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Novel method and system for pattern recognition and processing using data encoded as Fourier series in Fourier space

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Abstract

A method and system for pattern recognition and processing is reported that has a data structure and theoretical basis that are unique. This novel approach anticipates the signal processing action of an ensemble of neurons as a unit and intends to simulate aspects of brain that give rise to capabilities such as intelligence, pattern recognition, and reasoning that have not been reproduced with past approaches such as neural networks that are based individual simulated "neuronal units." Information representative of physical characteristics or representations of physical characteristics is transformed into a Fourier series in Fourier space within an input context of the physical characteristics that is encoded in time as delays corresponding to modulation of the Fourier series at corresponding frequencies. Associations are formed between Fourier series by filtering the Fourier series and by using a spectral similarity between the filtered Fourier series to determine the association based on Poissonian probability. The associated Fourier series are added to form strings of Fourier series. Each string is ordered by filtering it with multiple selected filters to form multiple time order formatted subset Fourier series, and by establishing the order through associations with one or more initially ordered strings to form an ordered string. Associations are formed between the ordered strings to form complex ordered strings that relate similar items of interest. The components of the system based on the algorithm are active based on probability using weighting factors based on activation rates.

Keywords: Pattern recognition; Novel Fourier series; Delayed Gaussian filter

1. Introduction

Attempts have been made to create pattern recognition systems using programming and hardware. A lot of effort has been spent on neural nets. Neural nets typically comprise three layers—an input layer, a hidden layer, and an output layer. In a common approach, the hidden layer comprises a series of nodes which serve to perform a weighted sum of the input to form the output. Output for a given input is compared to the desired output, and a back projection of the errors is carried out on the hidden layer by changing the weighting factors at each node, and the process is reiterated until a tolerable result is obtained. The strategy of neural nets is analogous to the sum of least squares algorithms. These algorithms are adaptive to provide reasonable output to variations in input, but they cannot create totally unanticipated useful output or discover associations between multiple inputs and outputs. Their usefulness to create novel conceptual content is limited; thus, advances in pattern recognition systems using neural nets is limited.

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The limitations can be ascertained from the definition of a neural network given by Muller et al. (1995):

Neural network models are algorithms for cognitive tasks, such as learning and optimization, which are in a loose sense based on concepts derived from research into the nature of the brain. In mathematical terms *a neural network model is defined as a directed graph with the following properties given by*:

1. A state variable n_i is associated with each node i.
2. A real-valued weight ω_{ik} is associated with each link (ik) between two nodes i and k.
3. A real-valued bias ϑ_i is associated with each node i.
4. A transfer function $f_i[n_k, \omega_{ik}, \vartheta_i, (k \neq i)]$ is defined, for each node i, which determines the state of the node as a function of its bias, of the weights of its incoming links, and of the states of the nodes connected to it by these links.

In standard terminology, the nodes are called *neurons*, the links are called *synapses*, and the bias is known as *activation threshold*. The transfer function usually takes the form $f(\sum_k \omega_{ik} n_k - \vartheta_i)$ where $f(x)$ is either a discontinuous step function or its smoothly increasing generalization known as a sigmoidal function. Nodes without links toward them are called *input* neurons; *output* neurons are those with no link leading away from them. A *feed-forward* network is one whose topology admits no closed paths.

There is no signal processing theory involved; thus, a major disadvantage of neural networks is the broad lack of understanding of how they actually solve a given cognitive task. This ignorance stems from the fact that neural networks do not break a problem down into its logical elements but rather solve it by a holistic approach. This is hard to penetrate logically, and it is impossible to determine whether the solution provided by the neural network is correct. The only method of testing the operation of a neural network is to check its performance for individual test cases, not a very enlightening technique. No one knows how to judge the performance of a neural network knowing only its architecture, and it is almost impossible to determine what task the network actually performs from pure knowledge of the synaptic efficiencies.

Recent advancements have added the steps of processing the input by Fourier and wavelet transforms and categorization of the transformed data or ''atom'' in terms of random high-dimensional context vectors which are representative of attributes of data such as an image (Caid and Hecht-Neilsen, 2001). The context vectors are then modified according to the spatial relationship and co-occurrence of the atoms in the images in a procedure called bootstrapping (Caid and Hecht-Neilsen, 2001). Image relevance is assessed by computing the dot product of each summary vector with the query context vector, and accumulating the results. A Gabor transform may be used to extract features from feature vectors in the frequency and orientation space to form associations (Greenspan et al., 1991). A vector-quantization learning algorithm defines a mapping from an N-dimensional input vector, X, to an M-dimensional output vector Y involving feature vectors, their quantization, clustering, and rule-based mappings (e.g. Bayesian classifier) (Greenspan et al., 1991). Alternatively, statistical pattern recognition uses measurements and transforms of the pattern structure as feature vectors (Dickhaus and Heinrich, 1996). Feature selection is often performed by sequential approaches, or sometimes more or less intuitively by the experience of experts (Dickhaus and Heinrich, 1996). Kortge (2000) also claims that feature recognition in new input compared to old input can be also achieved with a neural network by using class networks and determining indices of the most probable class based on the probability that the network would generate the input pattern when the input is presented to each class network. A Bayesian Rule approach is used by a classifier operating on signals such as feature activity from the class networks as well as prior class probabilities. Recent reviews of current trends and applications of intelligent systems are given by Liao (2003) and Abraham (2002).

Since brain neurons are the sole processing elements and they process information as time-and-space-cascaded action potentials, they cannot act on a data stream over an ensemble of detectors such as the retina and perform a Fourier transform (Siebert, 1986a) or perform other data operations associated with neural networks. Transform, rule, and probability-based data manipulation techniques have no parallel with the nature of the brain. In order to reproduce the functions of the brain, the data structure, method of encoding context, and method of processing with context must involve a data-encoded basis element. It is reported that a Fourier series in Fourier space comprising a series of Fourier components constructed by parameterization with the data can reproduce the data processing attributes of the brain wherein each Fourier component satisfies the condition of an appropriate basis element. The reported algorithm includes an Input Layer for receiving data representative of physical characteristics or representations of physical characteristics capable of transforming the data into a Fourier series in Fourier space. The data is received within an input context representative of the physical characteristics that is encoded in time as delays corresponding to modulation of the Fourier series at corresponding frequencies. Each component representative of a characteristic of a physical object is independent of any other component; whereas, each component of a conventional Fourier series has no meaning with regard to the representation any real world object. Only the totality of the components has any physical meaning, and no single component may be independently modified without losing the connection to the real world object which the total series represents.

Based on the definitions of standard transforms and neural networks and the corresponding mathematical representations and data processing operations, neural networks cannot perform the equivalent operations or replicate the capabilities associated with using Fourier series in Fourier space constructed by parameterization with the data. In the reported algorithm, the variable is frequency and the data parameters are constants. Each component is mathematically independent of any other. Thus, each "data element" comprising a Fourier component in Fourier space is independent of any other. This data construct is different from the standard Fourier transforms where (1) the Fourier series is in time or x, y, z space—not Fourier space, (2) the transform is not parameterized with the data, and (3) the transform has no meaning except in its entirety. The data parameterization and use of the resulting Fourier series in Fourier space in effect "compresses" the possible continuous stream of physical characteristics from the world and allows for physical representations and processing with much less data. Even in the conventional case of a Fourier series in the time domain potentially challenging objects having sharp edges such as a square pulse pose no difficulty in that it is fairly accurately represented by only seven terms (Siebert, 1986b). The same principle applies to information represented as a Fourier series in k, ω-space. Thus, in contrast to the prior processing methods based on standard Fourier series or transformed data stream and processing with neural networks, the resulting efficiency and universal applicability arise from this structure naturally and are based in signal processing theory.

2. Summary of the algorithm

A method and system for pattern recognition and processing involving processing information in Fourier space is reported. The theoretical results given previously (Mills, 1998) are that (1) action potentials carry information with digital and analog aspects that allow the brain to operate as a Fourier processor in Fourier space with encoding of context in the structure of transducers mapping one-to-one with corresponding structural elements of the memory, (2) an ensemble of interlinked neurons can filter information as delayed Gaussian filters, (3) the neuronal ensembles propagating cascaded action potentials may couple with Poison probability (Hogg and Tanis, 1977b) to form associations of information encoded in the action potentials, (4) ensembles of neurons as delayed Gaussian filters may order format information by forming associations of the corresponding filtered action potentials with memory elements, and (5) a predominant configuration of activation may arise that is analogous to that of interacting quantum levels with partition of energy as given by statistical thermodynamics (Nash, 1976). These aspects are modeled such that a simulation may be programmable on digital processing systems.

