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(54) **MULTI-LAYER OPTO-ELECTRONIC NEURAL NETWORK**

MEHRSCHICHTIGES OPTOELEKTRISCHES NEURONALES NETZWERK

RESEAU NEURONAL OPTO-ELECTRONIQUE MULTICOUCHE

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Description

TECHNICAL FIELD

[0001] This invention relates to a three-dimensional volume holographic medium in which a multi-layer, opto-electronic neural network is used to classify patterns, and to a method of operating same.

BACKGROUND ART

[0002] Multi-layer neural networks may be used to classify patterns. These networks typically consist of layers of nonlinear processing elements or "neurons" arranged in a highly interconnected hierarchy. Each neuron within the top layer of the network hierarchy accepts as input a weighted sum over all of the resolution elements of the pattern to be classified. Each of these sums is then nonlinearly processed by each top-layer neuron and outputted to the second layer of the network, in which each neuron accepts as input a weighted sum over all neural outputs of the first layer. This process continues until the output, or classification, layer of the network is reached. The outputs of this layer are then interpreted as the desired classification results.

[0003] Typically, no more than two or three layers are required to achieve pattern classification and typically the number of neurons in each layer decreases as the classification layer is approached. The network is trained to classify patterns by pre-selecting the weights that interconnect the various layers. A good theoretical description of multi-layer neural networks may be found in Parallel Distributed Processing: Explorations in the Microstructure of Cognition, Vol. 1: Foundations, by D. E. Rumelhart and J.L. McClelland (HIT Press, 1986).

[0004] Mathematically, the functioning of a single layer of a multi-layer neural network may be described as follows:

$$\vec{g}R^{(i)}\vec{\sigma}^{(i)}] = \vec{g}[\bar{f}^{(i)}] = \vec{\sigma}^{(i-1)} \; ; \; i = 1, 2, \ldots \text{N-1} \qquad 1)$$

where the pattern vector $\vec{\sigma}^{(i)}$ is the input to layer "*i* "; the matrix $R^{(i)}$ represents the neuron input weights; *N* is the number of network layers; and $\vec{g}[\bullet]$ is a nonlinear vector function which operates identically on each element of $\vec{f}^{(i)}$. Typically, $\vec{g}[\bullet]$ operates on each element "*k*" of $\vec{f}^{(i)}$ as indicated in Figure 1. The particular nonlinear transfer function illustrated in Figure 1 has what is commonly referred to as a sigmoidal shape, with adjustable threshold ("a") and saturation ("b") points.

[0005] Figure 2 shows an illustrative example of a three-layer neural network consisting of a three-resolution-element input pattern with two output classes. Each layer consists of a fully interconnected set of weights connecting the input to the summers. The output from the summers is fed through a nonlinearity, which completes the processing for that layer. The output from one layer serves as input to the next layer.

[0006] Pattern classification problems in which input patterns are two-dimensional images typically require two-layer neural networks which may contain as many as 10^2 classification-layer neurons and 10^3 input-layer neurons. For a 10^4-pixel image and fully interconnected layers, $R^{(1)}$ becomes a $10^4 \times 10^3$-element matrix and $R^{(2)}$ a $10^3 \times 10^2$-element matrix. Real-time (- 10^{-3} seconds) classification of unknown images therefore requires on the order of twenty billion operations per second [$= 2 \times (10^7 + 10^5) \times 10^3$]. Existing, all-digital electronic computers capable of such throughput occupy many cubic feet of volume and consume thousands of watts of power.

[0007] Optical devices in which the matrices $R^{(i)}$ may be stored in the form of two-dimensional Fourier-space holograms include those described by: D. Gabor in "Character Recognition by Holography" in Nature, 208, p. 422 (1965); J.T. LaMacchia and D.L. White in "Coded Multiple Exposure Holograms", Applied Optics, 7, p. 91 (1968); J.R. Leger and s.H. Lee in "Hybrid Optical Processor for Pattern Recognition and Classification Using a Generalized Set of Pattern Functions", Applied Optics, 21, p. 274 (1982); and D.A. Gregory and H.K. Liu in "Large-Memory Real-Time Multichannel Multiplexed Pattern Recognition", Applied Optics, 23, p. 4560 (1984). Additionally, in a paper by T. Jannson, H.M. Stoll, and C. Karaguleff ("The interconnectability of neuro-optic processors", Proceedings of the International society for Optical Engineering, Vol. 698, p. 157 (1986)), there is described, on page 162, an optical volume-holographic architecture for computing matrix-vector products. This disclosure is, however, in the context of providing interconnects for an all-optical, recurrent (feedback)-type neural network.

US 5121228 discloses a holographic learning machine comprising a holographic recording medium, photo detectors receiving light diffracted from the medium and N electrical circuits subtracting respective pairs of outputs of the photo detectors, thresholding the differences and comparing them to target-valves. A positive or negative error amplitude modulator in a 2N array is turned on to transmit to the recording medium light coherent with the image beam. The features of the preamble of the claims are known from that document.

[0008] It is one object of this invention to provide a method and apparatus that employs a three-dimensional volume holographic medium in which multi-layer, opto-electronic neural network interconnects are stored and used to multiply pattern vectors.

[0009] It is another object of this invention to provide nonlinear processing means by which the intermediate and output pattern vectors computed within a multi-layer opto-electronic neural network may be acted upon.

[0010] It is a further object of this invention to provide a compact (potentially less than 200 cubic inches), low-power (potentially less than 10 watts of prime electrical power), multi-layer, opto-electronic neural network capable of executing at least 2 x 10^{10} (twenty billion) arithmetic operations per second.

SUMMARY OF THE INVENTION

[0011] According to the present invention there is provided a multi-layer opto-electronic neural network (MLOENN) pattern classification apparatus, comprising:

a volume holographic medium having a plurality of Fourier-space volume holographs representing neural network weight vectors stored within;

means having an output optically coupled to said medium by a first Fourier transform lens means, for spatially modulating a spatially uniform laser beam in accordance with an unknown pattern;

means having an input optically coupled by a second Fourier transform lens means o an angular spectrum of plane waves generated by said medium in response to the output of said spatially modulating means for detecting plane waves that correspond to vector inner products generated within said medium in response to the unknown pattern;

means by which the output of said detection means are nonlinearly processed in a serial manner;

means by which said nonlinearly processed output is temporarily stored such that the network is virtual, in that only 1 layer exists at a time, intermediate results being stored in said temporary storage means

means by which the output of said temporary storage means may be selectively read out on feed back into said spatial modulating means for further processing by the MLOENN as input signals to a next layer of the MLOENN, characterised in that said spatial modulating means geometrically partitioned to permit the independent storage of individual MLOENN layer weight vectors, $\vec{v}^{(k,i)}$ (k = 1. 2, ..., K; i = 1, 2, ..., N - 1),

and the independent excitation of individual MLOENN layers by patterns

$$\vec{\sigma}^{(i)} \ (i = 1, 2, \ldots, N-1)$$

such that each $\vec{v}^{(k,i)}$ and $\vec{\sigma}^{(i)}$ occupy a same physical portion of said spatial modulating means , N being the number of vector layers, K being a number vector inner products

[0012] According to the present invention there is also provided a method for generating vector inner products(f_k [illegible]) comprising the steps of: loading an unknown pattern vector $\vec{\sigma}^{(i)}$ (i = 1, 2, ... , N - 1) into a spatial light modulator means using a same pre-determined and fixed lexicographic ordering scheme that was initially employed to load $\vec{v}^{(k,i)}$ (i = 1, 2, ... ,N - 1) weight vectors into a volume holographic medium;

spatially modulating a first plane-wave laser beam in accordance with the unknown pattern vector;

employing a phase encoder means to multiply the spatially modulated first plane-wave laser beam by a random, two-dimensional phase encoding function;

transmitting a phase encoded light pattern representative of the multiplied spatially modulated first plane-wave laser beam from the phase encoder means to a first Fourier transform lens means.

generating within the volume holographic medium, with the first Fourier transform lens means a Fourier transform of the phase encoded light pattern;

generating, within the volume holographic medium an angular spectrum of plane waves having amplitudes proportional to vector inner products $\vec{\sigma}^{(i)} \bullet \vec{v}^{(k,i)}$ (k = 1, 2, ... , K; i = 1, 2, ..., N)
and propagation angles of

$$\Psi_k \ (k = 1, 2, \ldots, K)$$

which are identical to reference plane wave angles. Ψ_k

focusing onto a detector means with a second Fourier transform lens means, plane waves of the angular spectrum of plane waves generated within the volume holographic medium,

reading out, from the detector means, signals representing vector inner products corresponding to the plane waves focused upon the detector means;

serially and nonlinearly processing the output of the detector means;

temporarily storing the nonlinearly processed output of the detector means as; and

selectively reading out the temporarily stored output of the detector means as pattern recognition results or feeding the temporarily stored output of the detector means back into the spatial modulating means for further neural network processing as input signals of a next pattern vector $\vec{\sigma}^{(i+1)}$ characterised in that said spatial modulating means is geometrically partitioned to permit the independent storage of individual MLOENN layer weight vectors $\vec{v}^{(k,i)}$ (k = 1, 2, ... , K; i = 1, 2, ... , N - 1), and the independent excitation of individual MLOENN layers by pattern

$$\vec{\sigma}^{(i)} \ (i = 1, 2, \ldots, N\text{-}1)$$

such that each $\vec{v}^{(k,i)'}$ and $\vec{\sigma}^{(i)}$ occupy a same physical portion of said spatial modulating means N being the number of vector layers, K being a number of vector inner products.

[0013] In accordance with the invention, a multi-layer neural network accepts as input a pattern vector $\vec{\sigma}^{(1)}$ and returns as output a classification vector $\vec{\sigma}^{(N)}$. All $\vec{\sigma}^{(i)}$ (i = 1, 2, ..., N-1) are assigned pre-determined portions of the network input transducer, which consists of a two-dimensional spatial light modulator (SLM) mounted onto or in close proximity to a two-dimensional phase encoder (diffuser). Neural network weight matrices, $R^{(i)}$, are stored in the form of three-dimensional, Fourier-space holograms, with each hologram corresponding to a single row of an individual $R^{(i)}$. These rows are referred to hereafter as weight vectors. All weight vectors of a given $R^{(i)}$ are accessed simultaneously (in parallel) by illuminating the volume holograms with the Fourier transform of the pattern or input vector, $\vec{\sigma}^{(i)}$, which is to be weighted (or multiplied) by the $R^{(i)}$ in question. Elements of the product vectors $\vec{f}^{(i)}$ (inner products between the weight vectors and $\vec{\sigma}^{(i)}$), are determined by measuring the properties of the light radiated by the volume holograms: the angle of each of the light rays radiated indexes the element (i.e., indicates which weight vector is being multiplied or dotted onto the input vector $\vec{\sigma}^{(i)}$) while the amplitude of each of the light rays radiated is proportional to the square of the magnitude of the indexed inner product. Nonlinear processing of the individual elements of the product vector, $\vec{f}^{(i)}$, is accomplished by focusing each radiated light ray onto a detector array element and further processing the detector array output using, for example, an electronic look-up table or a saturable electronic amplifier with adjustable thresholding and saturation points. The non-linearly processed $\vec{f}^{(i)}$ (equal to $\vec{\sigma}^{(i+1)}$) is then temporarily held in an electronic buffer memory prior to being loaded into that portion of the SLM allocated to layer "i+1". This procedure is continued until $\vec{\sigma}^{(N)}$ is produced.

