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"COGNITIVE" MEMORY

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Abstract— **Regarding the workings of the human mind, memory and pattern recognition seem to be intertwined. You generally do not have one without the other. Taking inspiration from life experience, a new form of computer memory has been devised. It has been used successfully in diverse applications such as visual aircraft identification, aircraft navigation, and human facial recognition. Other uses are being explored. The basic idea will have many new areas of application.**

I. INTRODUCTION

A preliminary cognitive memory design described herein is based on concepts derived from life experience, from the literature of psychology, psychiatry, and neurobiology [1], [2], [3], [4], [5], and from years of experience in working with artificial neural networks and adaptive and learning systems. Certain conjectures about human memory are key to the central idea. The design of a practical and useful memory system is contemplated, a memory system that may also serve as a model for many aspects of human memory.

The preliminary cognitive memory design would be able to store in a unified electronic memory system visual inputs (pictures and sequences of pictures), auditory inputs (acoustic patterns and sequences of patterns), tactile inputs, inputs from other kinds of sensors such as radar, sonar, etc., and to retrieve stored content as required.

The memory would not function like a computer memory where specific data is stored in specific numbered registers and retrieval is done by reading the contents of the specified memory register, or done by matching key words as with a document search. The stored sensory data would neither have key words nor would it be located in known or specified memory locations. Incoming sensory data would be stored at the next available empty memory location, and indeed could be stored redundantly at several empty locations. In any event, the location of any specific piece of recorded data would be unknown.

Retrieval would be initiated by a prompt signal from a current set of sensory inputs or patterns. A search through the memory would be made to locate stored data that correlates with or relates to the present real-time sensory inputs. The search would be done by a retrieval system that makes use of autoassociative artificial neural networks [6].

Applications of cognitive memory systems to analysis of aerial imagery, human facial images, sounds, rote-learning for game-playing, adaptive control systems, pattern recognition, and to other practical problems will be explored and implemented.

The proposed cognitive memory architecture would be scalable so that larger memories could store more sensory data, but storage and retrieval time would not increase with memory size. How this could work will be described below.

II. DESIGN OF A COGNITIVE MEMORY SYSTEM

Figure 1 shows architectural elements and structures of a preliminary mechanistic memory system that could behave to some extent like human memory. It would have practical engineering value and would be useful in solving practical problems. This mechanistic memory system is intended to model human memory function, and its workings will be described in human terms. The anatomical locations in the brain where the various architectural elements and components might be contained are mostly unknown. What is important is that the functions of these elements and components be performed.

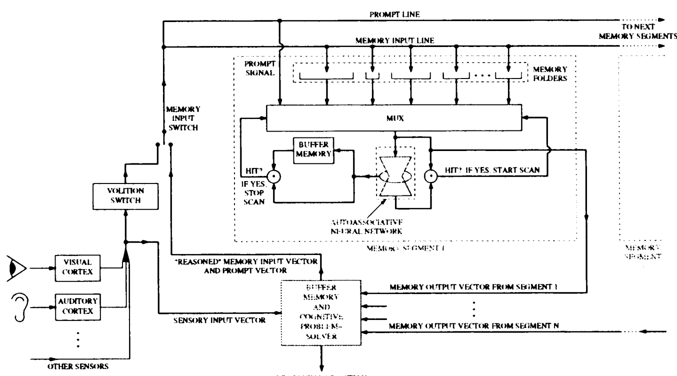

Fig. 1. Cognitive Memory

The design of the cognitive memory of Figure 1 is based on the following hypotheses about human memory:

1) During a lifetime, images, sounds, tactile inputs, etc. are stored permanently, if they were of interest when the sensory inputs were experienced. Human memory has enough storage capacity for a long lifetime. Old recordings are not deleted for lack of storage space.
2) Sensory inputs concerning a single object or subject are stored together as vectors in a single "file folder" or "memory folder." When the contents of the folder are retrieved, sights, sounds, tactile feel, smell, etc., are obtained all at the same time. Sensor fusion is a memory phenomenon. The sensory signals are not fused, but they are simply recorded together in the same folder and retrieved together.

