Published in the proceedings of the of 27th Applied Imagery Pattern Recognition (AIPR), Advances in Computer Assisted Recognition, SPIE, v. 3584, October 14-16, 1998, Washington, DC, pp.174-185.

DYNAMIC SUB-PATTERN MATCHING WITH HOLOGRAPHIC ASSOCIATIVE MEMORY

Javed I. Khan
Department of Math & Computer Science
Kent State University
233 MSB, Kent, OH 44242
Javed@kent.edu

ABSTRACT

This paper presents the result of our research on a new associative memory, which unlike any existing neural network based artificial associative memories (AAM), can dynamically localize (or focus) its search on any subset of the pattern space. This new ability now makes the power of associative computing available to a new class of pattern matching applications. Application areas which will particularly benefit from this model include (i) detection of small irregular patterns (medical diagnostics), (ii) detection of tiny targets, (iii) background varying target recognition, (iv) visual example based content-based image retrieval, (v) robust adaptive control systems which needs to continue operating with small number of surviving sensors, in the face of post learning loss of sensors.

Keywords: partial-pattern matching, associative computing, holographic memory, target recognition, adaptive control.

1.INTRODUCTION

Neural associative computing has a number of advantages attractive to high performance real time pattern matching applications. They are adaptive. Patterns of arbitrary complexity can be learned through general purpose learning algorithms. They are fast. Retrieval operations are generally constant time operation. As a result, once learned, massive amount of patterns can be searched and retrieved in near real time. They are also highly parallelizable [HiAn85]. Despite their superb characteristics, however, neural network based associative computing has found limited success in general pattern matching, except as a full frame adaptive filter, over the last 50 years [Carp89, CGMR92].

Since inception, it has been predicted that *artificial neural networks* (ANN) will have following three major categories of applications, (i) adaptive classification or filtering (ii) fast approximate optimization, and (iii) associative memory [Kulk94]. However, a look at the success stories of neuro-computing reveals that most of them are limited in the first area [Carp89]. Hardly any real application flourished over the associative recollection characteristics of neural models.

Since the invention of first artificial neuron by Mcculloch and Pitts, main research emphasis continued in improving the learning of artificial neuro-computing. During these period increasingly more intricate and complex properties of learning phenomena have been pursued in great depth. Versatility (how arbitrary complex associations can be learned), efficiency (how more patterns can be learned), learnability of causality and temporal relations (Grossberg 1967, Klopf 1987), self-organization (Kohonen 1987, Oja 1982), autonomous unsupervised adaptation (Grossberg 1976, Carpenter & Grossberg, 1987) are just few examples of the intricacies through which research in artificial learning matured [Gros67, Klop87, Koho89, Gros76, CGMR92]. Surprisingly, during this period of vigorous emphasis on the learning aspect of ANNs, very few attempts had been made to examine their recollection aspect, other than assuming a very simple model of retrieval. Almost all the proposed learning models since McCulloch and Pitts have been constructed on the assumption of a simple and restricted retrieval scenario, where the sample of the content that is used during query is a close replica of the target. However more complex and versatile retrieval formalism is not only conceivable but also seems to be an integral part of natural associative memories.

One such phenomenon is the ability to *focus dynamically* on sub-patterns. A neural network based *artificial associative memory* (AAM) can learn enormous number of patterns into its weight set. But, once learned, during retrieval, it requires all the elements in the pattern space to be present. After the learning is over, neither it is possible to confine the search dynamically during retrieval within a subset of the elements. Nor it is possible to use a tiny fragment of the pattern and obtain the match with respect to the specified fragment.

However, ability of dynamic search localization is central to many applications where the principal challenge is pattern matching. For example, in visual perception, it is natural that when we match information, we always focus on some specific objects in the pattern. We never do an indiscriminate pixel to pixel matching on the entire scene. Without search localization, it is not possible to focus on such any sub-pattern defining the visual object of interest. Similar dynamic search localization is needed when there are multiple objects in a scene and any of them can be a potential target of match. In adaptive control applications which need to remain functional against sensor failures at unpredictable locations, the ability to localize the control response generation process to the valid segments of input data (and shutting off the possibility of feeding dangerous noise from the malfunctioning sensors) on the fly is critical in order to obtain the best possible control response with respect to the information available from the surviving sensors. Consequently, despite their formidable adaptation and self-learning power, artificial neuro-computing gained very little ground in adaptive pattern matching applications.

In this research we demonstrate a new associative computing technique, based on a novel holographic representation which can overcome the above classical limitation of artificial associative computing. It can adaptively train like any other neural network based AAM and learn a massive number of patterns in its complex weight set. However, the difference is that, during retrieval any test pattern or any sub-pattern can be specified as object of focus for retrieval. An advantage of the ability of localize search is the ability to work with a small cue. A conventional AAM requires the effective cue to be statistically significant compared to the overall pattern size. It is well known, that even the most robust of the conventional AAM ceases to retrieve correctly when the pattern similarity between a stored pattern and the test pattern drops below 70% [Tajo90, Khan98].The proposed memory, with the ability of search localization can overcome this severe limitation of current AAMs. It can retrieve correctly even when the window of focus drops as low as 20%. The result is particularly important, because, multidimensional best-match partial pattern search degenerates to expensive exhaustive search even with known procedural algorithms [Khan95].

At the heart of this new memory lies a novel bi-modal representation of pattern, and a hologram like complex spherical weight state-space [PsFa95, Gabo69]. Besides the usual advantages of associative computing, this technique also has excellent potential for fast optical realization, because the underlying hyperspherical computations can be naturally implemented on optical computations.