[0014] In addition to providing computational throughputs far in excess of available or projected all-digital electronic neural networks, the present invention enables more weight-vector information (the product of weight-vector count and weight-vector size) to be accessed in parallel than do the aforementioned devices, wherein weight vectors are stored in the form of two-dimensional Fourier-space holograms. The ratio of storage capabilities (storage capacity of a three-dimensional-hologram device divided by the storage capacity of a two-dimensional hologram device) is equal to the maximum (linear) space-bandwidth product, or number of linearly ordered resolution elements, that can be achieved in an optical system. The latter number is typically on the order of 3,000.

[0015] More specifically, the invention provides a pattern classification apparatus and a method for operating same. The apparatus includes a volume-holographic medium having a plurality of Fourier-space volume holograms representing stored weight vectors. The apparatus further includes a spatial light modulator and a phase encoder. The phase encoder has an output optically coupled to the volume-holographic medium by a first Fourier transform lens. The spatial light modulator spatially modulates a spatially uniform laser beam in accordance with an unknown pattern which has been loaded into the spatial light modulator. The two-dimensional phase encoder causes the spatially modulated laser beam to be spatially distributed prior to application to the volume-holographic medium. The apparatus also includes a detector having an input optically coupled by a second Fourier transform lens means to an angular spectrum of plane waves generated by the volume-holographic medium in response to the output of the spatial modulator, phase encoder, and first Fourier lens. The detector detects focused plane waves that correspond to vector inner products generated within the volume-holographic medium in response to the unknown pattern vector. The apparatus further includes a nonlinear electronic device for serially processing the detected inner products, means for temporarily storing the nonlinearly processed inner products, and means for feeding the nonlinearly processed inner products back into the spatial light modulator.

BRIEF DESCRIPTION OF THE DRAWINGS

[0016] The above set forth and other features of the invention are made more apparent in the ensuing Detailed Description of the Invention, when read in conjunction with the attached drawings, wherein:

Fig. 1 depicts nonlinear processing of element "k" of the neural input vector, $[\vec{f}^{(i)}]_k$, to produce a corresponding element of the neural output vector, $[\vec{\sigma}^{(i+1)}]_k$, "a" and "b" being thresholding and saturation points, respectively, of the resulting sigmoidal neural transfer function;
Fig. 2 schematically depicts an example of a three-layer neural network;
Fig. 3 is a perspective drawing of a multi-layer opto-electronic neural network (MLOENN) of the invention;
Fig. 4 is a perspective drawing of the MLOENN illustrating the storage of weight vectors $\vec{v}^{(k,i)}$, (i = 1, 2, ..., N - 1) of a sequence of K weight vectors (k = 1, 2, ..., K);
Fig. 5 depicts the spatial light modulator geometry used to store the weight vectors $\vec{v}^{(k,i)}$, (i = 1, 2, ... , (N - 1));
Figs. 6(a), 6(b), and 6(c) illustrate the spatial light modulator geometry used to sequentially process patterns $\vec{\sigma}^{(1)}$ (the input pattern to the neural network) through $\vec{\sigma}^{(N-1)}$ (the input to the Nth layer of an N-layer neural network), with Fig. 6(a) indicating the first loading of $\vec{\sigma}^{(1)}$ into the same portion of the SLM used to load the $\vec{v}^{(k,1)}$ (k = 1, 2, ... , K), with Fig. 6(b) showing the subsequent loading of $\vec{\sigma}^{(2)}$ into the same portion of the SLM used to load the $\vec{v}^{(k,2)}$ (k = 1, 2, .. . , K), and Fig. 6(c) showing the loading process as continued until $\vec{\sigma}^{(N-1)}$. is loaded into the same portion of the SLM used to load the $\vec{v}^{(k,N-1)}$ (k = 1, 2, ... , K);
Fig. 7 is a plan view of the MLOENN illustrating the generation, detection, and nonlinear processing of a single vector inner product, $f_k^{(i)}$; and
Fig. 8 is a perspective drawing of a further embodiment of an MLOENN illustrating the storage of a single weight vector $\vec{v}^{(k,i)}$ (i = 1, 2, ... , N - 1) of a sequence of weight vectors (k = 1, 2, ... , K), this embodiment employing a reference plane-wave laser beam that is scanned in two dimensions in conjunction with a two-dimensional detector array.

MODES OF CARRYING OUT THE INVENTION

[0017] The Multi-Layer Opto-Electronic Neural Network (MLOENN) classifies patterns by repeatedly executing the algorithm described by Equation (1). This algorithm consists of: (1) calculating the matrix-vector product $R^{(i)}\vec{\sigma}^{(i)}$ to yield $\vec{f}^{(i)}$, and (2) nonlinearly processing $\vec{f}^{(i)}$ to yield $\vec{\sigma}^{(i+1)}$, which then becomes the input to the next network layer. The network is virtual in the sense that only one layer actually "exists" at a time: intermediate results (i.e., $\vec{\sigma}^{(i)}$ for i > 1) are temporarily stored in a buffer memory prior to being fed back into the MLOENN for further processing.
[0018] The MLOENN calculates $R^{(i)}\vec{\sigma}^{(i)}$ by computing, in parallel, the inner products between the rows of $R^{(i)}$ (hereafter referred to as weight vectors) and $\vec{\sigma}^{(i)}$. Mathematically, the MLOENN calculates:

$$\vec{v}^{(k,i)} \cdot \vec{\sigma}^{(i)} = f_k^{(i)};\ k = 1, 2, \ldots, K, \qquad (2)$$

where $\vec{v}^{(k,i)}$ is the transpose of the k^{th} row of $R^{(i)}$, $f_k^{(i)}$ is the k^{th} element of $\vec{f}^{(i)}$, and K is the number of rows of $R^{(i)}$. $\vec{\sigma}^{(i)}$ is a lexicographic representation of the input pattern $\sigma^{(i)}$ (or intermediate neural network result being processed), wherein each resolution element or pixel of $\sigma^{(i)}$ corresponds to a specific element of $\vec{\sigma}^{(i)}$.
[0019] The MLOENN nonlinearly processes the $f_k^{(i)}$ by serially passing the latter through any electronic device with an appropriate, nonlinear transfer function (as illustrated by the example shown in Figure 1).
[0020] A perspective illustration of the MLOENN is shown in Fig. 3. The MLOENN includes a two-dimensional spatial light modulator (SLM) 1, a two-dimensional phase encoder 2, a first Fourier transform lens 3, a medium 4 in which volume holograms are stored, a second Fourier transform lens 5, a linear detector array 6, a nonlinear processing device 12, and a buffer memory 13. Rays 9 represent plane waves generated within medium 4 (having amplitudes $f_k^{(i)}$, k = 1, 2, ... , K) and rays 10 represent waves (also having amplitudes $f_k^{(i)}$, k = 1, 2, ... , K) convergent (i.e., focused) on detector 6. With reference to Equation (1), $\vec{\sigma}^{(1)}$ represents the input pattern to be classified, $\vec{g}[\vec{f}^{(N)}]$ represents the ultimate classification result, and $\vec{\sigma}^{(i+1)}$ represents an intermediate layer (i = 1, 2, ... , N - 1) pattern vector.
[0021] In Fig. 3 SLM 1 includes means for electronically inputting a weight vector or pattern. By way of example only, SLM 1 may be comprised of a liquid crystal (LC) projection display device having a plurality of pixels that are modified in response to input from, for example, a digital computer. The use of a LC projection display device enables a new input pattern or weight vector to be stored within medium 4 every, for example, 1/30th of a second. Any one of a number of spatial light modulator types may be employed. These include ferroelectric liquid crystal, twisted nematic liquid crystal, silicon membrane (deformable mirror), and magneto-optic types. In other embodiments of the invention, SLM

1 may be simply a transparent substrate having a pattern formed thereon.

[0022] Two-dimensional phase encoder 2 causes the optical signal that passes through SLM 1 to be spatially distributed prior to application to medium 4. This function may be accomplished by constructing phase encoder 2 from a transparent substrate, such as glass, and providing an etched random pattern on a surface of the substrate. The linear dimension of the smallest feature of the random pattern defines the coherence length of phase encoder 2. The significance of the coherence length of the phase encoder is discussed below.

[0023] Fourier transform lenses 3 and 5 are typically spherical lenses.

[0024] A presently preferred volume hologram medium 4 is comprised of iron-doped lithium niobate ($LiNbO_3$:Fe). Representative dimensions of the active volume of medium 4 are one centimeter on a side. Holograms may be "permanently" fixed by heating the $LiNbO_3$:Fe to approximately 160° C for approximately twenty-five minutes (see, for example, D.L. Staebler, W.J. Burk, W. Phillips, and J.J. Amodei in "Multiple storage and exposure of fixed holograms in Fe-doped $LiNbO_3$", Applied Physics Letters, Vol. 26, p. 182 (1975)). Holograms fixed in such a manner are estimated to have a half-life of approximately 100,000 years at room temperature. Other suitable volume hologram media include, by example, strontium barium niobate ($SrBaNbO_3$), photorefractive photopolymers, and photochemical photopolymers.

[0025] Linear detector array 6 may be, for example, a charge-coupled device (CCD), a self-scanned diode array, a Schottky diode array, a pyroelectric device array, or other device capable of converting optical photons into an electronic voltage or current. Linear detector array 6 has a resolution, or number of photoresponsive elements, equal to the number of templates stored within medium 4.

[0026] Nonlinear processor 12 may be any electronic device with an appropriately shaped transfer function. Examples include digital electronic look-up tables and saturable electronic amplifiers. Buffer memory 13 may be any digital electronic memory. The output of buffer memory 13 may be fed back to SLM 1 for input to the next layer of the neural network.