The system includes an Input Layer for receiving data representative of physical characteristics or representations of physical characteristics capable of transforming the data into a Fourier series in Fourier space. The data is received within an input context representative of the physical characteristics that is encoded in time as delays corresponding to modulation of the Fourier series at corresponding frequencies. The system includes a memory that maintains a set of initial ordered Fourier series. The system also includes an Association Layer that receives a plurality of the Fourier series in Fourier space including at least one ordered Fourier series from the memory and forms a string comprising a sum of the Fourier series and stores the string in memory. The system also includes a String Ordering Layer that receives the string from memory and orders the Fourier series contained in the string to form an ordered string and stores the ordered string in memory. The system also includes a Predominant Configuration Layer that receives multiple ordered strings from the memory, forms complex ordered strings comprising associations between the ordered strings, and stores the complex ordered strings to the memory. The components of the system are active based on probability using weighting factors based on activation rates. The Layers serve specific functions that are separable and this aspect permits their independent activation according to the function of the Predominant Configuration Layer.

One aspect of the algorithm is directed to inputting information as data to the system within an input context and associating the data. This aspect of the algorithm includes encoding the data as parameters of at least two Fourier components in Fourier space, adding the Fourier components to form at least two Fourier series in Fourier space, the Fourier series representing the information, sampling at least one of the Fourier series in Fourier space with a filter to form a sampled Fourier series, and modulating the sampled Fourier series in Fourier space with the filter to form a modulated Fourier series. This aspect of the algorithm also includes determining a spectral similarity between the modulated Fourier series and another Fourier series, determining a probability expectation value based on the spectral similarity (Hogg and Tanis, 1977a), and generating a probability operand having a value selected from a set of zero and one, based on the probability expectation value. These steps are repeated until the probability operand has a value of one. Once the probability operand has a value of one, the modulated Fourier series and the other Fourier series are added to form a string of Fourier series in Fourier space, and the string of Fourier series is stored in the memory.

Another aspect of the algorithm is directed to ordering a string representing the information. This aspect of the algorithm utilizes a High Level Memory section of the memory that maintains an initial set of ordered Fourier series. This aspect includes obtaining a string from the memory and selecting at least two filters from a selected set of filters stored in the memory. This aspect also includes sampling the string with the filters such that each of the filters produce a sampled Fourier series. Each Fourier series comprises a subset of the string. This aspect also includes modulating each of the sampled Fourier series in Fourier space with the corresponding selected filter such that each of the filters produce an order formatted Fourier series. Furthermore, this aspect includes adding the order formatted Fourier series produced by each filter to form a summed Fourier series in Fourier space, obtaining an ordered Fourier series from the memory, determining a spectral similarity between the summed Fourier series and the ordered Fourier series, determining a probability expectation value based on the spectral similarity, and generating a probability operand having a value selected from a set of zero and one, based on the probability expectation value. These steps are repeated until the probability operand has a value of one. Once the probability operand has a value of one, this aspect includes storing the summed Fourier series to an intermediate memory section. Thereafter, this aspect includes removing the selected filters from the selected set of filters to form an updated set of filters, removing the subsets from the string to obtain an updated string, and selecting an updated filter from the updated set of filters. This aspect further includes sampling the updated string with the updated filter to produce a sampled Fourier series comprising a subset of the string, modulating the sampled Fourier series in Fourier space with the corresponding selected updated filter to produce an updated order formatted Fourier series, recalling the summed Fourier series from the intermediate memory section, adding the updated order formatted Fourier series to the summed Fourier series to form an updated summed Fourier series in Fourier space, and obtaining an updated ordered Fourier series from the memory. This aspect further includes determining a spectral similarity between the updated summed Fourier series and the updated ordered Fourier series, determining a probability expectation value based on the spectral similarity, and generating a probability operand having a value selected from a set of zero and one, based on the probability expectation value. These steps are repeated until the probability operand has a value of one, or all of the updated filters have been selected from the updated set of filters. If all of the updated filters have been selected before the probability operand has a value of one, then the intermediate memory section is clearer and the steps starting with selecting at least two filters from a selected set of filters is repeated. Once the probability operand has a value of one, the updated summed Fourier series is stored to the intermediate memory section and steps beginning with removing the selected filters from the selected set of filters to form an updated set of filters are repeated until one of the following set of conditions is satisfied: the updated set of filters is empty or the remaining subsets of the string are nil. If the remaining subsets of the string are nil, then the Fourier series in the intermediate memory section is stored in the High Level Memory section of the memory.

Another aspect of the algorithm is directed to forming complex ordered strings by forming associations between a plurality of ordered strings. This aspect includes recording ordered strings to the High Level Memory section, forming associations of the ordered strings to form complex ordered strings, and recording the complex ordered strings to the High Level Memory section. A further aspect of the algorithm is directed to forming a predominant configuration based on probability. This aspect includes generating an activation probability parameter, storing the activation probability parameter in the memory, generating an activation probability operand having a value selected from a set of zero and one, based on the activation probability parameter, activating any one or more components of the algorithm such as matrices representing functions, data parameters, Fourier components, Fourier series, strings, ordered strings, components of the Input Layer, components of the Association Layer, components of the String Ordering Layer, and components of the Predominant Configuration Layer, the activation of each component being based on the corresponding activation probability parameter, and weighting each activation probability parameter based on an activation rate of each component.

3. The artificial intelligence algorithm

3.1. Data constructs

The present algorithm is directed to systems and methods for performing pattern recognition and association based upon receiving, storing, and processing information. The information is based upon physical characteristics or representations of physical characteristics and a relationship of the physical characteristics, hereinafter referred to as physical context, of an item of interest. The physical characteristics and physical context serve as a basis for stimulating a transducer. The transducer converts an input signal representative of the physical characteristics and the physical context into the information for processing. The information is data and an input context. The data is representative of the physical characteristics or the representations of physical characteristics and the input context corresponds to the physical context based upon the identity of a specific transducer and its particular transducer elements. The physical context maps on a one to one basis to the input context. The information defines a Fourier series in Fourier space that represents the item of interest. In other words, a Fourier series in Fourier space represents the information parameterized according to the data and the input context. In addition, the input context maps on a one to one basis to an Input Layer section of a memory. Thus, there is a one to one map of physical context to input context to Input Layer section of a memory. The representation of information as a Fourier series in Fourier space allows for the mapping.

3.2. Layers

As illustrated in Fig. 1, at a high level, the system 10 includes several function specific layers. These include an Input Layer 12, an Association Layer 14, an String Ordering Layer 16 and a Predominant Configuration Layer 18. The Input Layer 12 receives the data within the input context and transforms the data into the Fourier series in Fourier space representative of the information. The system 10 also includes a memory 20 for storing information. The Input Layer 12 also encodes the input context as delays in time corresponding to a modulation factor of the Fourier series at corresponding frequencies. The Association Layer 14 receives a plurality of Fourier series in Fourier space, including at least one ordered Fourier series from the memory 20, forms a string comprising a sum of the Fourier series and stores the string to the memory 20. The String Ordering Layer 16 receives the string from the memory 20, orders the Fourier series contained in the string to form an ordered string and stores the ordered string in the memory 20. The Predominant Configuration Layer 18 receives multiple ordered strings from the memory 20, forms associations between the ordered strings to form a complex ordered string, also referred to as a predominant configuration string, and stores the predominant configuration string to the memory 20. The memory 20 may be partitioned in several distinct sections for storing different types of information or distinctly classified types of information. Specifically, the memory may include a High Level Memory section, an intermediate level memory section, etc. as will be described in more detail below.

