Signature Matching using Associative Memory with Reusing of Pruned Nodes

K. Nagi Reddy
Research Scholar,
R.No: TR.COMP.SCI 002
Rayalaseema University,
Kurnool, A.P., India

Dr.B Ravi Prasad
Professor in CSE
MLRITM, Hyderabad

Dr.K.Suvarchala
Professor,Dept. Of CSE
St.Mary's Group of Institutions
Hyderabad, India

Abstract

Signature matching has been a topic of interest for quite some time. The need for efficient and robust algorithms and systems for recognition is being experienced in India especially in the post and telegraph department, banking sector and police department. In this paper signature image database retrieval has been investigated with special consideration. In unformatted databases one of the important features is that the user tends to retrieve information based on approximate queries, which are quite common in practice and sometimes unintentional. Work has been done on signature matching earlier using conventional and hybrid methods which may not be very efficient for practical systems. The present work is a new direction in signature matching using artificial neural networks and an implementation of a comprehensive software, based on signature matching in practice. Our procedure involves capturing the signature image, preprocessing, indexing each signature image through wavelets, thresholding and retrieving the stored signature for the given query signature pattern using associative memory concept of Dynamical Neural Network (DNN) with reuse. It is proved that the performance of the dynamical neural network with reuse using the learning strategy for signature matching is very efficient.

Keywords

Associative memory, dynamical neural network, spurious states, string descriptor, thresholding, POSC

1. Introduction

Retrieving information from a very large database using approximate queries has been of prime interest of researchers in the recent years. The studies in this are a particularly for unformatted databases like protein databases [1] and methods like full text scanning, inversion, clustering and signature files are reported [2].

For example, in the case of library database user may not be sure of the exact set of key words to retrieve a specific book but may have an idea of the subject that the book deals with. In such case, query keywords may not match with all the keywords stored in the database. In another case the user may be aware of the keywords but uses them in the abbreviated form or with different spelling mistake or typographical mistakes. In the signature image database, determining approximate match is required for a query signature from the various classes of signatures already available in the database. This close proximity match in such large databases is one of the very important operations and there are many research reports in this context [3, 4].

Associative memory concept is related to the association of stored information for given input patterns. The distinct traits of ANN-based implementations as associative memory are their use of content based retrieval instead of address based retrieval of stored data, approximate instead of exact matching. Hence the present task of signature matching is represented as problem of association and can be accomplished by associative memory. The DNN with reuse is more suitable to accomplish the present task as it is having the properties like associative memory with 100% perfect recall, large storage capacity, avoiding spurious states and converging only to user specified states.

Since DNN with reuse operates with binary data while the information in signature image database is in bmp file format, it is required to map (convert) the bmp file form to a binary string. The network is not trained by the actual image data rather descriptors or binary strings are used as exemplar patterns to store them in DNN with reuse by training. The binary string of the query signature is presented to the network as a test pattern. The associative memory property of the network makes it to recall a closest pattern of the given query pattern among the memorized patterns. The experimental results are reported that high level of precision can be obtained for efficient recall of inexact queries using the proposed neural network.

This paper is organized as follows: section 2 contains the previous work on information retrieval, section 3 describes Proposed Signature Matching method, section 4 discusses Dynamical Neural Network with Reuse of Pruned nodes, implementation part is included in section 5, section 6 contains results and discussion and concluding remarks in section 7.

2. PREVIOUS WORK

An information retrieval system is concerned with the representation, storage, organization and accessing of information items. In principle no restriction is placed on the type of items handled in information retrieval. But retrieval systems are normally used to handle textual data. Hence in the present context we would like to describe the text retrieval problem, whose main concern is with the type or queries and the operation requirements. For the sake of completeness, a brief overview of some of the general methods used in text retrieval is presented below.

Faloutsos [2] has presented a review of access methods applicable to both formatted and unformatted data. He classifies text retrieval methods into the following four classes.