This paper first takes a fresh look at the general problem of partial-pattern matching in the context of associative computing. It takes an attempt to identify the types and forms of associative pattern matching. Then in section 3, 4, and 5 it presents the capabilities of current AAMs and MHAC. Finally, in section 6 it presents how the new capabilities of MHAC can expand the application horizon of associative computing. It demonstrates how application areas such as (i) detection of small irregular patterns (medical diagnostics), (ii) detection of tiny targets, (iii) background varying target recognition, (iv) visual example based content-based image retrieval, (v) robust adaptive control systems which needs to continue operating with small number of surviving sensors, in the face of post learning loss of sensors, can take advantage of associative computing.

2.ASSOCIATIVE PATTERN MATCHING

2.1. ASSOCIATIVE MEMORY

Let, $S^\mu = [s_1^\mu \; s_2^\mu \ldots s_N^\mu]$ is a stimulus pattern vector and $R^\mu = [r_1^\mu \; r_2^\mu \ldots r_M^\mu]$ is any response pattern vector. Here, the superscript refers to index of the pattern vector, and the subscript refers to the particular element in the pattern vector.

<u>Definition (Associative memory):</u> *Given a set of stimulus pattern vectors* $\mathrm{S} = \{S^\mu \mid 1 \le \mu \le P\}$ *and a set of response pattern vectors* $\mathrm{R} = \{R^\mu \mid 1 \le \mu \le P\}$*, an associative memory is capable of learning the correspondence between a stimulus member* $S^\mu \in \mathrm{S}$ *and a response member* $R^\mu \in \mathrm{R}$ *in such a way that, given a query pattern* S^Q*, it can retrieve a pattern* $R^R \approx R^T$ *such that* $R^T \in \mathrm{R}$*, and* S^Q *is closest to* $S^T \in \mathrm{S}$ *according to a matching criterion* D.

An associative memory system (Fig-1) is comprised of (i) a learning algorithm $\mathbf{A}_{\mathbf{learn}}$ which converts all the $\{S^{\mu}, R^{\mu}\}$ associations into some internal representation, (ii) a physical storage medium and representation formalism AAM to store the associations, (iii) a matching criterion D to measure the closeness of patterns.(iii) a decoding algorithm $\mathbf{A}_{\mathbf{retrieve}}$ to recollect stored information R^R from a given query stimulus pattern S^Q.

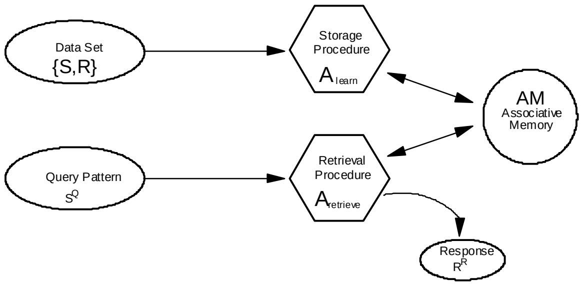

Fig-1 An AAM Model

2.2. Search Types

Concept of pattern distance is central to the search operation of any memory. Equation (1) states a generalized distance between two vectors:

$$D(S^a, S^b) = \left[\underset{i}{\overset{G}{M}} \delta_i \{dist(s_i^a, s_i^b)\} \right] \text{where, } \sigma(\cdot) = \left[\underset{i}{\overset{G}{M}} \delta_i(\cdot) \right] \quad \ldots(1)$$

Where, $dist(\cdot)$ is the *element distance measure* (EDM) function. It can be any arbitrary function with the constraint that it is monotonic with respect to $|s_i^a - s_i^b|$, and symmetric for all (s_i^a, s_i^b) pairs. ***M*** is a set operator with scope G. It can be a product or summation or anything else, which combines all or a subset G of the individual EDM functions. Generally, a summation is used such that $M = \sum\{\}$. The function $\delta(\cdot)$ is *modulator function* on individual EDMs. The combined selection of M and $\delta(\cdot)$, denoted by $\sigma(\cdot)$ determines the nature of *vector distance composition* (VDC) rule. It can be any function with the constraint that it too is monotonic with $dist(\cdot)$. The EDM and VDC together make the *vector distance measure* (VDM). Finally, VDM function is required to have the property, that $D(S^{\mu}, S^{\mu}) = c$, where c is a constant independent of specific pattern index μ.

Given a sample pattern S^Q an associative memory tries to converge to the closest learned pattern. Let $\Lambda^Q = [\lambda_1^Q\ \lambda_2^Q \ldots \lambda_n^Q]$ be the modulator vector. Consequently, based on the matching criterion of equation (1), we now define a generalized associative memory:

Definition (type-A AAM): *Given the modulator vector Λ^Q, a type-A AAM can retrieve response pattern $R^R \cong R^{T_a}$, where its associated stimulus pattern S^{T_a} is close to the query pattern S^Q in the following sense:*

$$D(S^Q, S^{T_a}, \Lambda^Q) = \min_{\mu}^{p} \left[\underset{t}{\overset{N}{M}} \lambda_i^Q dist(s_i^Q, s_i^{\mu}) \right] \quad \ldots(2)$$

Modulator vector can used to modify the significance or attention level of individual elements in the pattern during distance evaluation. They may be analog valued. For example, setting λ_i^Q to 1.0 will mean that the particular element is fully significant, to 0.0 will mean ignore it, to 0.2 will mean consider it partially. The vector $\Lambda^Q = [\lambda_1^Q \ \lambda_2^Q \ldots \lambda_n^Q]$ will referred as attention field in the subsequent discussions.