The following example illustrates how the algorithm processes the physical characteristics of an item of interest, specifically a triangle. In flat geometry, the physical characteristics of a triangle are three connected lines at angles aggregating to 180°. The physical characteristics provide spatial variations of light scattering. In one example, a light responsive transducer (not shown) of the system 10 transduces the light scattering into the data. An exemplary transducer is a charge coupled device (CCD) array. One data element at a point in time may be a voltage of a particular

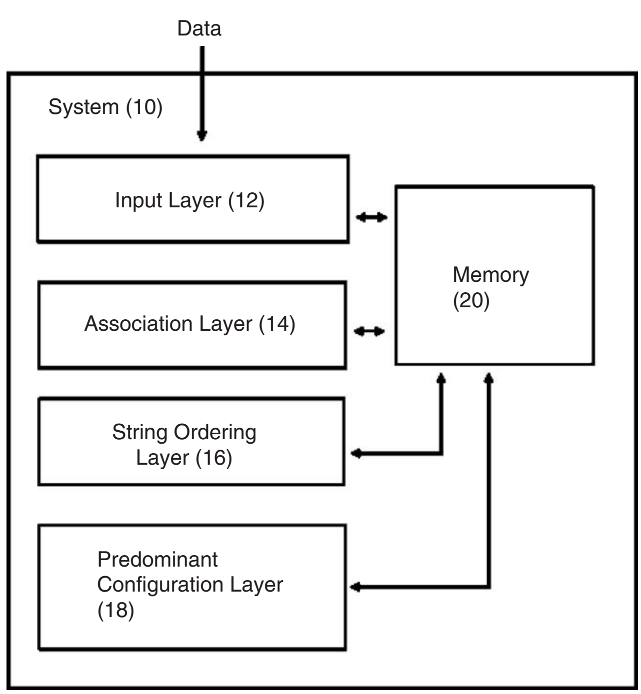

Fig. 1. A high level block diagram of the artificial intelligence algorithm comprising a system 10 and specific layers of an Input Layer 12, an Association Layer 14, an String Ordering Layer 16, a Predominant Configuration Layer 18, and a Memory 20.

CCD element of the CCD array. Each CCD element of the CCD array has a spatial identity. The physical context for the triangle is the relationship of the lines at the corresponding angles providing a spatial variation of light scattering. The input context is the identity of each CCD element that responds according to the physical context. For example, a CCD element (100,13) of a 512 by 512 CCD array will uniquely respond to light scattered by the lines and angular relations of the triangle relative to the other CCD elements of the CCD array. The response is stored in a specific memory register of an Input Layer section of the memory 20. The specific memory register is reflective of the input context. In the present algorithm, a Fourier series in Fourier space represents the information of the triangle parameterized according to the voltage and the CCD element identity.

3.3. Input

Referring to Fig. 2, in the first step, the Input Layer 12 receives the data from the transducer (not shown). A Fourier transform processor 22 encodes each data element as parameters of a Fourier component in Fourier space and stores the data parameter values to the Input Layer section 24 of the memory 20. Each Fourier component of the Fourier series may comprise a quantized amplitude, frequency, and phase angle. For example, the Fourier series in Fourier space may be:

$$\sum_{m=1}^{M}\sum_{n=-\infty}^{\infty}\frac{4\pi}{1+(k_z^2/k_\rho^2)}a_{0_m}N_{m_{\rho_0}}N_{m_{z_0}}\sin\left(\left(k_\rho-n\frac{2\pi}{\rho_{0_m}}\right)\frac{N_{m_{\rho_0}}\rho_{0_m}}{2}\right)\sin\left(\left(k_z-n\frac{2\pi}{z_{0_m}}\right)\frac{N_{m_{z_0}}z_{0_m}}{2}\right) \quad (1)$$

having a quantized amplitude, frequency, and phase angle, wherein a_{0_m} is a constant, k_ρ and k_z are the frequency variables, n, m, and M are integers, and $N_{m_{\rho_0}}$, $N_{m_{z_0}}$, ρ_{0_m}, and z_{0_m} are the data parameters.

The data parameters $N_{m_{\rho_0}}$ and $N_{m_{z_0}}$ of the Fourier series component are proportional to the rate of change of the physical characteristic. Each of the data parameters ρ_{0_m} and z_{0_m} of each Fourier component is inversely proportional to the amplitude of the physical characteristic. In the triangle example, the amplitude of the voltage at a given CCD

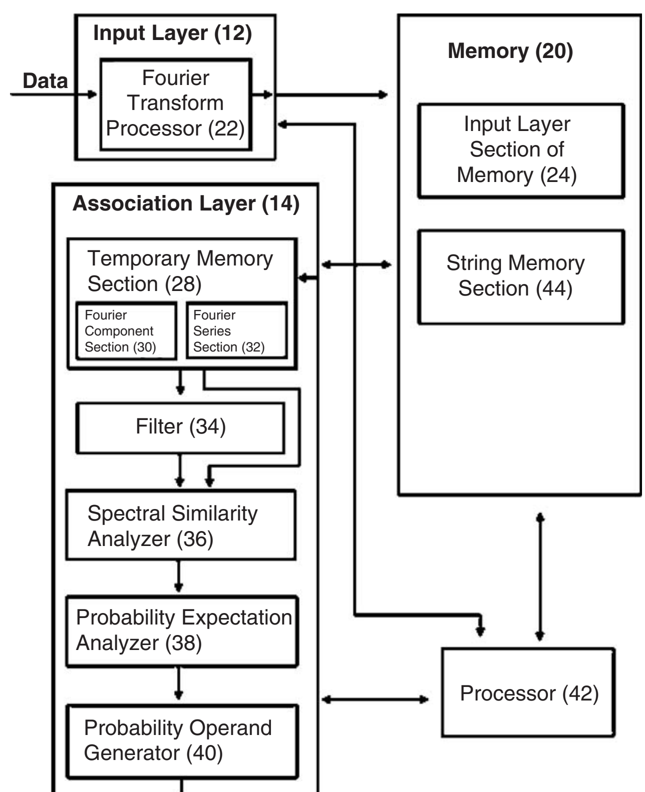

Fig. 2. A detailed block diagram illustrating an Input Layer 12, an Association Layer 14, and a Memory Layer 20 of the high level block diagram of Fig. 1. The components are as follows: 24-Input Layer section of the Memory 20, 22-Fourier transform processor, 28-temporary memory section, 30-Fourier component section of temporary memory Section 28, 32-Fourier series section of the temporary memory Section 28, 34-filter, 36-spectral similarity analyzer, 38-probability expectation analyzer, 40-probability operand generator, 42-processor, and 44-string memory section.

element relative to the neighboring CCD element defines the rate of change of the voltage which is converted into the data parameters $N_{m_{\rho_0}}$ and $N_{m_{z_0}}$. The inverse of the amplitude of the voltage of each CCD element is converted into the data parameters ρ_{0_m} and z_{0_m}. As illustrated in Fig. 3 and described above, for each CCD element, the Fourier series, parameterized accordingly, are stored to a specific subregister 27 of a specific register 26 of the Input Layer section 24 of the memory 20. Since the structure of a Fourier series is known, only the parameters need to be stored in a digital embodiment.

The number and types of transducers that may supply information to the system is only limited by available technology, hardware and economics, as is the number m of corresponding registers 26 for each transducer. Each register 26 may have any number d of subregisters 27, where the number d of subregisters of one register 26 is not necessarily the same as other registers 26. For example, "Level 1" register "1" may have 30 "Level 2" subregisters 27 and "Level 1" register "2" may have one-hundred subregisters 27. Furthermore, each "Level 2" register may have any number e of subregisters, where the number e of subregisters of one register 27 is not necessarily the same as other registers 27. For example, "Level 2" register "1" may have 50 "Level n" subregisters 29 and "Level 2" register "2" may have 70 "Level n" subregisters 29. Still further, each "Level n" register 29 may have any number f of time buffer elements 31, where the number f of time buffer elements 31 is not necessarily the same as other time buffer elements 31.

Alternatively, each of the data parameters $N_{m_{\rho_0}}$ and $N_{m_{z_0}}$ of the Fourier series component is proportional to the amplitude of the physical characteristic. Each of the data parameters ρ_{0_m} and z_{0_m} of each Fourier component is inversely proportional to the rate of change of the physical characteristic. As in the first embodiment, for each CCD element, these parameters are stored in a specific subregister of the Input Layer section of the memory.

In a third embodiment, each of the data parameters $N_{m_{\rho_0}}$ and $N_{m_{z_0}}$ of the Fourier series component is proportional to the duration of the signal response of each transducer. Each of the data parameters ρ_{0_m} and z_{0_m} of each Fourier component is inversely proportional to the physical characteristic. As in the first embodiment, for each CCD element, these parameters are stored in a specific subregister of the Input Layer section of the memory.