Full Text Scanning [5, 6] retrieval method the full text database is scanned for matching records. No extra storage overheads are incurred, but the method is relatively slow for large databases. In the Inversion [7] retrieval method each document can be represented by a list of (key) words, which describe the contents of the document for retrieval purpose. Fast retrieval can be achieved if we invert the keywords. This method uses an inverted file index, where key words are stored alphabetically. It is implemented in many commercial text retrieval systems. It provides relatively efficient query speeds, but can be very expensive in terms of storage. In addition another disadvantage is that the insertion times are slow in this method.

Clustering [8] method is also used for text retrieval where similar documents are grouped together to form clusters. Clustered documents can be stored physically together, facilitating efficient retrieval of related documents. A descriptor [16] is stored for each cluster and a search correlates, typically using a vector similarity function, these descriptors with the query descriptor to retrieve relevant documents. The main disadvantage of this method is the slow insertion time.

In Signature Files [9, 10] matching method, a descriptor or a signature or a binary string is associated with each record of document, the descriptor being a bit encoding of the values used to retrieve the record. When a query is processed, the file of descriptors, rather than the data records, is examined for possible matches. A query descriptor is formed using the same encoding technique that is used for forming record descriptors. The possible record matches are those records whose descriptors contain bits set in each position for which a bit is set in the query descriptor.

The signature (descriptor) file approach seems most promising for large databases. Signature file methods have good retrieval properties and required small storage overheads [11]. Notice that there is no restriction on the number of key words for any document, because documents can be divided into "logical blocks" (pieces of text that contain a constant number of key words). In other words the advantages are simplicity of implementation, efficiency in handling insertions, ability to handle queries on parts of words[15], ability to support a growing file and tolerance for typographical and spelling errors [2]. Since DNN with Reuse uses only binary data and in view of the above advantages, in the present context signature (descriptor) file method is more suitable.

3.Proposed Signature Matching method

Artificial neural networks are models obtained by the interconnection of processing elements, called neurons, which are similar to biological neurons in function. The Dynamical Neural Network with reuse is completely specified by the topology of interconnections between neurons and the rules of learning for obtaining the strength of connections between the neurons, called weights. Standard patterns which are presented to the system initially for learning are called exemplar and unknown patterns and the patterns which are to be recognized by the network are called test patterns.

Associative memory or content-addressable memory is a device by which storage and retrieval of information is based on partial knowledge of its context but without the knowledge of its storage location. Thus, the memory exhibits an ability to recognize an unknown pattern associated with one of the patterns stored in the device. It also has the property to recall the correct associated pattern of an unknown pattern presented which is noisy, distorted or incomplete. Since many real-life digital images have some quantitative noise, associative memories are ideal digital pattern recognition systems. They can also be used for recognition of patterns which are distorted.

Initially for experimentation on signature matching, we have collected a large number of signatures of different people and they were digitized using a scanner to a resolution of 1mm x 1 mm per pixel (Figure 1).

Figure 1 Digitized image of signatures

Individual signatures of different persons are extracted from the page containing all the signatures. We have made sure that two specimen signatures are collected from each person. Hence one set of signatures becomes training set for the DNN with reuse; another set of signature images becomes test patterns or query signature (Input pattern) for which a signature match is required from the trained data of the Dynamical Neural Network with reuse.

Figure 2 Compressed image through wavelets

Now each signature is a grey level image File. For the convenience with the wavelet transforms for image compression each signature image file is converted into a RAW file format (Descriptor). This necessitates for thresholding of each compressed raw file in the signature image database. After each signature image file (Raw file) is compressed through the wavelet decomposition to the optimal size i.e. 17x5 pixels (Figure 2), the compressed image file is stored as an ASCII file, in which each pixel is represented as one byte. The steps involved in thresholding of the signature images are given as an Algorithm (Figure 3). In the process of thresholding the average value of all the pixels is given by

Average=sum of all pixel values/No. of pixels

The average value is compared with each of the pixel values. If the average is higher than the pixel value, a '0' is placed at the respective pixel value, otherwise '1' is used. Thus for each image in the signature image database a descriptor is obtained, which are used as exemplar or test patterns for training the neural network.