Two other subclasses of this generalized memory with the definitions below are also of interest to us. For the special case, where the modulator vector elements (λ_i^Q) are restricted to binary enumeration, the modulator vector can be substituted by a scope restrictor function $F^Q \subseteq N$, F^Q representing a subset of the total element space N. F^Q ican be called as window of focus. Finally, a further special case with unary attention of the above two types can be defined where the scope is not restrictable.

Definition (type-B AAM): *Given a element subset $F^Q \in N$, a type-B AAM can retrieve response pattern $R^R \cong R^{T_a}$, where its associated stimulus pattern S^{T_a} is close to the query pattern S^Q in the following sense:*

$$D\left(S^Q, S^{T_a}, F^Q\right) = \min_{\mu}^{p}\left[\underset{t}{\overset{F^Q}{M}} \lambda_i^Q dist\left(s_i^Q, s_i^\mu\right)\right] \qquad \ldots(3)$$

Definition (type-U AAM): *A type-U AAM can retrieve response pattern $R^R \cong R^{T_a}$, where its associated stimulus pattern S^{T_a} is close to the query pattern S^Q in the following sense:*

$$D\left(S^Q, S^{T_a}\right) = \min_{\mu}^{p}\left[\underset{t}{\overset{N}{M}} dist\left(s_i^Q, s_i^\mu\right)\right] \qquad \ldots(4)$$

The above definitions refer to the ability to localize the search scope in the pattern space or 'focus' in the pattern. Associative pattern matching systems can be further classified in terms of the timing of focus. It is also important to know the time at which focus can be modulated. In any AAM, information is entered at two points, (i) during the encoding via $\mathbf{A}_{\mathbf{learn}}$, and (ii) during matching via $\mathbf{A}_{\mathbf{retrieve}}$ matching.

Definition (Hard-Focus): *If a memory allows focus specification during training, the focus is hard-encoded focus.*

This will require (i) an external pattern representation scheme which can incorporate vector Λ^μ for each stimulus pattern $S^\mu = [s_1^\mu \ s_2^\mu \ldots s_N^\mu]$ and an appropriate $\mathbf{A}_{\mathbf{learn}}$.

Definition (Dynamical Focus): *On the other hand, if it allows the acceptance of $\Lambda^Q = [\lambda_1^Q \ \lambda_2^Q \ldots \lambda_n^Q]$ during retreival, then we will call it* dynamical focus.

In the later, for a change of focus relearning will not be required. However, this will require, in addition to an appropriate $\mathbf{A}_{\mathbf{learn}}$ and external representation, an appropriate internal representation for its knowledge (weight set), and an appropriate retreival algorithm $\mathbf{A}_{\mathbf{retrieve}}$.

A third distinguishing factor for AAMs recollection is the ability to provide a feedback on the quality of match. An AAM, as an output recollects pattern R^R.

Definition (Qualyfying Recollection): *is one where an AAM can provide an estimate of the pattern distance D between the query pattern S^Q and the closest matching pattern $S^T \in \mathrm{S}$ based the matching criterion D.*

In practical pattern matching engines, qualification is an important property. For example, if we present a new (previously unseen) pattern during query, how an AAM can express that it is a previously unseen pattern? A conventional AAM, always computes an output pattern, but there is no way of knowing if that output pattern is a seen, unseen, or a combination of two seen patterns. A well trained AAM will always converge to the nearest seen pattern, however, will not provide a clue that how far is ‘nearest’.

3.RETRIEVAL IN CURRENT MODELS

The variety of architectural configuration and learning techniques that can be interpreted as a distributed and parallel model of artificial associative memory is staggering. However, the cell architecture of Fig-2 and the transfer function of equation below together specify the essential building blocks of any ANN or AAM.

$$y_i = g(w_{ij}, s_i) = \sum_{i}^{N} w_{ij} \cdot s_i + b_i \text{ and } z_i = f(y_i) \qquad \ldots(5)$$

Here, s_i represents the inputs to this cell and generally they assume values in the range from 0 to 1 or from -1 to 1. This cell has remained virtually unaltered since its invention by McCulloch and Pitts. Current AAMs vary among themselves based on (i) the pattern of interconnection network that connects these cells in a network (ii) mode and scenario of learning and/or (iii) the specific type of non-linearity function *f()*. Within the scope of this paper, we are interested in the underlying function that is optimized by the combined dynamics of the algorithm pair {$\mathbf{A_{learn}}$:$\mathbf{A_{retrieve}}$}, or the matching criteria D.

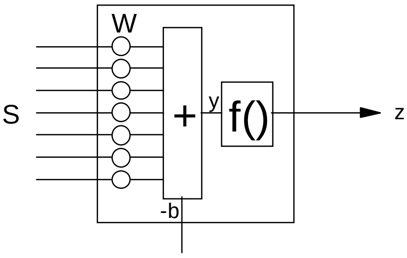

Fig-2 Basic Neuron Cell

The optimization criteria of existing neural models directly belong to type-U category. Models those use Hebbian class of learning maximize global dot-product of the patterns [Koho89, Gros69, Klop87, Sang89]. On the other hand, the models those use LMS class of learning maximize global mean square error [WiHo60, RuHW86]. There are also other distance measures which have been used in matching criterion (such as likelihood-ratio, entropy, etc.). Hopfield has given a unified perspective and demonstrated that all the neural networks minimize some form of energy function [Hopf82]. The key features to note in all of these functions are (i) the set operator is a summation process $M = \sum\{\}$, and (ii) the scope G of the set operator is all-element-inclusive and is based on entire element space or G=N, and (iii) the modulator function is only a function of distance $\delta = dist(\cdot)$. These properties of existing neural computation models together makes them a type-U memory.