[0027] Fig. 4 illustrates the storage of weight vectors within the medium 4. Weight vectors are stored within medium 4 in the following manner:

1. weight vectors $\vec{v}^{(k,i)}$ (i = 1, 2, ... , N - 1) are loaded into SLM 1 using a predetermined and fixed lexicographic ordering scheme;
2. SLM 1 spatially modulates a spatially uniform, plane-wave laser beam 7;
3. phase encoder 2 multiplies the light pattern transmitted by SLM 1 by a random, two-dimensional phase encoding function;
4. first Fourier transform lens 3 (which is positioned one focal length (f_1) from phase encoder 2 and one focal length (f_1) from the midpoint of medium 4) generates (at approximately the midpoint of medium 4) the Fourier transform of the light pattern transmitted by phase encoder 2;
5. simultaneously with step (4), reference plane-wave laser beam 8 (which is temporally coherent with plane-wave laser beam 7) illuminates medium 4 at angle Ψ_k to the Z_2 axis of medium 4 and within the X_2-Z_2 ,plane; and
6. weight vector hologram $v^{(k)}$ is stored within medium 4.
7. this procedure is repeated for k = 1, 2, ... , k until all Fourier-space holograms $V^{(k)}$ (k = 1, 2, ... , K) have been stored within medium 4.

[0028] As employed herein, a predetermined and fixed lexicographic ordering scheme is intended to mean that weight vectors are presented to the system in a consistent manner. For example, if the weight vector is derived from a television camera having a plurality of scanlines, the scanlines are input in the same order for each weight vector. The scanlines need not be input sequentially, so long as they are input consistently.

[0029] Figure 5 illustrates the SLM partitioning geometry used to store the weight vectors of an N-layer neural network. Since the weight vectors are, as indicated earlier, pre-selected, the k^{th} rows of all N-1 interconnect matrices $R^{(i)}$ (i = 1, 2, ... , N-1) may be stored simultaneously. The SLM geometry shown in Figure 5 is capable of storing N-1 interconnect matrices, each having a maximum of K rows. Matrices having fewer than K rows may be stored by simply blocking (i.e., electronically setting to zero) the appropriate portions of the SLM.

[0030] Figures 6(a), 6(b), and 6(c) illustrate the SLM geometry used to sequentially process patterns $\vec{\sigma}^{(1)}$ through $\vec{\sigma}^{(N-1)}$. $\vec{\sigma}^{(1)}$ (the input pattern to be classified) is first loaded into the SLM (all other regions of the SLM are electronically set to zero, i.e. to block plane-wave laser beam 7) as shown in Fig. 6(a). $\vec{\sigma}^{(2)}$ is then fetched from temporary memory 13 and loaded into the SLM as shown in Fig. 6(b). The same procedure is followed until $\vec{\sigma}^{(N-1)}$ has been loaded as shown in Fig. 6(c), at which time memory 13 contains the desired pattern classification results. The geometry shown in Figs. 6(a) - 6(c) corresponds exactly to the geometry shown in Fig. 5, i.e., $\vec{v}^{(k,i)}$ occupies the exact same physical portion of the SLM as $\vec{\sigma}^{(i)}$.

[0031] Plane-wave laser beam 7 may originate from, for example, an argon-ion laser having a wavelength of 4875 Å. The reference plane-wave laser beam 8 originates from the same source. It is also within the scope of the invention to maintain medium 4, if comprised of iron-doped lithium niobate, at a temperature of approximately 130° C while the weight vectors are being inputted. This results in a simultaneous storing and fixing of the weight vectors. For this case, some shrinkage of medium 4 occurs when same is cooled and plane-wave laser beam 7 is required to have a slightly shorter wavelength so as to compensate for the shrinkage of the material when applying an unknown pattern to the MLOENN.

[0032] During the storage of weight vectors within medium 4, phase encoder 2 beneficially diffuses or spreads out the light energy so that the energy is uniformly distributed throughout the volume of medium 4. If phase encoder 2 were not used, the light energy from successive weight vectors would be focused to within a small region within the volume of medium 4. This would result in a reduction in storage capacity and an increase in optical crosstalk.

[0033] Also during the storage of weight vectors, the reference laser beam is scanned through a plane of medium 4. As an example, reference plane-wave laser beam 8 may be scanned through plus or minus five degrees, referenced to the center of the medium 4, in 0.01 degree increments. That is, after a weight vector is stored, reference plane-wave laser beam 8 is shifted by 0.01 degrees before the storage of a next weight vector.

[0034] Fig. 3 illustrates the generation of vector inner products, $f_k^{(i)}$ (rays 9 and 10), which occurs in the following manner:

1. pattern vector $\vec{\sigma}^{(i)}$ is loaded into SLM 1 using the same pre-determined and fixed lexicographic ordering scheme used to load the $\vec{v}^{(k,i)}$;
2. SLM 1 spatially modulates plane-wave laser beam 7;
3. phase encoder 2 multiplies the light pattern transmitted by SLM 1 by a random, two-dimensional phase encoding function;
4. first Fourier transform lens 3 generates (at approximately the midpoint of medium 4) the Fourier transform of the light pattern transmitted by phase encoder 2;
5. volume hologram medium 4 generates an angular spectrum of plane waves 9 with amplitudes proportional to $\vec{v}^{(k,i)} \bullet \vec{\sigma}^{(i)}$ (k = 1, 2, ... , K) and propagation angles of Ψ_k (k = 1, 2, ... , K) which are identical to reference plane-wave angles Ψ_k ;
6. second Fourier transform lens 5 located one focal length (f_2) from the midpoint of medium 4, focuses each plane wave (of the angular spectrum of plane waves) generated within volume hologram medium 4 onto linear detector array 6 located one focal length (f_2) from second Fourier transform lens 5;
7. inner products $f_k(i)$ (corresponding to focused plane waves 10 emergent from second Fourier transform lens 5) are read out of detector array 6;
8. the output of the detector array is serially processed by nonlinear processor 12;
9. the output of nonlinear processor 12 is temporarily stored within buffer memory 13; and
10. the contents of buffer memory 13 are either read out and interpreted as classification results or fed back into SLM 1 for further, multi-layer network processing.

[0035] The above-described determination of f_k (for the sake of clarity, we hereafter omit the superscript "i" denoting network layer) may be understood in greater detail by considering the electric f ield distributions which, under appropriate conditions, exist at various points within the MLOENN.

[0036] Accordingly, referring to Fig. 7, for an electric field distribution incident on volume hologram medium 4 given by

$$E^{(1)} = F\{\sigma \cdot e^{i\beta}\}, \tag{3}$$

where σ is the two-dimensional electric field distribution which corresponds to $\vec{\sigma}$; β is the two-dimensional phase encoding function characteristic of phase encoder 2 (see, for example, C. N. Kurtz in "The transmittance characteristics of surface diffusers and the design of nearly band-limited binary diffusers", Journal of the Optical Society of America, Vol. 62, p. 982 (1972); and $F\{\cdot\}$ denotes Fourier transform; and for a refractive index distribution within volume hologram medium 4 proportional to

$$\sum_k \left[|A^k|^2 + |v^k|^2 + (A^k)^* v^k + A^k (v^k)^* \right], \tag{4}$$

where A^k is the amplitude of reference plane-wave laser beam 8 associated with weight vector v^k, $(\cdot)^*$ denotes complex conjugate, and v^k is the two-dimensional field distribution given by

$$\nu^k = F\{v^k \cdot e^{i\beta}\}; \qquad (5)$$

the electric field distribution within the plane of linear detector array 6 is given by

$$E^{(2)} = \sum_k \alpha^k * [(v^k \cdot e^{i\beta}) \star (\sigma \cdot e^{i\beta})], \qquad (6)$$

where α^k is the inverse Fourier transform of A^k, "*" denotes convolution, and "*" denotes correlation.

[0037] Spatial filtering of $E^{(2)}$ within the plane of detector array 6 (the correlation plane) is performed both within and perpendicular to the plane of Fig. 7. The inner product is detected in the form of light energy incident on detector array 6 a distance x_k from the center of array 6 (the common optical axis of lens 5 and holographic storage medium 4).

[0038] In-plane spatial filtering occurs as a natural result of Bragg selectivity within the volume hologram medium 4 (see, for example, T. Jannson, H.M. Stoll, and C. Karaguleff in "The interconnectability of neuro-optic processors", proceedings of the International Society for Optical Engineering, Vol. 698, p. 157 (1986)). Spatial filtering perpendicular to the plane of the processors occurs as a result of phase encoder 2's autocorrelation function of being much narrower (~ ten times) than either the autocorrelation function of σ or any of the autocorrelation functions of the v^k. These spatial filtering effects yield for the field distribution within the correlation plane:

$$E^{(3)} = \sum_k \alpha^k \cdot \iint v^k \cdot \sigma d\vec{r}^2, \qquad (7)$$

where the coherence length of phase encoder 2 is assumed to be significantly smaller than (e.g., less than 10% as large as) the smallest linear dimension of a resolution element of either σ or any of the v^k. The double integral in Equation (7) is taken over the correlation plane.

[0039] $E^{(3)}$ may, following lexicographic ordering, be rewritten as:

$$E^{(3)} = \sum_k \delta(x - x_k) \cdot [\vec{v}^k, \vec{\sigma}], \qquad (8)$$

where, for reference plane-wave laser beams A^k,

$$\alpha_k = \delta(x - x_k); \qquad (9)$$

$\delta(\cdot)$ is the dirac delta function; the x-dimension lies both within the correlation plane and within the plane of the holographic inner product processor; and $[\cdot,\cdot]$ denotes vector inner product. Field $E^{(3)}$ represents the inner product of $\vec{\sigma}$ with each of the weight vectors $\vec{v}^k$, which is the desired result.

[0040] Although described in the context of a bulk right-angle geometry system it should be realized that the hologram geometry may be provided instead in a transmission or a reflection (Lippmann) geometry.

[0041] Also, although the invention has been described as using a linear array of detectors 6 disposed along the correlation plane it should be realized that, as illustrated in Fig. 8, a two-dimensional detector array 11 may be employed for a system that scans, during weight vector storage, reference laser beam 8 in two dimensions. The two-dimensional detector array 11 may then be a staring type array. In this case, fractal storage geometry considerations are employed to select reference laser beam 8 angles, so as to avoid crosstalk within medium 4.

[0042] This invention has been described in conjunction with the illustrative embodiments enumerated above. This invention is not to be construed as being limited to only the illustrative embodiments, but should only be construed by reference to the appended claims.