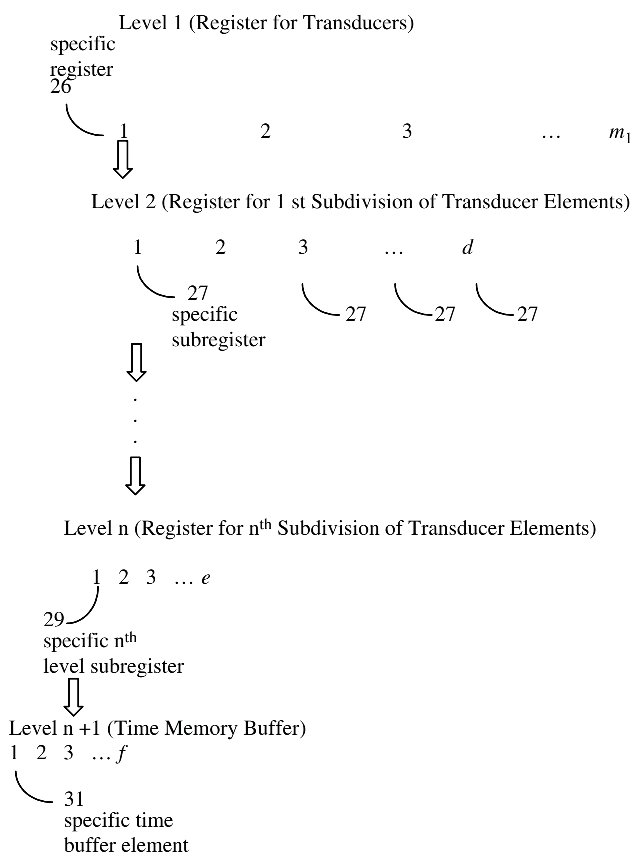

Fig. 3. A flow diagram of an exemplary transducer data structure of a time delay interval subdivision hierarchy wherein the data from a transducer having n levels of subcomponents numbering integer m per level is assigned a master time interval with $n+1$ subtime intervals in a hierarchical manner wherein the data stream from the final nth level transducer element is recorded as a function of time in the $n+1$th time coded submemory buffer. The components are as follows: 26-registers for each transducer, 27-specific subregister of a specific register 26 of the Input Layer Section 24 of the Memory 20, and 29-"Level n" subregisters, 31-time buffer elements. The memory structure encodes the input context.

As an alternative example, the Fourier series in Fourier space may be:

$$\sum_{m=1}^{M}\sum_{n=-\infty}^{\infty}\frac{4\pi}{1+(k_z^2/k_\rho^2)}\frac{4}{\rho_{0_m}z_{0_m}}a_{0_m}\,\sin\left(\left(k_\rho-n\frac{2\pi}{\rho_{0_m}}\right)\frac{N_{m_{\rho_0}}\rho_{0_m}}{2}\right)\sin\left(\left(k_z-n\frac{2\pi}{z_{0_m}}\right)\frac{N_{m_{z_0}}z_{0_m}}{2}\right) \tag{2}$$

having a quantized frequency, and phase angle, wherein a_{0_m} is a constant, k_ρ and k_z are the frequency variables, n, m, and M are integers, and $N_{m_{\rho_0}}$, $N_{m_{z_0}}$, ρ_{0_m}, and z_{0_m} are the data parameters. As described with respect to the previous example, for each CCD element, these parameters are stored in a specific subregister of the Input Layer section of the memory.

The physical context is conserved by mapping with a one to one basis between the physical context and the input context based on the identity of each transducer. The input context is conserved by mapping on a one to one basis to the Input Layer section 24 of memory 20. In an embodiment, the input context is encoded in time as a characteristic modulation frequency band in Fourier space of the Fourier series. The characteristic modulation frequency band in Fourier space represents the input context according to the identity of a specific transducer of the relationship of two transducer elements. The modulation within each frequency band may encode not only input context but context in a general sense. The general context may encode temporal order, cause and effect relationships, size order, intensity order, before–after order, top–bottom order, left–right order, etc. all of which are relative to the transducer.

Still referring to Fig. 3, the transducer has n levels of subcomponents. Each transducer is assigned a portion 26 of the Input Layer section 24 of the memory 20. The memory 20 is arranged in a hierarchical manner. Specifically, the memory is divided and assigned to correspond to a master time interval with $n+1$ subtime intervals. The hierarchy parallels the n levels of the transducer subcomponents. The nth level transducer subcomponent provides a data stream to the system 10. The data stream is recorded as a function of time in the $n+1$ subtime interval. The time intervals represent time delays which correspond to the characteristic modulation frequency band in Fourier space which in turn represents the input context according to the specific transducer or transducer subcomponent.

An exemplary complex transducer which may be represented by a data structure comprising a hierarchical set of time delay intervals is a CCD array of a video camera comprising a multitude of CCDs. Each CCD comprises a transducer element and is responsive to light intensity of a given wavelength band at a given spatial location in a grid. Another example of a transducer is an audio recorder comprising transducer elements each responsive to sound intensity of a given frequency band at a given spatial location or orientation. A signal within the band 300–400 MHz may encode and identify the signal as a video signal; whereas, a signal within the band 500–600 MHz may encode and identify the signal as an audio signal. Furthermore, a video signal within the band 315–325 MHz may encode and identify the signal as a video signal as a function of time of CCD element (100,13) of a 512 by 512 array of CCDs.

In one embodiment, the characteristic modulation having a frequency within the band in Fourier space is represented by $e^{-j2\pi f t_0}$. The modulation corresponds to the time delay $\delta(t-t_0)$ wherein f is the frequency variable, t the time variable, and t_0 the time delay. The characteristic modulation is encoded as a delay in time by storing the Fourier series in a specific portion of the Input Layer section of the memory wherein the specific portion has $n+1$ subtime intervals. Each subtime interval corresponds to a frequency band.

In an alternative embodiment, the characteristic modulation, having a frequency within the band is represented by $e^{-jk_\rho(\rho_{fb_m}+\rho_{t_m})}$. Thus, the Fourier series in Fourier space may be:

$$\sum_{m=1}^{M}\sum_{n=-\infty}^{\infty}\frac{4\pi}{1+(k_z^2/k_\rho^2)}a_{0_m}N_{m_{\rho_0}}N_{m_{z_0}}\,e^{-jk_\rho(\rho_{fb_m}+\rho_{t_m})}\,\sin\left(k_\rho\frac{N_{m_{\rho_0}}\rho_{0_m}}{2}-n\frac{2\pi N_{m_{\rho_0}}}{2}\right)\sin\left(k_z\frac{N_{m_{z_0}}z_{0_m}}{2}-n\frac{2\pi N_{m_{z_0}}}{2}\right) \tag{3}$$

wherein $\rho_{t_m}=v_{t_m}t_{t_m}$ is the modulation factor which corresponds to the physical time delay t_{t_m}, $\rho_{fb_m}=v_{fb_m}t_{fb_m}$ is the modulation factor which corresponds to the specific transducer time delay t_{fb_m}, v_{t_m} and v_{fb_m} are constants such as the signal propagation velocities of the neuronal model where this definition applies to similar data processing structures below, a_{0_m} is a constant, k_ρ and k_z are the frequency variables, n, m, and M are integers, and $N_{m_{\rho_0}}$, $N_{m_{z_0}}$, ρ_{0_m}, and z_{0_m} are data parameters. The data parameters are selected in the same manner as described above.

Transducer strings may be created by obtaining a Fourier series from at least two selected transducers and adding the Fourier series. Transducers that are active simultaneously may be selected. The transducer string may be stored in a distinct memory location of the memory. The characteristic modulation, having a frequency within the band in Fourier space can be represented by $e^{-j2\pi f t_0}$ which corresponds to the time delay $\delta(t-t_0)$ wherein f is the frequency variable, t is the time variable, and t_0 is the time delay.

Recalling any part of the transducer string from the distinct memory location may thereby cause additional Fourier series of the transducer string to be recalled. In other words the Fourier series are linked. Fourier series, in addition to those of transducer strings may be linked. In order to achieve linking of the Fourier series, the system generates a probability expectation value that recalling any part of one of the Fourier series from the memory causes at least another Fourier series to be recalled from the memory. The system stores the probability expectation value to memory. The system generates a probability operand having a value selected from a set of zero and one, based on the probability expectation value. The system recalls at least another Fourier series from the memory if the operand is one. The probability expectation value may increase with a rate of recalling any part of any of the Fourier series.

The system may be initialized by learning. The relationship between the data and the data parameters such as ρ_{0_m} and $N_{m_{\rho_0}}$ of each component of the Fourier series is learned by the system by applying standard physical signals. In the case of the triangle example, the standard physical signals are the scattered light from the physical characteristics of the triangle. The physical signals are applied to each transducer together with other information that is associated with the standard. A data base is established. This information that is associated with the standard is recalled and comprises input into the Association Layer and the String Ordering Layer.

The data parameters and the input context are established and stored in the Input Layer section 24 of the memory 20.