The reason that conventional AAMs have not succeeded in supporting Type-A or Type-B search lies right at the heart- the scalar product rule of synaptic efficacy. An associative memory constructed by interconnecting cells with the scalar product rule of synaptic transmission specified by (5) can not realize the retrieval of type-B, or type-A. The limitation, although never explicitly identified, but can be found in the experimentation reported by a number of other publications, including [Tajo90, Hopf82]. Although the formal proof is beyond the scope of this paper (can be found in [Khan95]), the following comments can be made about their behavior:

(i) What is generally referred to as the ' robustness' of a ANN originates from the effect of activation non-linearity. However, the same non-linearity that helps in correcting error may also catastrophically amplify error.

(ii) The exact weight of a particular erroneous element is decided by fixed vector W. Vector W is pre-decided during learning and can not be modified dynamically at query. This eliminates the possibility of multiplicative modification like making of synaptic inputs in proportion to their attention.

(iii) During training an AAM can adaptively determine the relative importance of the pixels in a pattern. This is reflected in the weight set. However, once trained, the focus cannot be changed. For every, input pattern, it non-deterministically converges to a single attractor. Whereas, dynamical search localization requires, that an AAM should be able to converge to separate attractors, based on the choice of focus.

(iv) What is generally known as robustness of ANN, is more specifically its robustness against noisy input. MP-neurons and the collective network built upon them, does not have direct mechanism to be robust against missing elements.

(v) An AAM retrieves a pattern, however, it has no representational or computational mechanism to generate recollection distance. On the other hand, in a classifier mode, the output of an ANN can be configured to convey the strength of membership for a single class. However, in this mode, it has no mechanism to retrieve the class pattern. In other words, conventional AAM do not produce qualifying recollection.

4.HOLOGRAPHIC ASSICIATIVE COMPUTING

4.1. Representation

MHAC represents information as a two tire quantity, the actual measurement and a meta-information “attention” (or focus) . For example for an image the pixel value is the measurement. Each pixel may also take an associated second meta-quantity representing the “importance” of the pixel. Computationally, this bi-modal information is represented as a *multidimensional complex number* (MCN) spanned in a hyperspherical space. In this scheme an element of information is represented as:

$$s_k = (\lambda_k, \alpha_k) \Rightarrow \lambda_k e^{[\sum_j^{d-1} \hat{i}_j \theta_{j,k}]} \qquad \ldots(6)$$

Here, α_k is the measurement and is mapped onto a set of phase elements $\theta_{j,k}$ in the range of $\pi \geq \theta \geq -\pi$. λ_k is the meta-quantity focus. Following are the representations of a complete stimulus pattern and a response pattern:

$$[S^\mu] = [\lambda_1^\mu e^{[\sum_j^{d-1} \hat{i}_j \theta_{j,1}^\mu]}, \lambda_2^\mu e^{[\sum_j^{d-1} \hat{i}_j \theta_{j,2}^\mu]}, \ldots, \lambda_n^\mu e^{[\sum_j^{d-1} \hat{i}_j \theta_{j,n}^\mu]}] \qquad \ldots(7a)$$

$$[R^\mu] = [\gamma_1^\mu e^{[\sum_j^{d-1} \hat{i}_j \phi_{j,1}^\mu]}, \gamma_2^\mu e^{[\sum_j^{d-1} \hat{i}_j \phi_{j,2}^\mu]}, \ldots, \gamma_m^\mu e^{[\sum_j^{d-1} \hat{i}_j \phi_{j,m}^\mu]}] \qquad \ldots(7b)$$

4.2. Training and Retrieval

Both the training and retrieval algorithms of MHAC have been derived from a digital adaptation of the optical transforms in holography [Gabo69,PsFa95]. Learning constitutes computation of individual complex associations, and superimposition of the associations on the holographic substrate. Following equation describes a reinforcement model of holographic learning:

$$[X^{t+1}] = [X^t] + [S][X]) \qquad \ldots(8)$$

The substrate [X] is stored as a MCN matrix. η is the learning constant. The substrate acts as the memory. The retrieval process is similar to optical convolution. During recall, an excitatory stimulus pattern $[S^e]$ is obtained from the query pattern:

$$[S^e]=[\lambda_1^e e^{[\sum_j^{d-1} \hat{i}_j \theta_{j,1}^e]}, \lambda_2^e e^{[\sum_j^{d-1} \hat{i}_j \theta_{j,2}^e]}, \ldots, \lambda_n^e e^{[\sum_j^{d-1} \hat{i}_j \theta_{j,n}^e]}] \qquad \ldots(9)$$

In the event, that this new stimulus resembles closely to a priory encoded stimulus, then the corresponding response pattern is generated with high magnitude. The decoding operation is performed by computing the inner product of the excitatory stimulus and the correlation matrix [X]:

$$[R^e]=\frac{1}{c}[S^e].[X], \text{ where } c=\sum_k^n \lambda_k \qquad \ldots(10)$$

The model treats the measurement component of information in a fundamentally different way than any NN. The elements of these vectors are complex numbers and measurement components are exponents. A complete theoretical and empirical analysis of the characteristics of this model can be found in [Khan95] and has appeared in [Khan98].

