a product of the corrective weight and the assigned coefficient of impact for all the synapses connected thereto; and

applying, via the weight correction calculator, a portion of the determined difference to each corrective weight used to generate the neuron sum according to the proportion established by the respective coefficient of impact.

14. The method of claim **13**, wherein the plurality of coefficients of impact is defined by an impact distribution function; the method further comprising:

receiving the input value into a value range divided into intervals according to an interval distribution function, such that the input value is received within a respective interval, and each corrective weight corresponds to one of the intervals; and

using, via the distributor, the received input value to select the respective interval, and to assign the plurality of coefficients of impact to the corrective weight corresponding to the selected respective interval and to at

least one corrective weight corresponding to an interval adjacent to the selected respective interval.

15. The method of claim **14**, further comprising additionally defining each corrective weight by a set of indexes, wherein the set of indexes includes:

an input index configured to identify the corrective weight corresponding to the input;

an interval index configured to specify the selected interval for the respective corrective weight; and

a neuron index configured to specify the corrective weight corresponding to the neuron.

16. The method of claim **15**, further comprising additionally defining each corrective weight by an access index configured to tally a number of times the respective corrective weight is accessed by the input signal during training of the neural network.

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