3.4. Forming associations

Referring again to Fig. 2, several parameterized Fourier components are input to the Association Layer to form associations of the Fourier series. The Fourier components may be stored in a Fourier component section 30 of a temporary memory section 28. The Fourier components are added to form multiple Fourier series which in turn may be stored in a Fourier series section 32 of the temporary memory section 28. At least one of the Fourier series stored in the Fourier series section 32 is input to a filter 34 wherein the filter 34 samples and modulates the Fourier series (Siebert, 1986c). The filtered Fourier series is input to a spectral similarity analyzer 36. The spectral similarity analyzer 36 determines the spectral similarity between the filtered Fourier series and another Fourier series stored in the Fourier series section 32 of the temporary memory section 28. A spectral similarity value is output from the spectral similarity analyzer 36 and input to a probability expectation analyzer 38. The probability expectation analyzer 38 determines a probability expectation value based on the spectral similarity value. The probability expectation value output from the probability expectation analyzer 38 is input to a probability operand generator 40. The probability operand generator 40 generates a probability operand value of one or zero based upon the probability expectation value. The probability operand value is output to a processor 42. If the probability operand value is zero, the processor 42 sends another Fourier series from the Fourier series section 32 of the temporary memory section 28 to the filter 34 and begins the process again. If the probability operand value is one, the filtered Fourier series and the other Fourier series are added to form a string and the string is stored in a string memory section 44.

The filter 34 can be a time delayed Gaussian filter in the time domain (Siebert, 1986d). The filter may be characterized in time by:

$$\frac{\alpha}{\sqrt{2\pi}}\,\mathrm{e}^{-(t-(\sqrt{N}/\alpha))^2/(2/\alpha^2)} \tag{4}$$

wherein $\sqrt{N}/\alpha$ is a delay parameter, α is a half-width parameter, and t the time parameter. The Gaussian filter may comprise a plurality of cascaded stages each stage having a decaying exponential system function between stages. The Central Limit Theorem of probability theory states in effect that, under very general conditions, the cascade of a large number of linear-time-invariant (LTI) systems will tend to have a delayed Gaussian impulse response, almost independent of the characteristics of the systems cascaded (Siebert, 1986d). The filter, in frequency space, can be characterized by:

$$\mathrm{e}^{-(1/2)(2\pi f/\alpha)^2}\,\mathrm{e}^{-\mathrm{j}\sqrt{N}(2\pi f/\alpha)} \tag{5}$$

wherein $\sqrt{N}/\alpha$ and α are a corresponding delay parameter and a half-width parameter in time, respectively, and f the frequency parameter. The probability distribution may be Poissonian. Thus, the probability expectation value can be based upon Poissonian probability. The probability expectation value may be characterized by

$$\prod_s \left[p_{\uparrow s} + (P - p_{\uparrow s})\exp\left[-\beta_s^{-2}\left(\frac{1-\cos 2\phi_s}{2}\right)\right]\cos(\delta_s + 2\sin\phi_s)\right] \tag{6}$$

wherein P is the maximum probability of at least one other Fourier series being associated with a first Fourier series, $p_{\uparrow s}$ is a probability of at least one other Fourier series being associated with a first Fourier series in the absence of coupling of the first Fourier series with the at least one other Fourier series, β_s^2 is a number that represents the amplitude of spectral similarity between at least two filtered or unfiltered Fourier series, ϕ_s represents the frequency difference angle between at least two filtered or unfiltered Fourier series, and δ_s, is a phase factor. β_s^2 may be characterized by

$$\beta_s^2 = (8\pi)^2 \frac{1}{\sqrt{2\pi}} \sqrt{\frac{\alpha_1^2 \alpha_s^2}{\alpha_1^2 + \alpha_s^2}} \sum_{m_1=1}^{M_1} a_{0_{m_1}} N_{m_1} \sum_{m_s=1}^{M_s} a_{0_{m_s}} N_{m_s} \exp -\left\{ \frac{(\alpha_1^2 \alpha_s^2/\alpha_1^2 + \alpha_s^2)((\sqrt{N_1}/\alpha_1) - (\sqrt{N_s}/\alpha_s) + (N_{m_1}\rho_{0_{m_1}}/2v_{m_1}) - (N_{m_s}\rho_{0_{m_s}}/2v_{m_s}))^2}{2} \right\} \tag{7}$$

$\sqrt{N_1}/\alpha_1$ and $\sqrt{N_s}/\alpha_s$ correspond to delay parameters of a first and sth time delayed Gaussian filter, respectively, α_1 and α_s corresponding half-width parameters of a first and sth time delayed Gaussian filter, respectively, M_1 and M_s are integers, $a_{0_{m_1}}$ and $a_{0_{m_s}}$ are constants, v_{m_1} and v_{m_s} are constants such as the signal propagation velocities, and N_{m_1}, N_{m_s}, $\rho_{0_{m_1}}$, and $\rho_{0_{m_s}}$ are data parameters. The data parameters are selected in the same manner as described above. ϕ_s may be characterized by

$$\phi_s = \frac{\pi((\sqrt{N_1}/\alpha_1) - (\sqrt{N_s}/\alpha_s) + \sum_{m_1=1}^{M_1}(N_{m_1}\rho_{0_{m_1}}/2v_{m_1}) - \sum_{m_s=1}^{M_s}(N_{m_s}\rho_{0_{m_s}}/2v_{m_s}))}{(\sqrt{N_1}/\alpha_1) + \sum_{m_1=1}^{M_1}(N_{m_1}\rho_{0_{m_1}}/2v_{m_1})} \tag{8}$$

$\sqrt{N_1}/\alpha_1$ and $\sqrt{N_s}/\alpha_s$ correspond to delay parameters of a first and sth time delayed Gaussian filter, respectively, α_1 and α_s corresponding half-width parameters of a first and sth time delayed Gaussian filter, respectively, M_1 and M_s are integers, $a_{0_{m_1}}$ and $a_{0_{m_s}}$ are constants, v_{m_1} and v_{m_s} are constants such as the signal propagation velocities, and N_{m_1}, N_{m_s}, $\rho_{0_{m_1}}$, and $\rho_{0_{m_s}}$ are data parameters. The data parameters are selected in the same manner as described above.

An exemplary string with a characteristic modulation having a frequency within the band represented by $e^{-jk_\rho(\rho_{fbm}+\rho_{tm})}$ is:

$$\sum_{s=1}^{S}\sum_{m=1}^{M_s}\sum_{n=-\infty}^{\infty} \frac{4\pi}{(1+k_z^2/k_\rho^2)} a_{0_{s,m}} N_{s,m_{\rho_0}} N_{s,m_{z_0}}\, e^{-jk_\rho(\rho_{fbs,m}+\rho_{ts,m})} \times \sin\left(\left(k_\rho - n\frac{2\pi}{\rho_{0_{s,m}}}\right)\frac{N_{s,m_{\rho_0}}\rho_{0_{s,m}}}{2}\right) \sin\left(\left(k_z - n\frac{2\pi}{z_{0_{s,m}}}\right)\frac{N_{s,m_{z_0}} z_{0_{s,m}}}{2}\right) \tag{9}$$

wherein $\rho_{t_{s,m}} = v_{t_{s,m}} t_{t_{s,m}}$ is the modulation factor which corresponds to the physical time delay $t_{t_{s,m}}$, $\rho_{fb_{s,m}} = v_{fb_{s,m}} t_{fb_{s,m}}$ is the modulation factor which corresponds to the specific transducer time delay $t_{fb_{s,m}}$, $v_{t_{s,m}}$ and $v_{fb_{s,m}}$ are constants such as the signal propagation velocities, $a_{0_{s,m}}$ is a constant, k_ρ and k_z are the frequency variables, n, m, s, M_s, and S are integers, and $N_{s,m_{\rho_0}}$, $N_{s,m_{z_0}}$, $\rho_{0_{s,m}}$, and $z_{0_{s,m}}$ are data parameters. The data parameters are selected in the same manner as described above.