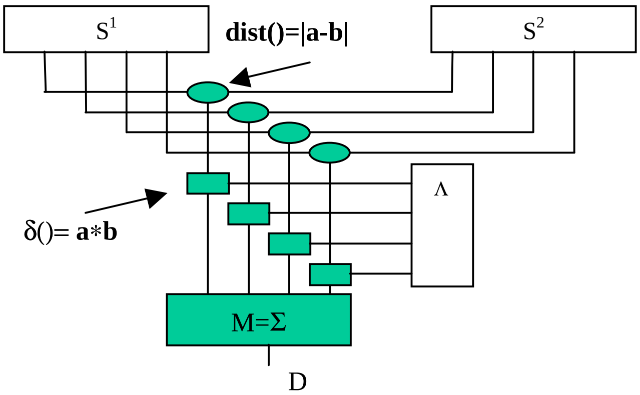

Fig-3 Distance Measure Function in MHAC

4.3. Capabilities of MHAC

This memory can accept focus mask both during encoding and retrieval. The masks are represented as the magnitude of the corresponding complex elements. The mask used during encoding is called the "*assertion mask*', and the mask used during recollection is called "*attention mask*". Also this memory generates a complex output during recollection. The magnitude values of these elements are related to the pattern distance. A normalized average of the retrieved pattern strength can be interpreted as a '*confidence feedback*' from the AAM for each retrieved pattern. The distance measure function of this memory is given by Fig-3. The pattern matching ability of this model is summarized below:

Lemma 3 (Assertion Control): *Given an encoded stimulus $[S^\mu]$ with unequal analog distribution of assertion of its element field specified by $\Lambda^\mu=[\lambda_1,\lambda_2,...,\lambda_n]$, and the memory dynamics specified by equations (8) and (10), the elements of the target pattern will contribute in the reconstruction of the target pattern $[R^R]$ in monotonic proportion based on the weighted importance specified in Λ^μ.*

Lemma 4 (Attention Control): *Given a query stimulus $[S^Q]$, with unequal analog distribution of attention distribution of its element field specified by $\Lambda^Q=[\lambda_1,\lambda_2,...,\lambda_n]$, the memory dynamics specified by equations (8) and (10) retrieves the pattern which best resembles $[S^Q]$, where, individual query elements contributes in the matching in monotonic proportion based on the weighted importance specified in Λ^Q.*

Published in the proceedings of the of 27th Applied Imagery Pattern Recognition (AIPR),
Advances in Computer Assisted Recognition, SPIE, v. 3584, October 14-16, 1998, Washington, DC, pp.174-185.

By adjusting individual λ_k's the contribution of each encoded stimulus element can be controlled during learning. A high λ_k will allow the kth term to contribute more in the phase average, and vice versa. At the extreme, setting λ_k=0 will completely attenuate this term. But, such analog control will have no multiplicative distortion effect on the phase plane. This mechanism corresponds to the process of learning with changeable assertion or the ability to incorporate focus during training. In a similar way, by adjusting individual λ_k's the contribution of each query stimulus element can be controlled during query. This mechanism corresponds to the process of retrieval with changeable attention or dynmical focus. Within the region of focus (either by assertion or attention) the match is still "statistical" like conventional AAMs. Thus, it maintains the usual error tolerance of AAMs.

Finally, the above computational framework can also reconstruct a measure of match as a fundamental part of bi-modal representation. This measure of match is named *mean normalized confidence* (MNC).

Lemma 5 (Confidence Feedback): *Given a query stimulu* $[S^Q]$ *the memory dynamics specified by equation (8) and (10) generates a bi-modal output pattern* $[R^R]$ *, the phase of which corresponds to the retreived pattern, and the magnitude of which is inversely proportional to the distance between* $[S^Q]$ *and* $[R^R]$

4.4. A Scheme for Partial Pattern Matching

Now a scheme is described for associative partial pattern matching using MHAC. In its simplest form, a large number of patterns are first "folded" into the correlation memory substrate of MHAC using a generalized multidimensional differential version of the Hebbian learning algorithm. It is called the holograph. During the encoding, each input pattern is first converted into an MCN stimulus pattern S. This pattern is associated with the MCN response pattern called Response Label Pattern (RLP). To generate the pattern S, the encoder also accepts one *assertion mask* along with each of the patterns. Assertion mask specifies the partial patterns inside each stored patterns which should take part in the match. The MCN learning algorithm in addition to "enfolding" the individual measurements of the pattern elements (in the phase plane) also learns the relative importance of the elements (in the magnitude plane) via these assertion values. During the recollection process, the memory receives a sample pattern and an *attention mask*. These two is used to obtain the MCN query pattern. Once the query pattern is constrcuted, the associative search mechanism of MHAC performs associative recall. It returns an MCN pattern that corresponds to the RLP of the best match among the stored image. The recalled RLP pattern contains MCN elements with phases and magnitudes. A vector constructed out of the phase elements identifies the actual matching pattern. The magnitude vector corresponds to the MHAC's feedback *confidence*. High magnitude of the retrieved index pattern corresponds to potential match. Similarly, low magnitude corresponds to potential absence of the given object in the holograph.