Claims

1. A multi-layer opto-electronic neural network (MLOENN) pattern classification apparatus, comprising:

    a volume holographic medium (4) having a plurality of Fourier-space volume holograms representing neural network weight vectors stored within;

    means (1), having an output optically coupled to said medium by a first Fourier transform lens means (3), for spatially modulating a spatially uniform laser beam (7) in accordance with an input unknown pattern;

    means (6,11) having an input optically coupled by a second Fourier transform lens means (5) to an angular spectrum of plane waves generated by said medium (4) in response to the output of said spatially modulating means (1), for detecting plane waves that correspond to vector inner products generated within said medium (4) between the weight vectors and the unknown pattern;

    means (12) by which the output of said detection means (6, 11) are nonlinearly processed in a serial manner;

    means (13) by which said nonlinearly processed output is temporarily stored such that the network is virtual, and wherein only one layer exists at a time, the intermediate results being stored in said temporary storage means;

    means by which the output of said temporary storage means may be selectively read out or fed back into said spatial modulating means (1) for further processing by the MLOENN as input signals pattern vector to a next layer of the MLOENN, **characterised in that** said spatial modulating means (1) is geometrically partitioned to permit the independent storage of individual MLOENN layer weight vectors, $\vec{v}^{(k,i)}$ (k = 1, 2, ... , K; i = 1, 2, ... , N - 1), and the independent excitation of individual MLOENN layers by patterns $\vec{\sigma}^{(i)}$ (i = 1, 2, ... , N-1) such that each $\vec{v}^{(k,i)}$ and $\vec{\sigma}^{(i)}$ occupy a same physical portion of said spatial modulating means (1), N being the number of layers of the neural network, K being a number vector inner products.

2. A multi-layer opto-electronic neural network (MLOENN), pattern classification apparatus as set forth in Claim 1 wherein said spatial modulating means (1) further includes a phase encoder (2) which diffuses the spatially modulated spatially uniform laser beam in accordance with a random, two-dimensional phase encoding function.

3. A multi-layer opto-electronic neural network (MLOENN) pattern classification apparatus as set forth in Claim 1 wherein said detector means (6,11) includes a linear array (6) of photoresponsive elements disposed within and along a correlation plane of said second Fourier transform lens (5), said correlation plane being the plane onto which said planewaves are focussed by said second Fourier transform lens.

4. A multi-layer opto-electronic neural network (MLOENN) pattern classification apparatus as set forth in Claim 1 wherein said nonlinear processing means (12) has a sigmoidal transfer function with adjustable threshold and saturation points.

5. A multi-layer opto-electronic neural network (MLOENN) pattern classification apparatus as set forth in Claim 4 wherein said nonlinear processing means (12) is either an electronic look-up table or an electronic saturable amplifier.

6. A multi-layer opto-electrical neural network (MLOENN) pattern classification apparatus as set forth in Claim 1 wherein said temporary storage means (13) is a digital electronic memory.

7. A multi-layer opto-electronic neural network (MLOENN) pattern classification as set forth in Claim 1 wherein said volume holographic medium (4) provides spatial filtering, within the correlation plane, of an electric field distribution, the spatial filtering being provided in accordance with the Bragg selectively of said volume holographic medium (4), said correlation plane being the plane onto which said plane waves are focussed by said second Fourier transform lens (5).

8. A multi-layer opto-electronic neural network (MLOENN) pattern classification apparatus as set forth in Claim 1 wherein said volume holographic medium (4) is comprised of a material selected from the group consisting of iron-doped lithium niobate ($LINbO_3$:Fe), strontium barium niobate ($SrBaNbO_3$), photorefractive photopolymers, and

photochemical photopolymers.

9. A multi-layer opto-electrical neural network (MLOENN) pattern classification apparatus as set forth in Claim 1 wherein said spatial light modulator means (1) is comprised of means selected from the group consisting of ferro-electric liquid crystal devices, twisted nematic liquid crystal devices, deformable mirror devices and magneto-optic devices.

10. A multi-layer opto-electrical neural network (MLOENN) pattern classification apparatus as set forth in Claim 1 wherein said detector (6,11) includes a two-dimensional array of photoresponsive elements.

11. A method of generating vector inner products (f_k(i) for multi-layer-onto-electronic neural network (MLOENN) pattern classification comprising the steps of:

loading an unknown pattern vector $\vec{\sigma}^{(i)}$ (i = 1; 2, ..., N - 1) into

a spatial light modulator means (1) using a same pre-determined and fixed lexicographic ordering scheme that was initially employed to store the weight vectors $\vec{v}^{(k,i)}$ (k = 1, 2, ... k ; i = 1, 2, ... N - 1) into a volume holographic medium (4) by recording the interferences between reference plane wave beams having propagation angles ψ_k and beams reflecting the weight vectors $\vec{v}^{(k,i)}$; |

spatially modulating a first plane-wave laser beam in accordance with the unknown pattern vector;

employing a phase encoder means (2) to multiply the spatially modulated first plane-wave laser beam by a random, two-dimensional phase encoding function;

transmitting a phase encoded light pattern representative of the multiplied spatially modulated first plane-wave laser beam from the phase encoder means (2) to a first Fourier transform lens means (3);

generating within the volume holographic medium (4), with the first Fourier transform lens means (3) a Fourier transform of the phase encoded light pattern;

generating, within the volume holographic medium (4) an angular spectrum of plane waves having amplitudes proportional to vector inner products $\vec{\sigma}^{(i)}\bullet\vec{v}^{(k,i)}$ (k = 1, 2, ..., K; i = 1, 2, ..., N-1) and propagation angles of Ψ_k (k = 1, 2, ... , k) which are identical to the reference plane wave angles Ψ_k.

focusing onto a detector means (6,11) with a second Fourier transform lens means (5), plane waves of the angular spectrum of plane waves generated within the volume holographic medium (4);

reading out, from the detector means (6,11) signals representing vector inner Products corresponding to the plane waves focused upon the detector means (6,11);

serially and nonlinearly processing the output of the detector means (6,11);

temporarily stating the nonlinearly processed output of the detector means (6,11); and

selectively reading out the temporarily, stored output of the detector means (6,11) as pattern recognition results or feeding the temporarily stored output of the detector means (6,11) back into the spatial modulating means (1) for further neural network processing as input signals of a next pattern vector $\vec{\sigma}^{(i-1)}$ **characterised in that** said spatial modulating means (1) is geometrically partitioned to permit the independent storage of individual MLOENN layer weight vectors $\vec{v}^{(k,i)}$ (k = 1,
2, ..., K; · i = 1, 2, ..., N - 1), and the independent excitation of individual MLOENN layers by pattern $\vec{\sigma}^{(i)}$ (i = 1, 2, ..., N=1) such that each $\vec{v}^{(k,i)}$ and $\vec{\sigma}^{(i)}$ occupy a same physical portion of said spatial modulating means (1) N being the number of pattern vector layers, K being a number of vector inner products.

Patentansprüche

1. Musterklassifikationsvorrichtung mit einem mehrschichtigen opto-elektronischen neuralen Netzwerk (MLOENN), das umfaßt:

ein holographisches volumenmedium (4) mit einer Vielzahl von Fourierraumvolumenhologrammen, die darin gespeicherte Wichtvektoren des neuralen Netzwerkes darstellen;

Mittel (1), die einen Ausgang aufweisen, der optisch an das Medium über erste Fouriertransformationslinsenmittel (3) gekoppelt sind, zur räumlichen Modulation eines räumlich gleichförmigen Laserstrahls (7) gemäß einem unbekannten Eingangsmuster;

Mittel (6, 11), die einen Eingang aufweisen, der optisch über zweite Fouriertransformationslinsenmittel (5) an ein Winkelspektrum ebener Wellen gekoppelt ist, die durch das Medium (4) als Reaktion auf den Ausgang der Mittel (1) zur räumlichen Modulation erzeugt werden, zum Detektieren von ebenen Wellen, die den inneren Vektorprodukten entsprechen, die in dem Medium (4) zwischen den Wichtvektoren und dem unbekannten Muster erzeugt werden;

Mittel (12), durch die der Ausgang der Detektionsmittel (6, 11) auf eine serielle Weise nichtlinear verarbeitet wird;

Mittel (13), durch die der nichtlinear verarbeitete Ausgang temporär derart gespeichert wird, daß das Netzwerk virtuell ist, und wobei nur eine Schicht zu einer Zeit existiert, wobei die Zwischenergebnisse in dem temporären Speichermitteln gespeichert werden;

Mittel, durch die der Ausgang der temporären Speichermittel selektiv ausgelesen werden kann oder in die Mittel (1) zur räumlichen Modulation zur Weiterverarbeitung durch den MLOENN als ein Mustervektor der Eingangssignale für eine nächste Schicht von dem MLOENN zurückgeführt werden kann,

dadurch gekennzeichnet, daß die Mittel (1) zur räumlichen Modulation geometrisch partitioniert sind, um die unabhängige Speicherung einzelner MLOENN-Schichtwichtvektoren $\nu^{(k,i)}$ (k = 1, 2, ..., K; i = 1, 2, ..., N - 1), und die unabhängige Anregung einzelner MLOENN-Schichten durch Muster $\sigma^{(i)}$ (i = 1, 2, ..., N-1) zu ermöglichen, derart, daß alle $\nu^{(k,i)}$ und $\sigma^{(i)}$ einen gleichen physikalischen Anteil der Mittel (1) zur räumlichen Modulation belegen, wobei N die Anzahl von Schichten des neuralen Netzwerkes ist, und K eine Anzahl innerer Vektorprodukte ist.

2. Musterklassifikationsvorrichtung mit einem mehrschichtigen opto-elektronischen neuralen Netzwerk (MLOENN) nach Anspruch 1, bei dem die Mittel (1) zur räumlichen Modulation des weiteren einen Phasenencoder (2) umfassen, der den räumlich modulierten, räumlich gleichförmigen Laserstrahl gemäß einer zweidimensionalen Phasenencodierzufallsfunktion zerstreut.

3. Musterklassifikationsvorrichtung mit einem mehrschichtigen opto-elektronischen neuralen Netzwerk (MLOENN) nach Anspruch 1, bei dem die Detektionsmittel (6, 11) ein lineares Feld (6) photoempfindlicher Elemente umfassen, die in und entlang einer Korrelationsebene der zweiten Fouriertransformationslinse (5) angeordnet sind, wobei die Korrelationsebene die Ebene ist, auf der die ebenen Wellen durch die zweite Fouriertransformationslinse fokussiert werden.