An exemplary string with each Fourier series multiplied by the Fourier transform of the delayed Gaussian filter represented by $e^{-(1/2)(v_{s\rho 0}(k_\rho/\alpha_{s\rho 0}))^2} e^{-j(\sqrt{N_{s\rho 0}}/\alpha_{s\rho 0})(v_{s\rho 0}k_\rho)} e^{-(1/2)(v_{sz0}(k_z/\alpha_{sz0}))^2} e^{-j(\sqrt{N_{sz0}}/\alpha_{sz0})(v_{sz0}k_z)}$ that established the association to form the string is:

$$\sum_{s=1}^{S}\sum_{m=1}^{M_s}\sum_{n=-\infty}^{\infty} \frac{4\pi}{1+(k_z^2/k_\rho^2)} a_{0_{s,m}} N_{s,m_{\rho_0}} N_{s,m_{z_0}}\, e^{-(1/2)(v_{s\rho 0}(k_\rho/\alpha_{s\rho 0}))^2} e^{-j(\sqrt{N_{s\rho 0}}/\alpha_{s\rho 0})(v_{s\rho 0}k_\rho)} e^{-(1/2)(v_{sz0}(k_z/\alpha_{sz0}))^2} e^{-j(\sqrt{N_{sz0}}/\alpha_{sz0})(v_{sz0}k_z)} e^{-jk_\rho(\rho_{fbs,m}+\rho_{ts,m})} \sin\left(\left(k_\rho - n\frac{2\pi}{\rho_{0_{s,m}}}\right)\frac{N_{s,m_{\rho_0}}\rho_{0_{s,m}}}{2}\right) \sin\left(\left(k_z - n\frac{2\pi}{v_{s,m}t_{0_{s,m}}}\right)\frac{N_{s,m_{z_0}} z_{0_{s,m}}}{2}\right) \tag{10}$$

wherein $v_{s\rho 0}$ and v_{sz0} are constants such as the signal propagation velocities in the ρ and z directions, respectively, $\sqrt{N_{s\rho 0}}/\alpha_{s\rho 0}$ and $\sqrt{N_{sz0}}/\alpha_{sz0}$ are delay parameters and $\alpha_{s\rho 0}$ and α_{sz0} are half-width parameters of a corresponding Gaussian filter in the ρ and z directions, respectively, $\rho_{t_{s,m}} = v_{t_{s,m}} t_{t_{s,m}}$ is the modulation factor which corresponds to the physical time delay $t_{t_{s,m}}$, $\rho_{fb_{s,m}} = v_{fb_{s,m}} t_{fb_{s,m}}$ is the modulation factor which corresponds to the specific transducer time delay $t_{fb_{s,m}}$, $v_{t_{s,m}}$ and $v_{fb_{s,m}}$ are constants such as the signal propagation velocities, $a_{0_{s,m}}$ is a constant, k_ρ and k_z are the frequency variables, n, m, s, M_s, and S are integers, and $N_{s,m_{\rho_0}}$, $N_{s,m_{z_0}}$, $\rho_{0_{s,m}}$, and $z_{0_{s,m}}$ are data parameters. The data parameters are selected in the same manner as described above.

Therein, the Association Layer forms associations between Fourier series and sums the associated Fourier series to form a string. The string is then stored in the string memory section.

3.5. Ordering

The next aspect of the present algorithm is the ordering of the strings stored in the string memory section 44. The ordering may be according to any one of the following: temporal order, cause and effect relationships, size order, intensity order, before–after order, top–bottom order, or left–right order. Referring to Fig. 4, the method for ordering the strings stored in the string memory section 44 entails the following:

(a) obtaining a string from the string memory section 44 and storing the string to a temporary string memory section 46;
(b) selecting at least two filters 48, 50 from a selected set of filters 52;
(c) sampling the string with the filters 48, 50, each of the filters forming a sampled Fourier series, each Fourier series comprising a subset of the string;
(d) modulating each of the sampled Fourier series in Fourier space with the corresponding selected filter 48, 50, each forming an order formatted Fourier series;
(e) adding the order formatted Fourier series to form a summed Fourier series in Fourier space;
(f) obtaining an ordered Fourier series from the High Level Memory section 54;
(g) determining a spectral similarity with a spectral similarity analyzer 56 between the summed Fourier series and the ordered Fourier series;
(h) determining a probability expectation value, with a probability expectation value analyzer 58 based on the spectral similarity;
(i) generating a probability operand, with a probability operand generator 60 having a value selected from a set of zero and one, based on the probability expectation value;
(j) repeating steps (b)–(i) until the probability operand has a value of one as determined by the processor 42;
(k) storing the summed Fourier series to an intermediate memory section 62;
(l) removing the selected filters from the selected set of filters 52 to form an updated set of filters 52;
(m) removing the subsets from the string to obtain an updated string;
(n) selecting an updated filter 64 from the updated set of filters;

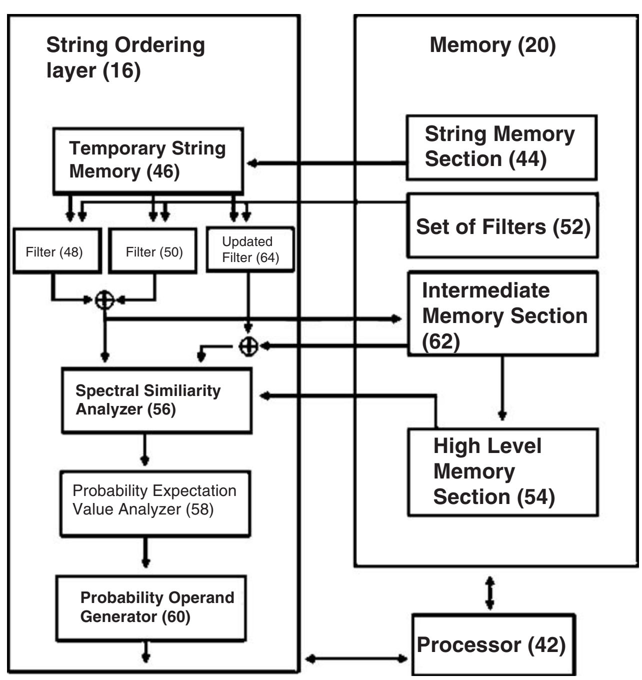

Fig. 4. A detailed block diagram illustrating an String Ordering Layer 16 and the Memory Layer 20 of the high level block diagram of Fig. 1. The components are: 42-processor, 44-string memory section, 46-temporary string memory section, 48-filter, 50-filter, 52-selected set of filters, 54-high level memory section, 56-spectral similarity analyzer, 58-probability expectation value analyzer, 60-probability operand generator, 62-intermediate memory section, and 64-updated filter.

(o) sampling the updated string with the updated filter to form a sampled Fourier series comprising a subset of the string;
(p) modulating the sampled Fourier series in Fourier space with the corresponding selected updated filter to form an updated order formatted Fourier series;
(q) recalling the summed Fourier series from the intermediate memory section 62;
(r) adding the updated order formatted Fourier series to the summed Fourier series from the intermediate memory section to form an updated summed Fourier series in Fourier space;
(s) obtaining another ordered Fourier series from the High Level Memory section 54;
(t) determining a spectral similarity between the updated summed Fourier series and the another ordered Fourier series;
(u) determining a probability expectation value based on the spectral similarity;
(v) generating a probability operand having a value selected from a set of zero and one, based on the probability expectation value;
(w) repeating steps (n)–(v) until the probability operand has a value of one or all of the updated filters have been selected from the updated set of filters as determined by processor 42;
(x) if all of the updated filters have been selected before the probability operand has a value of one, then clearing the intermediate memory section and returning to step (b);
(y) if the probability operand has a value of one, then clearing the intermediate memory section and storing the updated summed Fourier series to the intermediate memory section;
(z) repeating steps (l)–(y) until the one of the following set of conditions is satisfied: the updated set of filters is empty, or the remaining subsets of the string of step (m) is nil as determined by the processor 42;
(aa) storing the Fourier series of intermediate memory section to the High Level Memory section 54.

Each filter of the set of filters can be a time delayed Gaussian filter having a half-width parameter α which determines the amount of the string that is sampled. Each filter of the set of filters can be a time delayed Gaussian filter having a delay parameter $\sqrt{N}/\alpha$ which corresponds to a time point. Each Fourier series of the ordered string can be multiplied by the Fourier transform of the delayed Gaussian filter represented by $\mathrm{e}^{-(1/2)(v_{s\rho 0}(k_\rho/\alpha_{s\rho 0}))^2}$ $\mathrm{e}^{-\mathrm{j}(\sqrt{N_{s\rho 0}}/\alpha_{s\rho 0})(v_{s\rho 0}k_\rho)}$ $\mathrm{e}^{-(1/2)(v_{sz0}(k_z/\alpha_{sz0}))^2}$ $\mathrm{e}^{-\mathrm{j}(\sqrt{N_{sz0}}/\alpha_{sz0})(v_{sz0}k_z)}$. The filter established the correct order. The ordered string can be represented by:

$$\sum_{s=1}^{S}\sum_{m=1}^{M_s}\sum_{n=-\infty}^{\infty}\frac{4\pi}{1+(k_z^2/k_\rho^2)}a_{0_{s,m}}N_{s,m_{\rho_0}}N_{s,m_{z_0}}\,\mathrm{e}^{-(1/2)(v_{s\rho 0}(k_\rho/\alpha_{s\rho 0}))^2}\,\mathrm{e}^{-\mathrm{j}(\sqrt{N_{s\rho 0}}/\alpha_{s\rho 0})(v_{s\rho 0}k_\rho)}\,\mathrm{e}^{-(1/2)(v_{sz0}(k_z/\alpha_{sz0}))^2}\,\mathrm{e}^{-\mathrm{j}(\sqrt{N_{sz0}}/\alpha_{sz0})(v_{sz0}k_z)}$$
$$\mathrm{e}^{-\mathrm{j}k_\rho(\rho_{fb_{s,m}}+\rho_{t_{s,m}})}\sin\left(\left(k_\rho-n\frac{2\pi}{\rho_{0_{s,m}}}\right)\frac{N_{s,m_{\rho_0}}\rho_{0_{s,m}}}{2}\right)\sin\left(\left(k_z-n\frac{2\pi}{v_{s,m}t_{0_{s,m}}}\right)\frac{N_{s,m_{z_0}}z_{0_{s,m}}}{2}\right) \tag{11}$$

wherein $v_{s\rho 0}$ and v_{sz0} are constants such as the signal propagation velocities in the ρ and z directions, respectively, $\sqrt{N_{s\rho 0}}/\alpha_{s\rho 0}$ and $\sqrt{N_{sz0}}/\alpha_{sz0}$ are delay parameters and $\alpha_{s\rho 0}$ and α_{sz0} are half-width parameters of a corresponding Gaussian filter in the ρ and z directions, respectively, $\rho_{t_{s,m}} = v_{t_{s,m}}t_{t_{s,m}}$ is the modulation factor which corresponds to the physical time delay $t_{t_{s,m}}$, $\rho_{fb_{s,m}} = v_{fb_{s,m}}t_{fb_{s,m}}$ is the modulation factor which corresponds to the specific transducer time delay $t_{fb_{s,m}}$, $v_{t_{s,m}}$ and $v_{fb_{s,m}}$ are constants such as the signal propagation velocities, $a_{0_{s,m}}$ is a constant, k_ρ and k_z are the frequency variables, n, m, s, M_s, and S are integers, and $N_{s,m_{\rho_0}}$, $N_{s,m_{z_0}}$, $\rho_{0_{s,m}}$, and $z_{0_{s,m}}$ are data parameters. The data parameters are selected in the same manner as described above.

The probability expectation value may be based upon Poissonian probability. The probability expectation value is represented by

$$\prod_s\left[p_{\uparrow s}+(P-p_{\uparrow s})\exp\left[-\beta_s^{-2}\left(\frac{1-\cos 2\phi_s}{2}\right)\right]\cos(\delta_s+2\sin\phi_s)\right] \tag{12}$$

wherein P is the maximum probability of at least one other Fourier series being associated with a first Fourier series, $p_{\uparrow s}$ is a probability of at least one other Fourier series being associated with a first Fourier series in the absence of coupling of the first Fourier series with the at least one other Fourier series, β_s^2 is a number that represents the amplitude of spectral similarity between at least two filtered or unfiltered Fourier series, ϕ_s represents the frequency difference angle between at least two filtered or unfiltered Fourier series, and δ_s, is a phase factor. β_s^2 may be characterized by

$$\beta_s^2 = (8\pi)^2 \frac{1}{\sqrt{2\pi}} \sqrt{\frac{\alpha_1^2\alpha_s^2}{\alpha_1^2+\alpha_s^2}} \sum_{m_1=1}^{M_1} a_{0_{m_1}} N_{m_1} \sum_{m_s=1}^{M_s} a_{0_{m_s}} N_{m_s} \exp - \left\{ \frac{(\alpha_1^2\alpha_s^2/\alpha_1^2+\alpha_s^2)((\sqrt{N_1}/\alpha_1)-(\sqrt{N_s}/\alpha_s)+((N_{m_1}\rho_{0_{m_1}}/2v_{m_1})+(\rho_{fb_{m_1}}/v_{fb_{m_1}})+(\rho_{t_{m_1}}/v_{t_{m_1}}))-((N_{m_s}\rho_{0_{m_s}}/2v_{m_s})+(\rho_{fb_{m_s}}/v_{fb_{m_s}})+(\rho_{t_{m_s}}/v_{t_{m_s}})))^2}{2} \right\} \tag{13}$$

wherein $\rho_{t_{m_1}} = v_{t_{m_1}} t_{t_{m_1}}$ and $\rho_{t_{m_s}} = v_{t_{m_s}} t_{t_{m_s}}$ are the modulation factors which correspond to the physical time delays $t_{t_{m_1}}$ and $t_{t_{m_s}}$, respectively, $\rho_{fb_{m_1}} = v_{fb_{m_1}} t_{fb_{m_1}}$ and $\rho_{fb_{m_s}} = v_{fb_{m_s}} t_{fb_{m_s}}$ are the modulation factors which correspond to the specific transducer time delay $t_{fb_{m_1}}$ and $t_{fb_{m_s}}$, respectively, $v_{t_{m_1}}$, $v_{t_{m_s}}$, $v_{fb_{m_1}}$, and $v_{fb_{m_s}}$ are constants such as the signal propagation velocities, $\sqrt{N_1}/\alpha_1$ and $\sqrt{N_s}/\alpha_s$ correspond to delay parameters of a first and sth time delayed Gaussian filter, respectively, α_1 and α_s corresponding half-width parameters of a first and sth time delayed Gaussian filter, respectively, M_1 and M_s are integers, $a_{0_{m_1}}$, $a_{0_{m_s}}$ are constants, v_{m_1} and v_{m_s} are constants such as the signal propagation velocities, and N_{m_1}, N_{m_s}, $\rho_{0_{m_1}}$, and $\rho_{0_{m_s}}$ are data parameters. The data parameters are selected in the same manner as described above. ϕ_s may be represented by

$$\phi_s = \frac{\pi\left((\sqrt{N_1}/\alpha_1)-(\sqrt{N_s}/\alpha_s)+\sum_{m_1=1}^{M_1}((N_{m_1}\rho_{0_{m_1}}/2v_{m_1})+(\rho_{fb_{m_1}}/v_{fb_{m_1}})+(\rho_{t_{m_1}}/v_{t_{m_1}}))-\sum_{m_s=1}^{M_s}((N_{m_s}\rho_{0_{m_s}}/2v_{m_s})+(\rho_{fb_{m_s}}/v_{fb_{m_s}})+(\rho_{t_{m_s}}/v_{t_{m_s}})\right)}{(\sqrt{N_1}/\alpha_1)+\sum_{m_1=1}^{M_1}((N_{m_1}\rho_{0_{m_1}}/2v_{m_1})+(\rho_{fb_{m_1}}/v_{fb_{m_1}})+(\rho_{t_{m_1}}/v_{t_{m_1}}))} \tag{14}$$

wherein $\rho_{t_{m_1}} = v_{t_{m_1}} t_{t_{m_1}}$ and $\rho_{t_{m_s}} = v_{t_{m_s}} t_{t_{m_s}}$ are the modulation factors which correspond to the physical time delays $t_{t_{m_1}}$ and $t_{t_{m_s}}$, respectively, $\rho_{fb_{m_1}} = v_{fb_{m_1}} t_{fb_{m_1}}$ and $\rho_{fb_{m_s}} = v_{fb_{m_s}} t_{fb_{m_s}}$ are the modulation factors which correspond to the specific transducer time delay $t_{fb_{m_1}}$ and $t_{fb_{m_s}}$, respectively, $v_{t_{m_1}}$, $v_{t_{m_s}}$, $v_{fb_{m_1}}$, and $v_{fb_{m_s}}$ are constants such as the signal propagation velocities, $\sqrt{N_1}/\alpha_1$ and $\sqrt{N_s}/\alpha_s$ correspond to delay parameters of a first and sth time delayed Gaussian filter, respectively, α_1 and α_s corresponding half-width parameters of a first and sth time delayed Gaussian filter, respectively, M_1, and M_s are integers, $a_{0_{m_1}}$ and $a_{0_{m_s}}$ are constants, v_{m_1} and v_{m_s} are constants such as the signal propagation velocities, and N_{m_1}, N_{m_s}, $\rho_{0_{m_1}}$, and $\rho_{0_{m_s}}$ are data parameters. The data parameters are selected in the same manner as described above.

The String Ordering Layer produces an ordered string of Fourier series, wherein the ordered string is stored in the High Level Memory section.

3.6. Predominant configuration

The next aspect of the algorithm is the formation of a predominant configuration by forming complex ordered strings through the association of ordered strings. Referring to Fig. 5, the method for forming the complex ordered strings from strings stored in the string memory section entails the following. The Predominant Configuration Layer 18 receives ordered strings from the High Level Memory section 54 and forms more complex ordered strings by forming associations between the ordered strings. The complex ordered strings are stored in the complex ordered string section 72 of the memory 20.