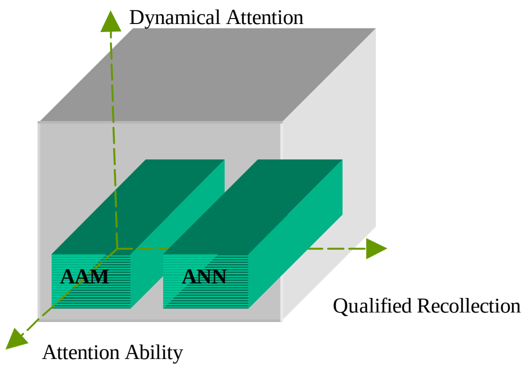

Fig-4 Pattern Matching Types

5.CAPABILITY COMPARISON

Fig-4 and Table-1 present a comparative picture of the pattern matching abilities of various neural computing models. The pattern matching abilities of associative computing can be categorized along three dimensions. First based on their attention ability (ability to perform performing Type-U or Type-A/B search). Then, based on their ability to perform Type-A or Type-B search on test patterns (dynamical attention). Finally based on their ability to perform Qualifying Recollection. Conventional AAMs and ANNs do not have the ability to accept any specification of external significance during encoding or during retrieval. AAMs can retrieve the patterns but cannot provide qualification. On the other hand ANNs can provide qualification but cannot generate patterns. In comparison MHAC encompasses the entire range of above search types.

Table-1 Pattern Matching Capabilities

	ANN	**AAM**	**MHAC**
Full Frame (Type-U)	**Y**	**Y**	**Y**
Binary Attention (Type-B)			**Y**
Analog Attention (Type-A)			**Y**
Hard-Encoded Focus	**Y**	**Y**	**Y**
Dynamical Focus			**Y**
Pattern Recollection		**Y**	**Y**
Qualifying Recollection	**Y**		**Y**

6.APPLICATION MODELS

6.1. Small and Irregular Target Detection

MHAC technique, along with the dynamical recollection ability can be used to retrieve small targets, even if they are irregular. Conventional ANN, although robust, still requires about 50-70% of the sample pattern to match an encoded pattern. As a result, if the target is small, it can not detected conveniently. The dynamic focus and the MNC feedback abilities of MHAC can be combined to detect small targets. In this scheme a set of patterns can be encoded using usual MHAC encoding algorithm. The recovery will require preparation of a set of template patterns. The templates are constructed in two steps, first, by applying the attention mask on a sample image containing the target. Since, attention can be specified for every pixel, therefore the irregularity of the target pattern does not effect the recognition capability. Experiments have demonstrated that the 'attention mask' can work with a window size as small as 10-20%, which far exceed the capability of any conventional ANN. In the second step, a set of translated search templates are generated by spatially sliding the focus window and object pixels on the pattern space. For example, for two dimensional image patterns, the template can be translated on grid of size 4x4. Finally, for each grid location, a holographic decoding is performed. Each decoding returns a distinct response pattern and corresponding MNC. A 3D plot of the MNCs at grid locations reveals the points of high resonance. Points of high resonance indicate the existence of matching images at those locations. Notably, such a search cannot be performed on a non-qualifying engine.

6.2. Background Varying Target Recognition

Background varying target recognition is an important pattern matching application and poses some serious challenge to ANN. If the area of background is much larger than the target in the image pattern, then it becomes extremely difficult for neural networks to detect the target. In most cases, the automatic recognition process is baffled by the background. In general, an ANN can only learns only what is significant statistically. If the background is statistically large, it can be easily mislead to learn the background as the significant part of the training set. Some limited improvements of performance can be achieved by specially doctoring the training set, where statistical prominence of the target object is established by presenting large number of training sample. MHAC, with its ability to focus can efficiently handle background varying target recognition. Its training process is much simple. If the background is known, the assertion mask can be used to directly encode the significance of the target compared to the background. During recollection, the background can be specified by its dynamic attention mask. In this process first the background region in the test pattern is externally segmented. The "attention mask" is then used to differentiate the background regions by assigning $\lambda_k = 0$ (very low value) for the pixels. The pixles within the focus is assigned $\lambda_k = 1$. Notably, MHAC does not need a precise segmentation algorithm. In many natural scene it is not possible to segment clearly the background from fore ground. For ambiguous regions a value between 0-1, can be assigned.

6.3. Content-Based Image Retrieval

Content based image retrieval (CBIR) is another difficult application for conventional AAMs. Besides, the problem of small and background varying pattern recognition its also needs to deal with multiple visual objects. In content-based image retrieval a pattern is retrieved from a part of it. However, generally these parts (or visual objects), those are used as index are selected by the inquirer during query time. It is quite difficult to isolate what objects in a particular picture will be important for a later query during encoding. Also, the definitions of visual objects are fuzzy. Also a single encoded picture may have multiple objects inside it. Thus, based on the object of focus, a single test pattern can result in different answer. Also the visual objects used for similarity are congnitivically significant, and quite often they are not statistically significant in the encoded and target patterns. This posed a serious difficulty for AAMs. The focus ability of MHAC can be utilized to perform content-based image retrieval. The general pattern recognition scheme presented earlier can be used. Although in principle, associative memories can directly recall the target image, however, an index RLP should be used. There are two advantages of going through the indirection of index patterns (RLPs). First, the recalled patterns may contain some noise. Because of the indirection recalled RLPs can be 'cleaned' and images can be retrieved crisp. RLPs can be specially designed and spaced in phase space for symmetry to facilitate noise reduction and removal. The second advantage is the volume of the holograph. As is evident from the encoding equation (8) the volume of the holograph is the product of the sizes of the two associated patterns and the dimensionality of the complex elements. The number of elements in the index pattern can be of logarithmic order with respect to the number of images. RLP is generally much smaller than the image. For example, if we want to store 1024 images in a holograph, then only 10 element index patterns will be needed even assuming most liberal binary spacing. This means that just an extra 1% space will be needed to support content based search. The holographic search can provide extremely fast retrieval ability for CBIR. It can be noted from the decoding algorithm that the retrieval process is a single convolution process. The recollection time does not depend on the number of patterns in the holograph.