4. Musterklassifikationsvorrichtung mit einem mehrschichtigen opto-elektronischen neuralen Netzwerk (MLOENN) nach Anspruch 1, bei dem die nicht-linearen Verarbeitungsmittel (12) eine Sigmodial-Übertragungsfunktion mit einstellbarem Schwellwert und Sättigungspunkten umfassen.

5. Musterklassifikationsvorrichtung mit einem mehrschichtigen opto-elektronischen neuralen Netzwerk (MLOENN) nach Anspruch 4, bei dem die nicht-linearen Verarbeitungsmittel (12) entweder eine elektronische Nachschlagtabelle oder ein elektronisch sättigbarer Verstärker sind.

6. Musterklassifikationsvorrichtung mit einem mehrschichtigen opto-elektronischen neuralen Netzwerk (MLOENN) nach Anspruch 1, bei dem die temporären Speichermittel (13) ein digitaler elektronischer Speicher sind.

7. Musterklassifikationsvorrichtung mit einem mehrschichtigen opto-elektronischen neuralen Netzwerk (MLOENN) nach Anspruch 1, bei dem das holographische Volumenmedium (4) räumliche Filterung in der Korrelationsebene einer elektrischen Feldverteilung schafft, wobei die räumliche Filterung in Übereinstimmung mit dem Bragg-Gesetz selektiv für das holographische Volumenmedium (4) geschaffen wird, wobei die Korrelationsebene die Ebene ist, auf die die ebenen Wellen durch die zweite Fouriertransformationslinse (5) fokussiert werden.

8. Musterklassifikationsvorrichtung mit einem mehrschichtigen opto-elektronischen neuralen Netzwerk (MLOENN) nach Anspruch 1, bei dem das holographische Volumenmedium (4) ein Material umfaßt, das aus der Gruppe ausgewählt ist, die aus eisendotiertem Lithiumniobat ($LINbO_3$:Fe), Strontium, Bariumniobat ($SrBaNbO_3$), lichtbrechenden Photopolymeren und photochemischen Photopolymeren besteht.

9. Musterklassifikationsvorrichtung mit einem mehrschichtigen opto-elektronischen neuralen Netzwerk (MLOENN) nach Anspruch 1, bei dem die Mittel (1) zur räumlichen Lichtmodulation Mittel umfassen, die aus der Gruppe ausgewählt sind, die aus ferroelektrischen Flüssigkristallvorrichtungen, gedrehten nematischen Flüssigkristallvorrichtungen, verformbaren Spiegelvorrichtungen und magnetooptischen Vorrichtungen besteht.

10. Musterklassifikationsvorrichtung mit einem mehrschichtigen opto-elektronischen neuralen Netzwerk (MLOENN) nach Anspruch 1, bei dem der Detektor (6, 11) ein zweidimensionales Feld photoempfindlicher Elemente umfaßt.

11. Verfahren zum Erzeugen innerer Vektorprodukte ($f_k^{(i)}$) zur Musterklassifikation mit mehrschichtigen opto-elektronischen neuralen Netzwerken (MLOENN) mit den folgenden Schritten:
Laden eines unbekannten Mustervektors $\sigma^{(i)}$ (i = 1, 2, ..., N - 1)
in
Mittel zur räumlichen Lichtmodulation (1) unter Verwendung eines gleichen vorbestimmten und festen lexiographischen Ordnungsschemas, das anfänglich eingesetzt wurde, um die Wichtvektoren
$\nu^{(k,i)}$ (k = 1, 2, ... K; i = 1, 2,....., N - 1)
in ein holographisches Volumenmedium (4) zu speichern, indem die Interferenzen zwischen Referenzstrahlen ebener Wellen mit Fortpflanzungswinkeln Ψ_k und Strahlen aufgezeichnet werden, die die Wichtvektoren $\nu^{(k,i)}$ reflektieren:
räumliches Modulieren eines ersten Laserstrahls ebener Wellen gemäß dem unbekannten Mustervektor;
Verwenden von Phasenenkodermitteln (2), um den räumlich modulierten ersten Laserstrahl ebener Wellen mit einer zweidimensionalen phasenenkodierenden Zufallsfunktion zu multiplizieren;
Übertragen eines phasenenkodierten Lichtmusters, das für den multipliziertem räumlich modulierten ersten Laserstrahl ebener Wellen represäntativ ist, von den Phasenenkodermitteln (2) zu ersten Fouriertransformationslinsenmitteln (3);
Erzeugen einer Fouriertransformation des phasenenkodierten Lichtmusters in dem holographischen Volumenmedium (4) mit den ersten Fouriertransformationslinsenmitteln (3);
Erzeugen eines Winkelspektrums ebener Wellen mit Amplituden, die proportional zu inneren Vektorprodukten
$\sigma^{(i)} \bullet \nu^{(k,i)}$ (k = 1, 2, ... K; i = 1, 2, ... ,N-1)
und Fortpflanzungswinkeln Ψ_k (k = 1, 2, ..., K), die identisch zu den Referenzebenenwellenwinkeln Ψ_k sind, in dem holographischen Volumenmedium (4),
Fokussieren von ebenen Wellen des Winkelspektrums der ebenen Wellen, das in dem holographischen Volumenmedium (4) erzeugt wurde, auf Detektionsmittel (6, 11) mit zweiten Fouriertransformationslinsenmitteln (5);
Auslesen von Signalen aus den Detektionsmitteln (6, 11), die innere Vektorprodukte repräsentieren, die den ebenen Wellen entsprechen, die auf die Detektionsmittel (6, 11) fokussiert wurden;
serielles und nichtlineares Verarbeiten des Ausgangs der Detektionsmittel (6, 11);
temporäres Speichern des nichtlinear verarbeiteten Ausgangs der Detektionsmittel (6, 11); und
selektives Auslesen des temporär gespeicherten Ausgangs der Detektionsmittel (6, 11) als Mustererkennungsergebnisse oder Zurückführen des temporär gespeicherten Ausgangs der Detektionsmittel (6, 11) zurück in die Mittel (1) zur räumlichen Modulation zur weiteren neuralen Netzwerkverarbeitung als Eingangssignale eines nächsten Mustervekors $\sigma^{(i+1)}$,
dadurch gekennzeichnet, daß die Mittel (1) zur räumlichen Modulation geometrisch partitioniert sind, um die unabhängige Speicherung der einzelnen MLOENN-Schichtwichtvektoren
$\nu^{(k,i)}$ (k = 1,
2,..., K; i = 1, 2, ..., N - 1),
und die unabhängige Anregung individueller MLOENN-Schichten durch Muster $\sigma^{(i)}$ (i = 1, 2,....., N-1) zu ermöglichen, derart, daß alle $\nu^{(k,i)}$ und $\sigma^{(i)}$ einen gleichen physikalischen Anteil der Mittel (1) zur räumlichen Modulation einnehmen, wobei N die Anzahl von Mustervektorschichten und K eine Anzahl von inneren Vektorprodukten ist.

Revendications

1. Dispositif de classification de motifs par réseau neuronal opto-électronique à couches multiples (MLOENN), comprenant :

   un milieu holographique (4) volumique comportant une pluralité d'hologrammes de volumiques d'espace de Fourier représentant des vecteurs de pondération de réseau neuronal stockés à l'intérieur ;
   un moyen (1), ayant une sortie couplée optiquement audit milieu par un premier moyen (3) formant lentille de transformée de Fourier, pour moduler spatialement un faisceau laser (7) uniforme spatialement en fonction d'un motif inconnu d'entrée ;
   un moyen (6, 11) ayant une entrée couplée optiquement par un deuxième moyen (5) formant lentille de transformée de Fourier à un spectre angulaire d'ondes planes généré par ledit milieu (4) en réponse à la sortie dudit moyen (1) de modulation spatiale, pour détecter des ondes planes qui correspondent à des produits internes vectoriels générés dans ledit milieu (4) entre le vecteur de pondération et du motif inconnu ;
   un moyen (12) par lequel la sortie dudit moyen (6, 11) de détection est traitée de manière non linéaire et en série ;
   un moyen (13) par lequel ladite sortie traitée de manière non linéaire est stockée temporairement, de telle sorte que le réseau est virtuel, et dans lequel il n'existe qu'une couche à la fois, les résultats intermédiaires étant stockés dans ledit moyen de stockage temporaire ;
   un moyen par lequel la sortie dudit moyen de stockage temporaire peut être lue de manière sélective ou réappliquée dans ledit moyen (1) de modulation spatiale pour un autre traitement par le MLOENN en tant que vecteur de motif de signaux d'entrée pour une couche suivante du MLOENN, **caractérisé en ce que** ledit moyen (1) de modulation spatiale est partionné géométriquement pour permettre le stockage indépendant de vecteurs individuels de pondération de couche MLOENN, $\vec{v}^{(k,i)}$ (k = 1, 2, ..., K; i = 1, 2, ..., N - 1), et l'excitation indépendante de couches individuelles de MLOENN par des motifs $\vec{\sigma}^{(i)}$ (i = 1, 2, ..., N - 1), de telle sorte que chaque $\vec{v}^{(k,i)}$ et $\vec{\sigma}^{(i)}$ occupent une même partie physique dudit moyen (1) de modulation spatiale, N étant le nombre de couches du réseau neuronal et K étant un nombre de produits internes vectoriels.

2. Dispositif de classification de motifs par réseau neuronal opto-électronique à couches multiples (MLOENN) selon la revendication 1, dans lequel ledit moyen (1) de modulation spatiale comporte en outre un codeur (2) de phase qui diffuse ledit faisceau laser uniforme modulé spatialement conformément à fonction de codage aléatoire de phase en deux dimensions.

3. Dispositif de classification de motifs par réseau neuronal opto-électronique à couches multiples (MLOENN) selon la revendication 1, dans lequel ledit moyen (6, 11) formant détecteur comporte un réseau linéaire (6) d'éléments photosensibles disposés dans et le long d'un plan de corrélation de ladite deuxième lentille (5) de transformée de Fourier, ledit plan de corrélation étant le plan sur lequel lesdites ondes planes sont focalisées par ladite deuxième lentille de transformée de Fourier.

4. Dispositif de classification de motifs par réseau neuronal opto-électronique à couches multiples (MLOENN) selon la revendication 1, dans lequel ledit moyen (12) de traitement non linéaire a une fonction de transfert sigmoïdale avec des points de seuil et de saturation réglables.

5. Dispositif de classification de motifs par réseau neuronal opto-électronique à couches multiples (MLOENN) selon la revendication 4, dans lequel ledit moyen (12) de traitement non linéaire est, soit une table de consultation électronique, soit un amplificateur saturable électronique.