The Predominant Configuration Layer 18 also activates components within the Input Layer 12, the Association Layer 14, and the String Ordering Layer 16. The layers of the present algorithm may be treated and implemented as abstract data types (ADTs) relating to object-oriented programming. The components of the layers therefore refer to all classes, instances, methods, attributes, behaviors, and messages of the layer abstractions as defined above. A class is the implementation of an ADT. It defines attributes and methods implementing the data structure and operations of the ADT, respectively. Instances of classes are called objects. Consequently, classes define properties and behavior of sets of objects. An object can be uniquely identified by its name and it defines a state which is represented by the values of its attributes at a particular time. The behavior of an object is defined by the set of methods which can be applied to it. A method is associated with a class. An object invokes a method as a reaction to receipt of a message.

Thus, the components of a layer comprise all entities in any way related to or associated with the layer such as inputs, outputs, operands, matrices representing functions, systems, processes, methods, and probability parameters. In a digital embodiment, activation results in the recall of the component from memory and may further result in

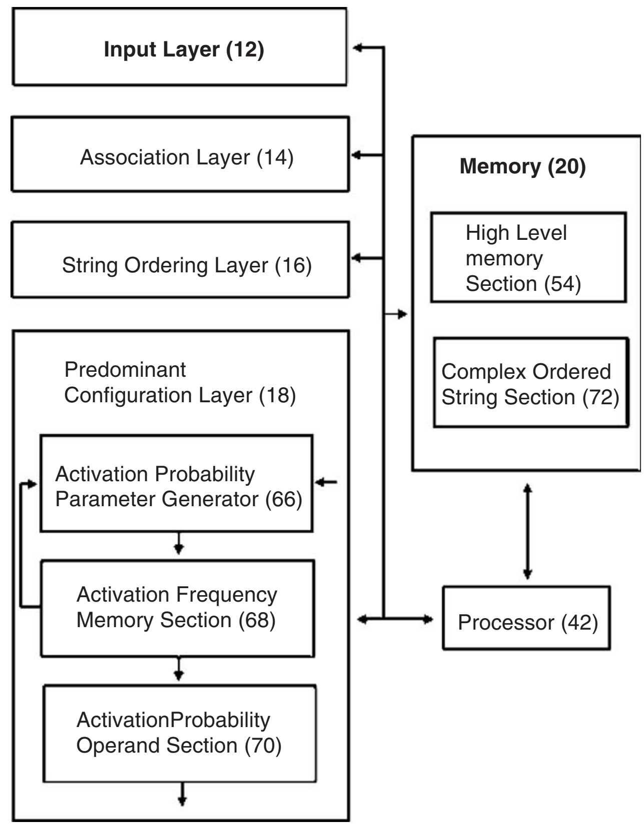

Fig. 5. A detailed block diagram illustrating a Predominant Configuration Layer 18 and the Memory 20 of the high level block diagram of Fig. 1 in relation to the Input Layer 12, the Association Layer 14, and the String Ordering Layer 16. The components of the Predominant Configuration Layer are as follows: 42-processor, 54-high level memory section, 66-activation probability parameter generator, 68-activation frequency memory section, 70-activation probability operand generator, and 72-complex ordered string section of the Memory 20.

processing steps such as matrix multiplication of matrices representing functions. Activation involves generating an activation probability parameter. The activation probability parameter is a parameter responsible for activating any component of the system and is dependent on a prior activation history of each component in the system.

The Predominant Configuration Layer 18 includes an activation probability parameter generator 66. The activation probability parameter generator 66 receives a listing of prior activation frequencies of all of the available components of the present algorithm such as matrices representing functions, data parameters, Fourier components, Fourier series, strings, ordered strings, components of the Input Layer, components of the Association Layer, components of the String Ordering Layer, and components of the Predominant Configuration Layer from an activation frequency memory section 68. The activation probability parameter generator 66 also receives a listing of all active components from the processor 42. Alternatively, the activation probability parameter generator 66 may receive a listing of all active components directly from the active components. The activation probability parameter is stored in memory 20. The activation probability parameter is input to an activation probability operand generator 70. The activation probability operand generator 70 generates a probability operand value of one or zero based upon the activation probability parameter. The probability operand value is output to the processor 42. Any one or more of the components are activated when the probability operand corresponding to each component has a value of one as determined by the processor 42. Thus, the activation of each component is based on the corresponding activation probability parameter. Each activation probability parameter is weighted based on the activation rate of the component. The activation process continues while the system is on. Thus, the activation process is akin to an operating system kernel in a forever loop.

3.7. Example of forming novel information relevant to a triangle

The system is initialized by inputting standard information with associated data with input context using the data structure given in Section 3.3. In the example of a triangle, the geometric form with properties such as angle sum and different forms of triangles are input. Structures in the form of a triangle such as a sailboat, church steeple, and sail are input with the information of a triangle and the relevance of the triangle to the function of each of the objects. Only the data parameters need be stored since the formatting of the memory encodes the Fourier series in Fourier-space and the input context as given in Eq. (6). Then, each of these objects are associated based on spectral similarity by the Association Layer and by inputting the strings of the initialized data and the associated data. As given in Section 3.4, the association can be formed by calculating β_s^2 of Eq. (7) and ϕ_s of Eq. (8) which are input to Eq. (6) to calculate a probability expectation value as the input to the probability operand. The strings formed at this stage are then ordered in the String Ordering layer according to the algorithm given in Section 3.5. Complex order strings (Step (f) of Section 3.5) such as the architecture and engineering of churches and the aerodynamics and stresses in sails as a function of the angles and lengths of the three sides of the triangular form can be used to order the associated strings. Complex novel information with context can be created by the spectral similarity determination and the ordering procedure such as the relationship of the aerodynamics of the steeple and its triangular form to the structural integrity of the church.

4. Conclusion

A unique algorithm is reported which has as its goal to simulate the capabilities of the brain where the theory was given previously (Mills, 1998). The system includes an Input Layer for receiving data representative of physical characteristics or representations of physical characteristics capable of transforming the data into a Fourier series in Fourier space. The data is received within an input context representative of the physical characteristics that is encoded in time as delays corresponding to modulation of the Fourier series at corresponding frequencies. The system includes a memory that maintains a set of initial ordered Fourier series. The system also includes an Association Layer that receives a plurality of the Fourier series in Fourier space including at least one ordered Fourier series from the memory and forms a string comprising a sum of the Fourier series and stores the string in memory. Associations are formed between Fourier series by filtering the Fourier series and by using a spectral similarity between the filtered Fourier series to determine the association based on Poissonian probability. The associated Fourier series are added to form strings of Fourier series. The system also includes a String Ordering Layer that receives the string from memory and orders the Fourier series contained in the string to form an ordered string and stores the ordered string in memory. Each string is ordered by filtering it with multiple selected filters to form multiple time order formatted subset Fourier series, and by establishing the order through associations with one or more initially ordered strings to form an ordered string. Associations are formed between the ordered strings to form complex ordered strings that relate similar items of interest. The system also includes a Predominant Configuration Layer that receives multiple ordered strings from the memory, forms complex ordered strings comprising associations between the ordered strings, and stores the complex ordered strings to the memory. The components of the system are active based on probability using weighting factors based on activation rates.

Each Fourier series in Fourier space is unique relative to conventional Fourier transforms to give Fourier spectra. The unique data structure provides for unique memory structure and unique processing steps such as the determination of the spectral similarity. The data format also allows for encoding context as a modulation of each Fourier component in Fourier space corresponding to delays. The representations of physical objects with physical context as a Fourier series in Fourier space may also be performed by using a equivalent memory structure wherein the memory formatted data is used directly during processing such as in the determination of β_s^2 of Eq. (13) without even needing the step of constructing the Fourier series in Fourier space as given Section 3.3. Each component representative of a characteristic of a physical object is independent of any other component; whereas, each component of a conventional Fourier series has no meaning with regard to the representation any real world object. Only the totality of the components has any physical meaning, and no single component may be independently modified without losing the connection to the real world object which the total series represents. Consequently, the method of order formatting of strings according to the method given in Section 3.5 cannot be reproduced using standard Fourier series with neural networks. The ability to encode context of the ordered stings using modulation of the Fourier series at data parameterized frequencies can not be reproduced by using conventional Fourier series. In addition, the application of probability as the basis of forming associations and using probability based on prior activation rate as a basis to activate the components are unique.

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