6.4. Robust Adaptive Control

The advantages of MHAC in control applications are several-fold. First of all current ANS methods do not lend themselves well particularly to analog control because of the nature by which most operate in a binary mode. They operate either as non-qualifying filter or as a classifier with no control pattern output. Whereas MHAC operates inherently in analog domain and can generate smooth control output as well as MNC for advanced feedback control. In addition, the dynamic focusing ability allows the design of a specially robust control system that will be able to work, if a subset of sensors are lost dynamically. In such a situation it will find the best match with respect to the surviving sensor inputs. If at any moment, if a control decision is due with respect to a subset of sensor inputs, the attention mask have to be activated differentiating the surviving sensors from the lost ones. The design and training of the control systems with MHAC is similar in most respects to the neural configuration for classification applications. The principal difference is in the manner in which the response filed should be structured. Design of control application offers a different input/cell ratio for neural systems than image applications. Firstly, is control applications the number of input elements are generally much smaller compared to the control sequences that have to be remembered. Secondly, control applications typically demand complex arbitrary non-linear function approximation ability of the network. These requirements can be satisfied using higher order holographic encoding of the following form [Suth90]. The sensor patterns can be converted into higher order terms by collecting higher-order statistics terms generated from the original sensor stimulus. The following general equation can be used for generating higher order statistics.

$$x_k = \prod_{m=1}^{M} \lambda_{r(k,m)} e^{-i\theta_{r(k,m)}} \qquad \ldots(11)$$

The actual encoding, and retrieval can be performed between the higher-order expanded stimulus pattern $X^\mu = [x_1^\mu \; x_2^\mu \ldots x_L^\mu]$ and the associatied sensor response term R^μ. Here $r(k,m)$ is some arbitrary function that selects the input data elements as a function of k and the product term m. Each high order input term contains a set of base sensor inputs anded togather. Thus, the represent the net focus value (assertion or attention) for the generated term. If a particular sensor has to be ignored, its effect is propagated to the derivative terms via the product form. The number of distinct term generated by the above is combinatorial in nature and is:

Published in the proceedings of the of 27th Applied Imagery Pattern Recognition (AIPR), Advances in Computer Assisted Recognition, SPIE, v. 3584, October 14-16, 1998, Washington, DC, pp.174-185.

$$\frac{(N+M-1)!}{(N-1)!M!}$$

With higher order encoding, the capacity (number of input/output mapping) that can be stored in a network can be increased almost limitlessly. Fig-5(a) provides a schematic of a control system which can learn an enormous number of time series of stimulus and response pairs. During encoding the assertion mask is generally set to all 1.0. Fig-5(b) shows the decoder arrangement. The assertion mask can be used to select any working set of sensors.