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3) Thoughts, conclusions, and problem solutions are also stored in memory, just like sensory signals.
4) The same information stored in a memory folder may be stored redundantly in a number of separate folders.
5) There may be many folders storing different information about the same subject, recorded on different days. Suppose you have a Bernard Widrow folder containing many different images of his face taken during a one hour visit, with various lighting conditions, scale, perspective, rotation, translation, with zoom-in images of his eyes, nose and other facial details. The folder also contains the sounds of the conversation. After many visits, there will be many Bernard Widrow folders. During one of the conversations, the name of his wife was mentioned. During retrieval, the contents of that particular folder would need to be read in order to recall the name of his wife.
6) Retrieval of stored information results from reading the contents of a folder when triggered by a prompt from a set of current sensory inputs, or by a thought process. Recalling the name of Widrow's wife would require a prompt, such as seeing Widrow, and the need at the end of the conversation of saying, "please give my best regards to Ronna Lee."
7) Current sensory inputs would have very little meaning and would be puzzling if they did not trigger the reading of the contents of folders containing related information. Current sensory inputs would trigger or prompt the delivery of the contents of folders containing experience that is related to the present input environment. For example, listening to and understanding the speech of another person requires access to the memory folders storing the sounds and associated meaning of each word and each combination of words or phrases. Without memory and memory access, one could hear speech but not understand it, similar to hearing a person speak an unknown foreign language.
8) Retrieval of the contents of the sought after folder or folders is done by association of the current sensory input or prompt signal with the folder contents. One would need to scan through the folders to make the association and find the right folder or folders. This needs to be done rapidly, using a method that allows the size of the memory to be increased without increasing the retrieval time.
9) When a search is prompted by current sensory inputs and a folder containing related information is found, all of the folder contents could provide prompt signals to find additional related folders that were not found in the initial search.
10) A problem-solving process could create new patterns from sensory inputs. These new patterns could be stored in memory and could prompt new searches.
11) Associations are made by pattern matching or vector matching.
12) Features of patterns are portions of the patterns themselves, often zoomed-in portions.
13) The memory is organized in segments. Each segment contains a finite number of folders. Each segment contains its own retrieval system for searching its folders. When a search is prompted, separate but parallel searches take place in all memory segments simultaneously. Thus, search time does not increase with the number of segments or with the total size of the memory.

III. The Workings of the Cognitive Memory System of Figure 1

The preliminary cognitive memory system of Figure 1 has the capability of performing in accord with all of the above hypotheses. Sensory inputs are brought into the system in the lower left of the figure. These inputs could be visual, auditory, tactile, olfactory, etc. or, in a mechanistic system, optical, radar, sonar, etc. These inputs are made available to a short-term buffer memory that is part of a cognitive problem-solver, to be described below. The sensory inputs go through a "volition switch" before being stored. This allows only "interesting" inputs to go to permanent storage.

The memory input is a signal vector that goes to all memory segments simultaneously. This same signal vector serves as a prompt signal for searching memory. Separate prompt and memory input lines are shown in the figure because there is evidence that in human memory, these are separate circuits [22]. In a true mechanistic system, a single line would serve for prompting and for memory input to the folders. The memory input vector to be stored goes from segment to segment looking for an empty folder. The memory input vector may be stored in more than one folder and in more than one segment for redundancy.

The recalled memory output vector is delivered to a buffer memory and, along with the sensory input vector, feeds data to a cognitive problem-solver. The recalled memory output vector may actually be the desired memory output. Or it may be used as an important input to the problem-solver. A simple form of reasoning can be done by a problem-solver which, at the present time, is envisioned to be based on the classical work of Arthur Samuel. His checker-playing program embodies a reasoning process that plays by the rules, plays tentative moves ahead, and makes optimized decisions in order to win the game of checkers.

Game playing is a good model for a general reasoning process. Samuel's checker-player dating back to the 1950's and 1960's is still recognized as one of the finest pieces of work done in the field of artificial intelligence [23], [24].

Computed outputs from the problem-solver can be stored and later retrieved from memory. A memory input switch, shown in Figure 1, selects the memory input and prompt vector from the current sensory inputs, from computed data from the problem-solver, or from retrieved memory outputs. The operation of this switch is volitional.

The working of a single preliminary memory segment is described below

IV. Details of the Working of a Single Memory Segment

Memory segment 1 is shown in Figure 1. The memory input line delivers input vectors for permanent storage, looking for empty memory folders, if available in this segment. Some of the memory folders are large, some small, depending on the amount of storage space needed for the given memory input.

A prompt vector from the prompt line can initiate a search in this memory segment containing folders with stored data. The multiplexer switch (MUX) starts in an initial state that causes its output to pass the prompt signal through to the autoassociative neural network, whose output is then stored in the buffer memory.

This multilayer neural network has been trained with all of the pattern vectors stored in all the memory folders. This network is trained mostly off-line (perhaps at night, during sleep, for humans [25]). One pattern vector at a time is used as an input to the neural network, which is trained (using the back-propagation algorithm of Werbos [26], [27] in mechanistic systems) to produce an output pattern vector matching the input pattern vector. The training is iterative, one pattern at a time, obtained by repeatedly scanning the MUX over the set of memory folders. Thousands of patterns could be trained into the neural network to replicate themselves at the network output. When more input pattern vectors are stored in this segment, they are added to the set of training patterns. The autoassociative neural network has a finite capacity to store training pattern responses depending on the number of neural layers, the number of neurons per layer, and the number of adaptive weights per neuron. The capacity of this neural network determines the number of folders whose contents can be trained in, thus determining the size of the memory segment. Training can be done by cyclically scanning the MUX or, better yet, by randomly scanning the MUX.