6. Dispositif de classification de motifs par réseau neuronal opto-électronique à couches multiples (MLOENN) selon la revendication 1, dans lequel ledit moyen (13) de stockage temporaire est une mémoire électronique numérique.

7. Dispositif de classification de motifs par réseau neuronal opto-électronique à couches multiples (MLOENN) selon la revendication 1, dans lequel ledit milieu (4) holographique de volumique fournit un filtrage spatial, dans le plan de corrélation, d'une distribution de champ électrique, le filtrage spatial étant obtenu conformément à la sélectivité de Bragg, dudit milieu (4) holographique volumique, ledit plan de corrélation étant le plan sur lequel lesdites ondes planes sont focalisées par ladite deuxième lentille (5) de transformée de Fourier.

8. Dispositif de classification de motifs par réseau neuronal opto-électronique à couches multiples (MLOENN) selon la revendication 1, dans lequel ledit milieu (4) holographique volumique est constitué d'un matériau sélectionné

parmi le groupe consistant en niobate de lithium dopé au fer ($LINbO_3$: Fe), niobate de baryum et strontium ($SrBaNbO_3$), photopolymères photoréfractifs, et photopolymères photochimiques.

9. Dispositif de classification de motifs par réseau neuronal opto-électronique à couches multiples (MLOENN) selon la revendication 1, dans lequel ledit moyen (1) formant modulateur spatial de lumière est constitué d'un moyen sélectionné parmi le groupe consistant en dispositifs à cristal liquide ferroélectrique, dispositifs à cristal liquide nématique hélicoïdal, dispositifs à miroir déformable, et dispositifs magnéto-optiques.

10. Dispositif de classification de motifs par réseau neuronal opto-électronique à couches multiples (MLOENN) selon la revendication 1, dans lequel ledit détecteur (6, 11) comporte un réseau en deux dimensions d'éléments photosensibles.

11. Procédé de génération de produits internes vectoriels ($f_k^{(i)}$) pour classification de motifs par réseau neuronal opto-électronique à couches multiples (MLOENN), comprenant les étapes :

de chargement d'un vecteur de motifs inconnu $\vec{\sigma}^{(i)}$ (i =1, 2, ..., N - 1) dans un moyen (1) formant modulateur spatial de lumière en utilisant un même schéma d'ordonnancement lexicographique prédéterminé et fixe que celui qui a été utilisé initialement pour stocker les vecteurs de pondération $\vec{v}^{(k,i)}$ (k = 1, 2, ..., K ; i = 1, 2, ..., N - 1) dans un milieu (4) holographique volumique par enregistrement des interférences entre des faisceaux d'onde plane de référence ayant des angles de propagation Ψ_k et des faisceaux réfléchissant le vecteur de pondération $\vec{v}^{(k,i)}$;

de modulation spatiale d'un premier faisceau laser d'onde plane en fonction du vecteur de motifs inconnu ;

d'utilisation d'un moyen (2) formant codeur de phase pour multiplier le premier faisceau laser d'onde plane modulé spatialement par une fonction aléatoire de codage de phase en deux dimensions ;

de transmission d'un motif de lumière codée en phase, représentative du premier faisceau laser d'onde plane modulé spatialement multiplié en provenance du moyen (2) formant codeur de phase, à un premier moyen (3) formant lentille de transformée de Fourier ;

de génération dans le milieu (4) holographique volumique, avec le premier moyen (3) formant lentille de transformée de Fourier, d'une transformée de Fourier du motif de lumière codée en phase ;

de génération, dans le milieu (4) holographique volumique, d'un spectre angulaire d'ondes planes ayant des amplitudes proportionnelles aux produits internes vectoriels $\vec{\sigma}^{(i)} \cdot \vec{v}^{(k,i)}$ (k = 1, 2, ..., K ; i =1, 2, ..., N -1) et des angles de propagation de Ψ_k (k = 1, 2, ..., K) qui sont identiques aux angles Ψ_k d'onde plane de référence ;

, de focalisation, sur un moyen (6, 11) formant détecteur avec un deuxième moyen (5) formant lentille de transformée de Fourier, d'ondes planes du spectre angulaire d'ondes planes généré dans le milieu (4) holographique volumique ;

de lecture, à partir du moyen (6, 11) formant détecteur, de signaux représentant des produits internes vectoriels correspondant aux ondes planes focalisées sur le moyen (6, 11) formant détecteur ;

de traitement en série et de manière non linéaire de la sortie du moyen (6, 11) formant détecteur;

de stockage temporaire de la sortie traitée de manière non linéaire du moyen (6,11) formant détecteur ; et

de lecture de manière sélective de la sortie stockée temporairement du moyen (6, 11) formant détecteur en tant que résultats de reconnaissance de motif, ou de ré-application de la sortie stockée temporairement du moyen (6, 11) formant détecteur dans le moyen (1) de modulation spatiale pour un autre traitement de réseau neuronal en tant que signaux d'entrée d'un vecteur de motif suivant $\vec{\sigma}^{(i+1)}$, **caractérisé en ce que** ledit moyen (1) de modulation spatiale est partitionné géométriquement pour permettre le stockage indépendant de vecteurs de pondération de couche MLOENN individuelles $\vec{v}^{(k,i)}$ (k = 1, 2, ..., K; i = 1, 2, ..., N - 1), et l'excitation indépendante des couches MLOENN individuelles par motif $\vec{\sigma}^{(i)}$ (i = 1, 2, ..., N -1), de telle sorte que chaque $\vec{v}^{(k,i)}$ et $\vec{\sigma}^{(i)}$occupent une même partie physique dudit moyen (1) de modulation spatiale, N étant le nombre de couches vectorielles de motif, et K étant un nombre de produits internes vectoriels.

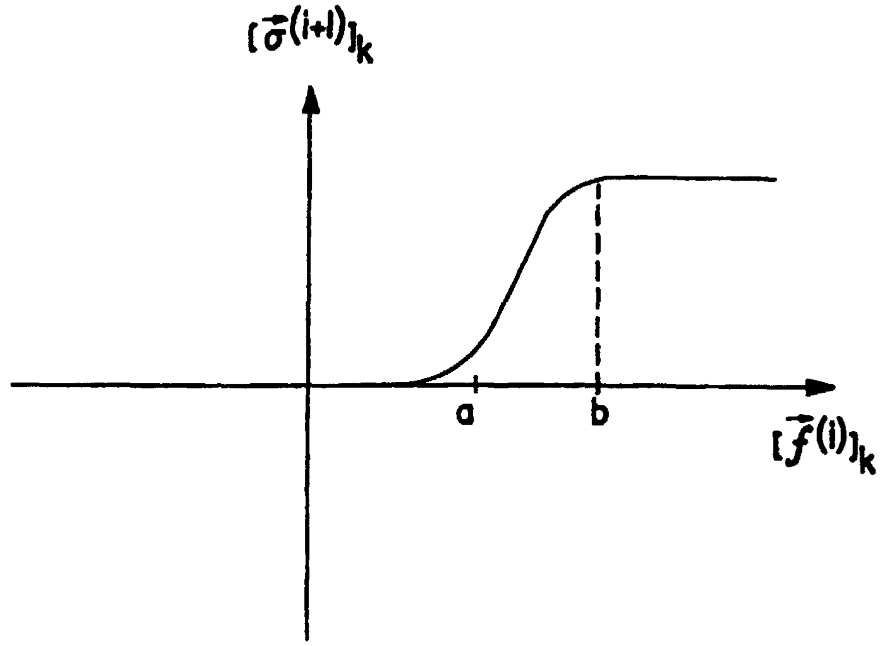

FIG. 1

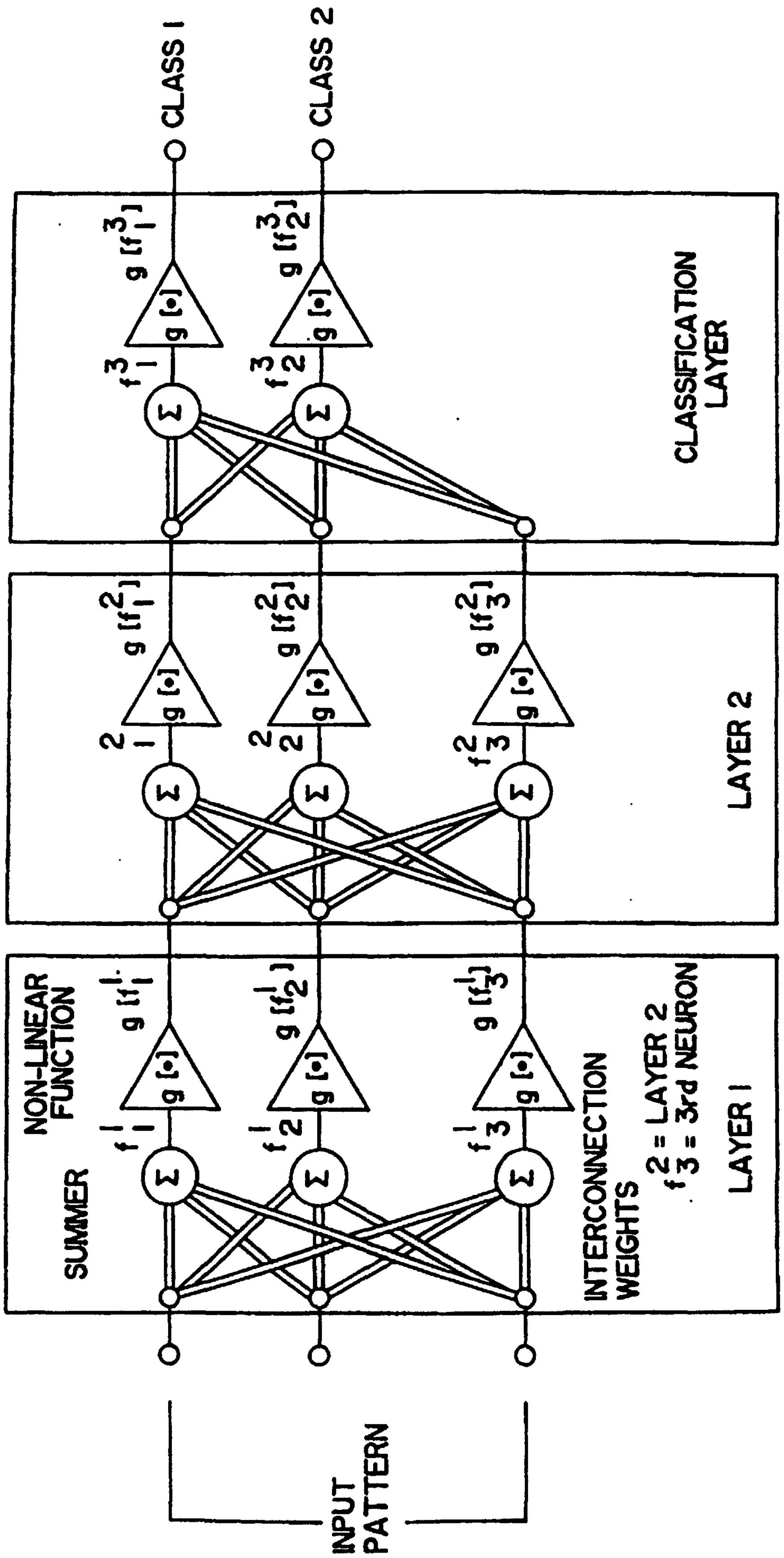
CLASS 1
CLASS 2
CLASSIFICATION LAYER
LAYER 2
LAYER 1
SUMMER
NON-LINEAR FUNCTION
INTERCONNECTION WEIGHTS
f 2 = LAYER 2
3 = 3rd NEURON
INPUT PATTERN