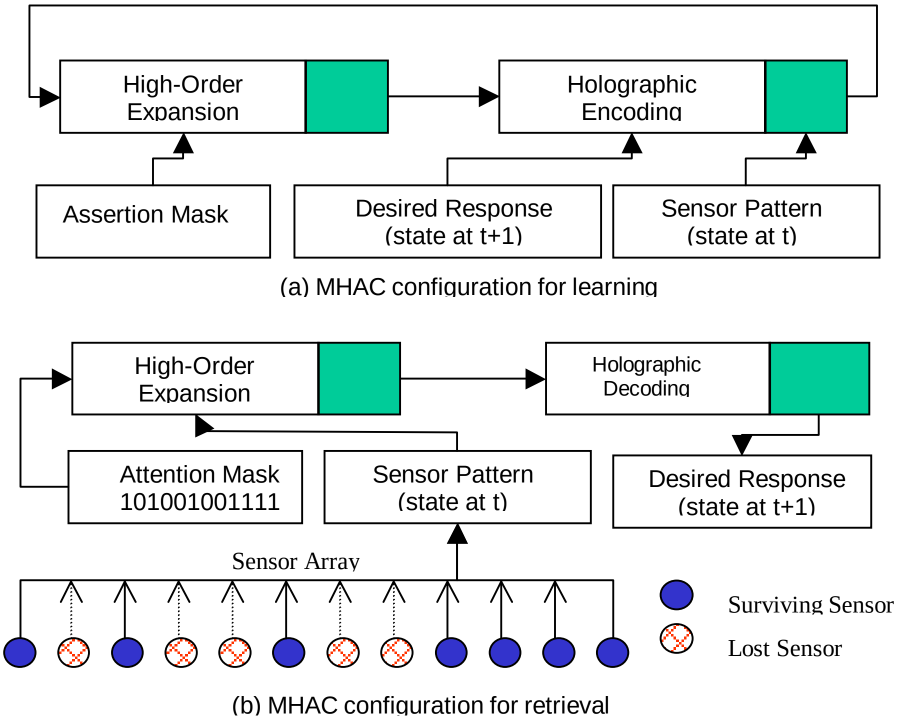

Fig-5 MHAC Configuration for Time Series Learning in Control Application

7.CONCLUSIONS

Neural associative computing has a number of advantages attractive to high performance real time pattern matching applications. They are adaptive. Patterns of arbitrary complexity can be learned through general purpose learning algorithms. They are fast. Retrieval operations are generally constant time operation. As a result, once learned, massive amount of patterns can be searched and retrieved in near real time. They are also highly parallelizable Despite their superb characteristics, however, neural network based associative computing has found limited success in general pattern matching, except as a full frame adaptive filter, over the last 50 years. One of the limiting reason is their inability to perform dynamic search localization. In this paper, an attempt have been made to formally identify the requirements for an advanced associative memory model which can perform search with localized attention within the paradigm of parallel and distributed associative computing. Also an instance of an advanced memory MHAC, which satisfies much of the criterion, including dynamic search localization, has been demonstrated. It also retains the key attractive properties of associative computing. In addition this particular memory has excellent potential for fast optical realization [Khan95,MiFa90]. This type of memory is applicable in numerous pattern matching and memory retrieval problems. The above memory has been applied for content-based image retrieval. Currently, we are experimenting two other attentive learning models based on principal component analysis [KhYu94,Sang89], and self-organizing feature map [Koho89]. Diverse models of attentive memories are potentially realizable (to suit specific applications) within the generalized representation and synaptic efficacy function family demonstrated in this paper with appropriate transformation of many current learning models.

8.BIBLIOGRAPHY

[Carp89] Carpenter, G. A., "Neural Network Models for Pattern Recognition and Associative Memory", Neural Networks, v.2, 1989.

[CGMR92] Carpenter G. A., S. Grossberg, N. Markuzon, J. H. Reynolds, & D. B. Rosen, "Attentive Supervised learning and Recognition by Adaptive Resonance Systems", Neural Networks for Vision and Image Processing, Ed. G. A. Carpenter, S. Grossberg, MIT Press, 1992, pp364-383.

[Gabo69] Gabor, D., "Associative Holographic Memories", IBM Journal of Research and Development, 1969, I3, p156-159

[Gros67] Grossberg, S., "Nonlinear Difference-Differential Equations in Prediction and Learning Theory", Proc. Of National Academy of Science, v.58, n.4, October 1967, pp1329-1334.

[Gros69] Grossberg, S., "Embedding Fields: A Theory of Learning with Physiological Implications", J. of Mathematical Psychology, v.6, 1969, pp209-239.

[Gross76] Grossberg, S., "On the Development of Feature Detectors in the Visual Cortex with Applications to Learning and Reaction-Diffusion Systems", Biological Cybernetics, v.21, n.3, 1976, pp145-159.

[HiAn85] Hinton, G.E., J. A. Anderson, Parallel Models of Associative Memory, Lawrance Erlbaum, NJ, 1985.

[Hopf82] Hopfield, J. J., "Neural Networks and Systems with Emergent Collective Computational Abilities", Proc. of National Academy of Science, USA, v.79, April 1982, pp2554-2558.

[Khan98] Khan Javed. I., Characteristics of Holographic Associative Memory in Retrieval with Localizable Attention, IEEE Transactions on Neural Networks, Vol-9, Issue-7, May '98, p.389-406.

[Khan95] Khan, J. I., "Attention Modulated Associative Computing and Content Associative Search in Images", Ph.D. Dissertation, Department of Electrical Enginnering, University of Hawaii, July, 1995.

[KhYu94] Khan J. I.,& D. Yun, "Feature Based Contraction of Sparse Holographic Associative Memory", Proceedings of World Congress on Neural Networks, WCNN'94, v.4, San Diego, June, 1994, pp26.

[Klop87] Klopf, A. H., "Drive-Reinforcement Learning: A Real Time Learning Mechanism for Unsupervised Learning", Proc. of 1st IEEE Conf. on Neural Networks, Vol.II, N.J., 1987, pp441-445.

[Koho89] Kohonen, T., Self-Organization and Associative Memory, 3rd Ed., Springler Verlag, Berlin, 1989.

[Kulk94] Kulkarni, A. D., Artificial Neural Networks for Image Understanding, Van Nostrand Reinhold, New York, 1994, pp15.

[KuWo91] Kumar, B. V. K., P. H. Wong, "Optical Associative Memories", Artificial Neural Networks and Statistical Pattern Recognition, I. K. Sethi and A.K. Jain (Eds.), Elsevier Science Publisheres, 1991, pp219-241.

[MiFa90] Michel, A. N., J.A. Farrel, "Associative Memories via Artificial Neural Networks", IEEE Control Systems,v.10,no.3, April 1990, pp6-17.

[PsFa95] Psaltis, D, Fai Mok, Holographic Memories, Scientific American, November 1995, pp70-76.

[RuHW86] Rumelhart, D.E., G.E.Hinton, R.J.Williams, "Learning Representations by Backpropagation Errors", Nature, 323, 1986, pp533-536.

[Sang89] Sanger, T. D., "Optimul Unsupervised Learning in a Single layer Linear Feedforward Network", Neural Networks, v.2,1989, pp459-473.

[Suth90] Sutherland, J., "Holographic Models of Memory, learning and Expression", International J. Of Neural Systems, 1(3), 1990, pp356-267.

[Tajo90] Tai, Heng-Ming, T. L., Jong, "Information Storage in High-order Neural Networks with Unequal Neural Activity", J. of Franklin Institute, v.327, n.1, 1990, pp16-32.

[WiHo60] Widrow, B., M.E. Hoff, "Adaptive Switching Circuits", IRE WESCON Convention Record, part 4, 1960, pp96-104.

Published in the proceedings of the of 27th Applied Imagery Pattern Recognition (AIPR),
Advances in Computer Assisted Recognition, SPIE, v. 3584, October 14-16, 1998, Washington, DC, pp.174-185.