A simple configuration for an autoassociative neural network could be architected in accord with the following example. Let the first layer have 16 neurons, the second have 8 neurons, the third have 4 neurons, the fourth have 8 neurons, and the fifth have 16 neurons. The configuration is like an hourglass, as sketched in Figure 1. The choke point is the third layer. Without a choke point, it would be possible for the network to be trained to replicate its input at the network output, for all input patterns. With the choke point, the information contained in the first layer input pattern becomes compressed at the choke point. Only a finite number of input patterns can be trained-in to replicate themselves at the network output. This number is statistical, depending on the nature of the input patterns. The average of this number is the capacity of the network, and this is being determined by computer simulation for many different configurations of the network.

Once the autoassociative network is trained, the trained-in patterns replicate themselves at the network output. Other patterns not trained-in will not replicate themselves. Thus, the trained autoassociative neural network enables the classification of all input patterns as "seen before" or "not seen before." Autoassociative neural networks have been simulated, and we have observed the above-mentioned useful properties.

Once the neural network is trained, the response to a new memory input pattern vector is almost instantaneous. When a prompt vector is applied as an input to the trained neural network, the output pattern response can immediately be compared with the input pattern, and if the patterns match, there is a hit. Therefore, a vector identical to the prompt vector must have been stored in one of the folders and trained into the autoassociative neural network. In other words, the prompt vector has been seen before. MUX scanning starts, and the contents of each folder in sequence are tested with the neural network for a match to the prompt vector. Once a match is found, MUX scanning stops and the entire stored contents of the folder are read, not just the portion of the contents that matches the prompt vector. The total contents are delivered as the memory output vector.

Suppose that a search is under way with the current sensory input signal being the prompt vector. The prompt vector is fed to the autoassociative neural network, and immediately it is known that there is presently no match between the input and output of this network because this prompt pattern has not been seen before. A mechanistic form of the "visual cortex" will try for a match by creating new patterns by "electronically" zooming in and out of the visual image, translating up and down, etc., relative to the pattern in the field of vision. A mechanistic form of "head and eyes" will move to get a different perspective, different lighting, etc., all in an attempt to create a pattern that will match itself at the neural network output. If a match can be achieved, then it will be known that the face being looked at is familiar. Then, the MUX begins a scan, the appropriate memory folder is found, and information stored in the folder can be retrieved. Because the trained neural network responds so quickly, varying the current sensory input vector by "head motion" and "visual cortex" action can be done continuously and rapidly to see if a hit can be obtained. If so, the person looked at is first recognized, and then, after a short while, information about the person is recalled as the contents of the relevant folder are read. If not, the person is not recognized.

We have all had the experience of walking down the street and coming upon a familiar face. Recognition takes place very rapidly. But what is this person's name? That may take a few minutes to recall, while searching for the memory folder containing the desired information.

Suppose that Widrow is seen. The image of his face prompts a search. Rapid variations of the sensory input are made to try to make a hit. In the Widrow folder, there are many images of his face, with different sizes, rotations, translations, perspectives, lighting, and zoomed in images of his nose, eyes, ears, facial details, etc. If any variation of the input image causes a match at the autoassociative neural network output, Widrow is recognized. Then, a search through the folders of the segment is made, and information spills from the Widrow folder, such as the sound of his name, the sound of previous conversations, and the name of his wife, if all of this was originally deemed "interesting" and permanently stored in the folder.

The proposed cognitive memory system performs pattern recognition but differs significantly from the usual pattern recognition systems [28], [27]. Most adaptive pattern recognition systems learn to classify patterns by adapting to a set of training patterns. Once trained, the training patterns are discarded. When new input patterns are applied to the trained classifier, these patterns are classified in accord with the training experience [27]. The cognitive memory, on the other hand, stores the training patterns (visual, auditory, etc.) in folders and recalls the entire contents of the folder when prompted by a new input pattern that may match only one set of patterns in the folder. If the patterns in the folder are identified by their meanings or classes, then the new input pattern gains meaning or class by induction or association.

A good example is the analysis or diagnosis of mammograms. Systems have been in development for the automatic analysis of mammograms, spotting lesions that may be cancerous [29], [30], [31]. These systems are trained or designed to classify mammographic X-ray images and have done this with some success. New unknown mammogram images have been applied to the trained system and have, in many cases, been classified correctly.

A cognitive memory could also be applied to this problem. Folders for thousands of patients could be established, each containing a series of mammograms taken from a patient over a number of years. A history of the patient giving the age, weight, height, blood work, biopsy, the treatment given, and the outcome would all be recorded in the folder. When a new patient comes into the system, the new mammogram prompts a search and, adjusting the tolerance or closeness of the image matching, hits take place with a number of folders. The physician then has a number of previous cases that are similar to the present one. From this experience, a treatment plan can be formulated.

The way the physician currently deals with this problem may be similar to the cognitive memory approach. The physician has had years of experience in reading mammograms and treating patients [32]. When a new problem arises, the physician thinks of previous similar cases. What was done and what was the outcome? The pattern recognition system answers the question, "what do I see?" The cognitive memory system answers the questions, "what do I see?" and "what do I know about that?"

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