FIG. 2

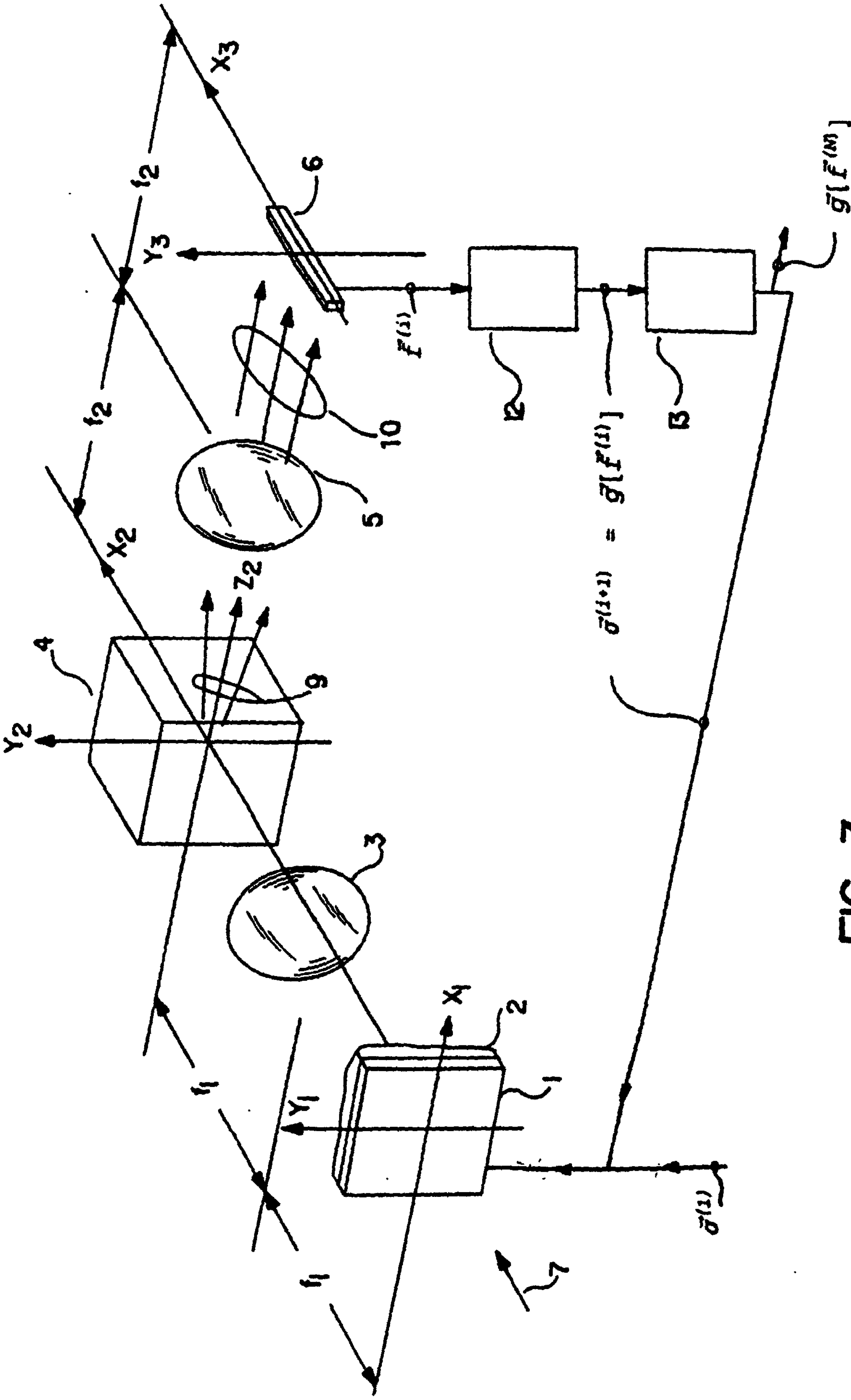

FIG. 3

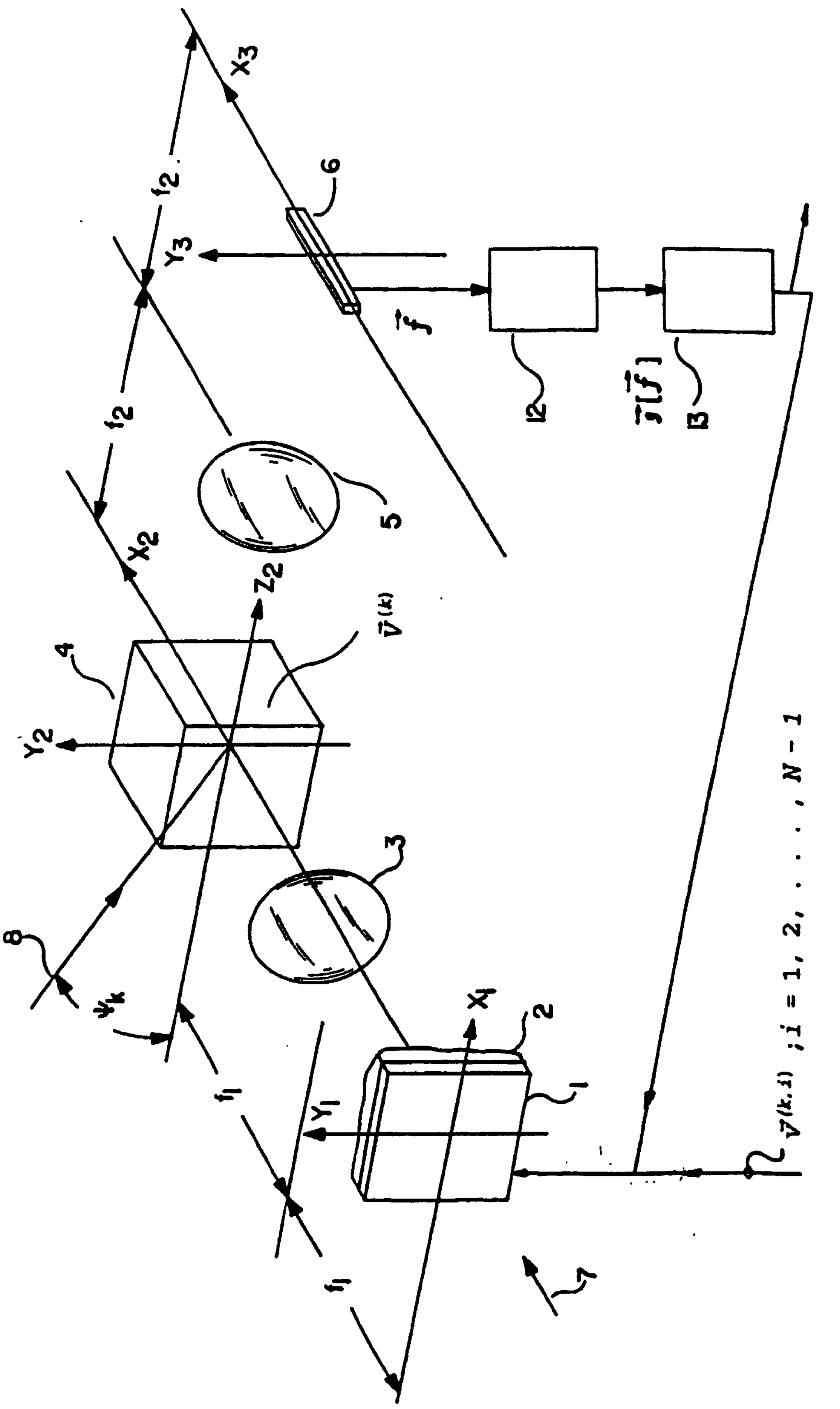

FIG. 4

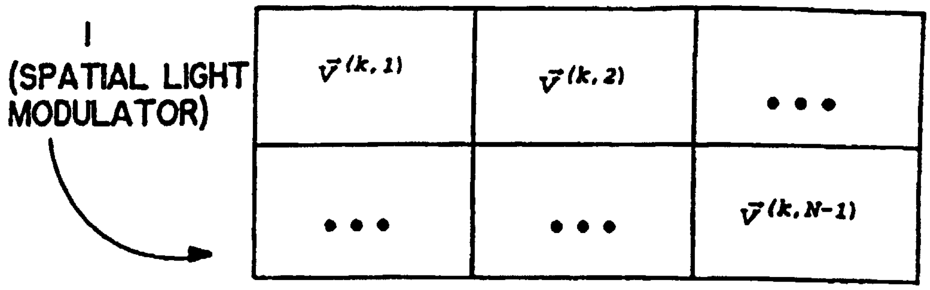

FIG. 5

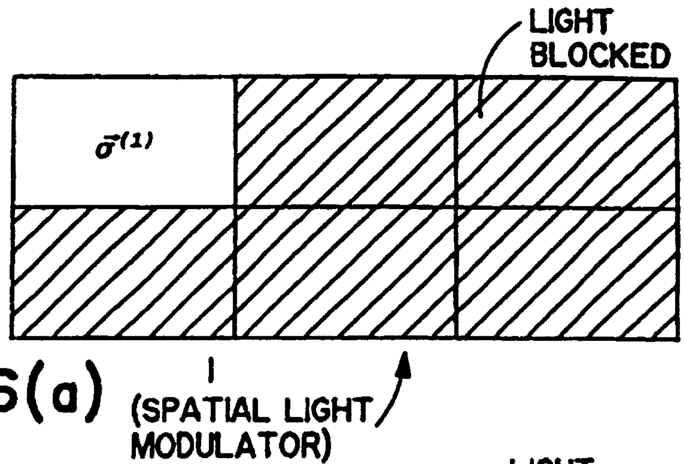

FIG. 6(a)

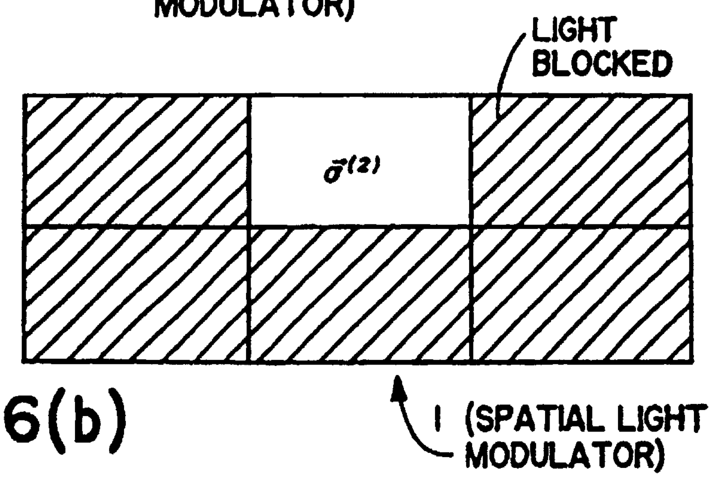

FIG. 6(b)

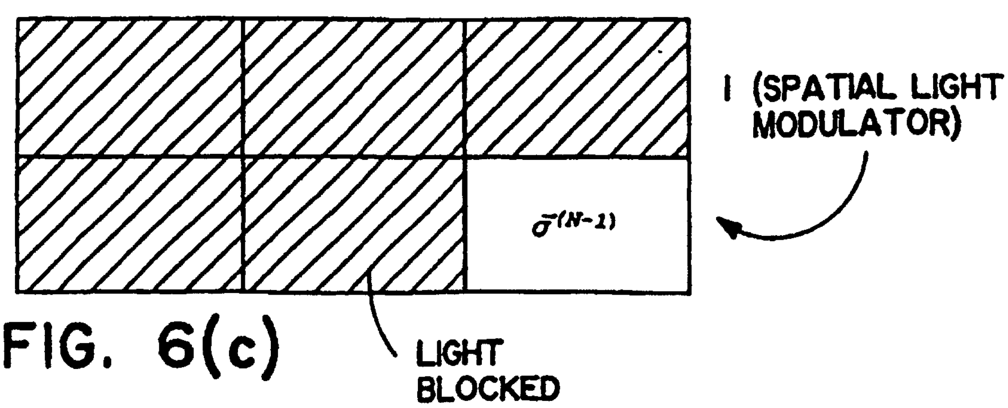

FIG. 6(c)

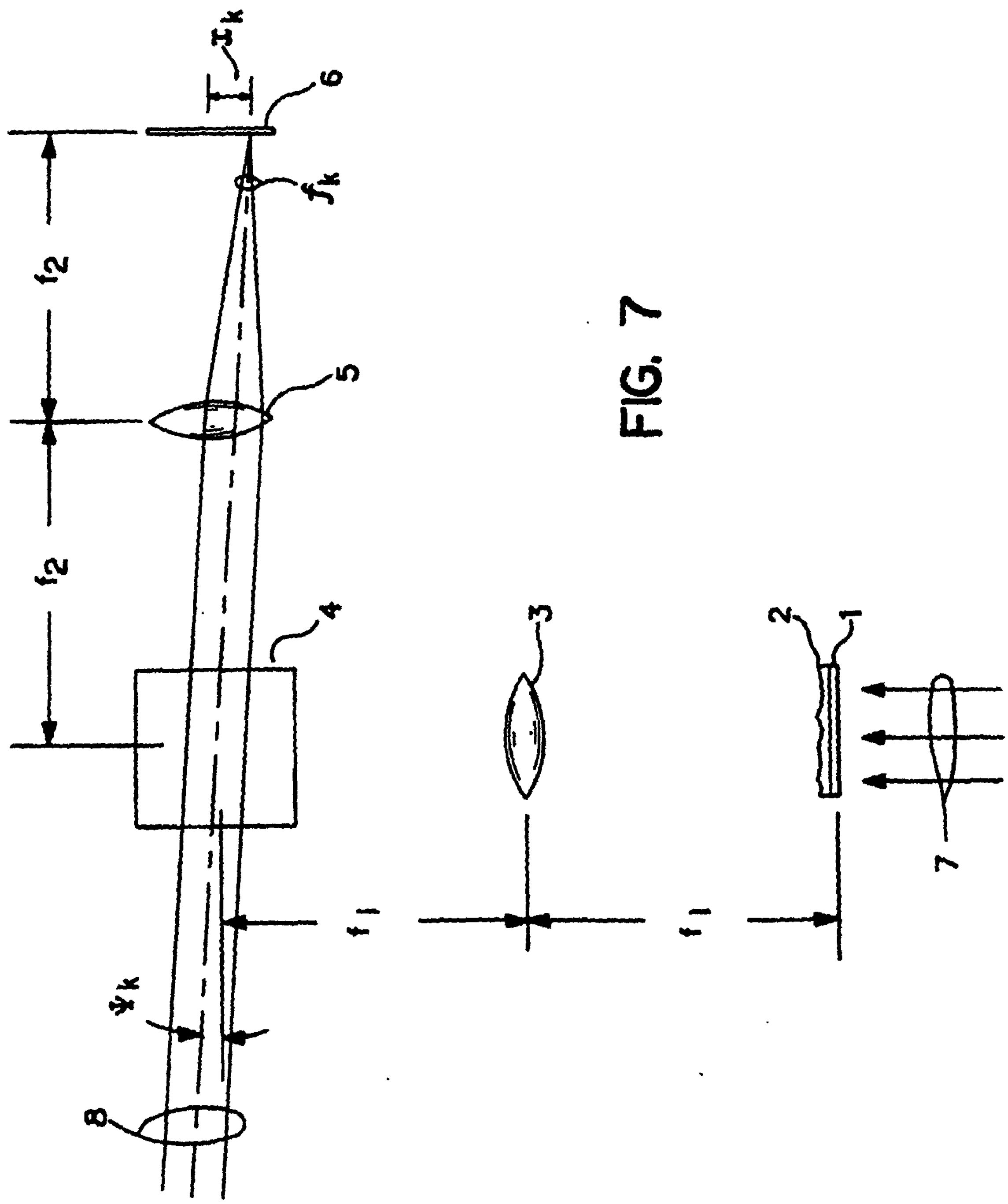

FIG. 7

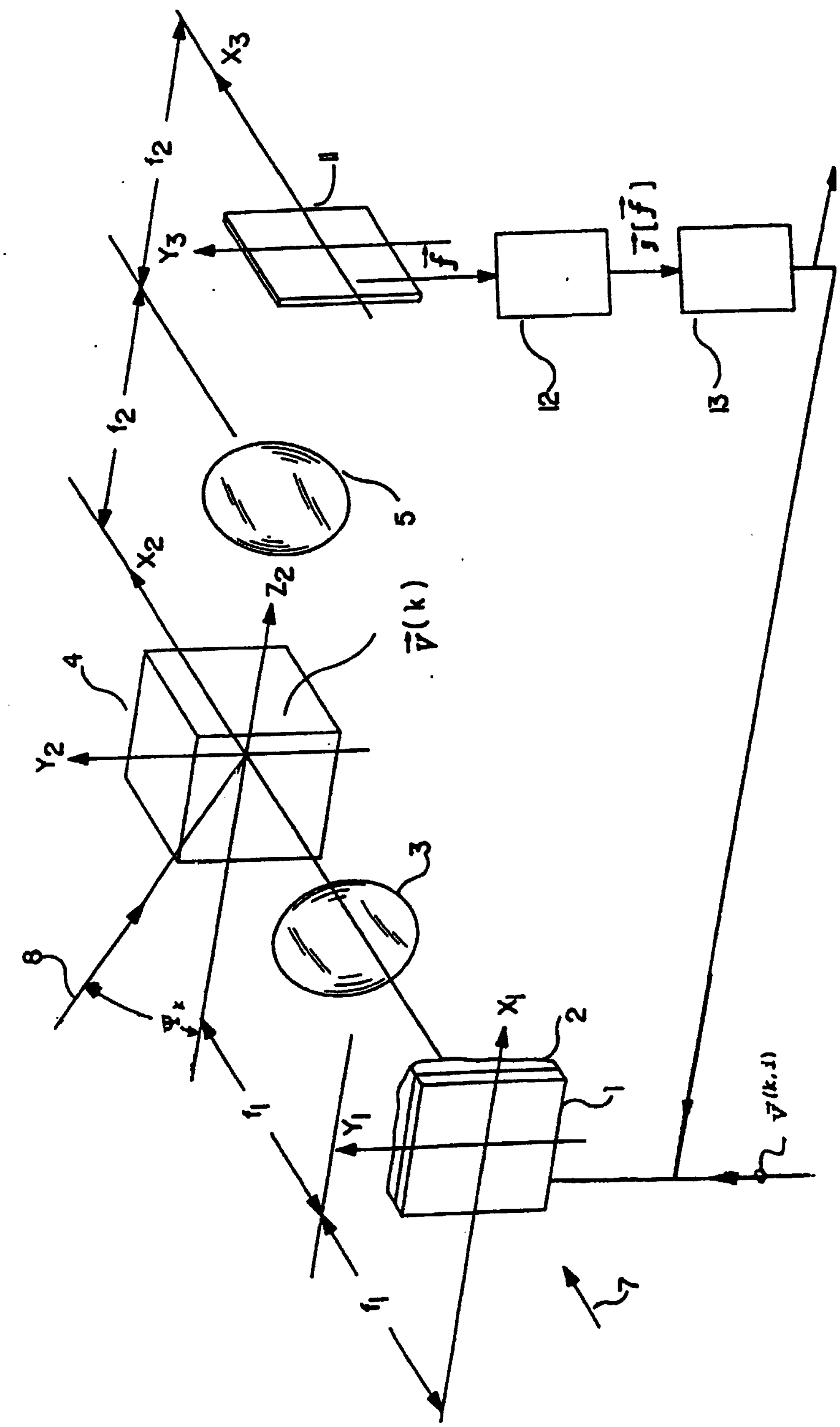

FIG. 8