Input : I – Input image m x n
Output : O – Descriptor or binary sting of the input image.
Procedure Threshold (I: in; O: out)

1 pic [i][j] = Read input image
2 sum = 0
3 for i = 1 to m do
4 for j = 1 to n do
5 sum = sum + pic [i][j]
6 end do
7 end do
8 evaluate average of pixel values
9 If pic [i][j] < avg /* pixel value is compared with average */
10 The corresponding pixel of input image is replaced by 0 otherwise 1
11 O ⟵ Binary strings of input image
12 end

Figure 3 Algorithm for Thresholding

4.Dynamical Neural Network with Reuse of Pruned Nodes

The Practical storage capacity limitaion of a Hopfield model of neural network has prompted us to devise a new mechanism for recognizing a test pattern when the number of exemplars to be stored in a network is greater than the storage capapcity of a single network. For a network with n neurons the maximum theoretical storage capacity in 2n patterns [12], whereas with Hebb's learning rule, it is 0.15n [13]. The practical optimal storage capacity (POSC) of an associative memory may be defined as the number of exemplars which can be trained in a reasonable amount of time and test patterns corresponding to one of the trained exemplars recognized accurately. This is found in literature to be approximately 0.15n for Hebb's learning [14]. If the number of exemplars to be stored in a network were to be more than this figure, the network would fail to perform efficiently.

To improve the POSC of a Hopfield model of associative memory, a new network model called Dynamical Neural Network with reuse associative memory is proposed. In this method, the exemplars to be trained are divided into groups. Each group is trained into a separate network of same typology. The test pattern to be matched is presented to each of these networks. The patterns to which each of the networks converges are then made as exemplars to train further levels of networks. The unknown test pattern (query signature) presented to the further levels of the network can be recognized by it.

Each node of DNN with reuse associative memory model is a Hopfield network with the modified learning strategy [1]. Each node of the network has the same number of N Neurons arranged as a two dimensional matrix (hxw) for the binary character image. If exemplars are to be trained in the network, values of the N x N weights connecting the neurons are calculated by the learning method [1]. Now the test pattern (Query Signature) to be matched with the memorized patterns is presented to all the nodes of network. Iterations are carried out in discrete time steps to evaluate $S_i(1)$, $S_i(2)$ … using equations,

$$h_i\,(t) = \sum_{t=l}^{N} W_{ij}\, S_i\,(t)$$

and $$S_i(t+l) = \mathrm{sgn}[h_i\,(t)]$$

The network is said to have converged when $S_i(t)$ remains unchanged with increasing t. The converged values of S_i obtained, at each iteration by the presentation of a test pattern to each of the node now serves as a set of exemplars for further iterations of the network nodes. The W_{ij} for these nodes of the DNN with reuse are computed. The test pattern (Query signature) is presented for these nodes and $S_i(t)$ is calculated for increasing t in each of the iterations the S_i's are computed, till these remain same for subsequent iterations (convergence). The binary image obtained from these converged S_i's is the pattern recognized by the DNN with reuse associative memory.

5. Implementation

To facilitate the implementation of the Dynamical Neural Network with reuse associative memory architecture, the signature image data base created into two groups as exemplar patterns, which are used to train the network and test pattern group respectively, for which a signature matching is required. We have to make sure that the exemplar patterns will contain all the signatures for which signature matching is required.

As explained in the previous sections, it requires to have a scanned signature or digitized image (Figure 1) files from which each individual signature is isolated. It is seen that original signature image of size 130x40 pixels. This boils down to a size of about 5200 bytes of data for each signature. This is a very large amount of data for DNN with Reuse to handle. It is to be noted that if the Dynamical Neural Network training data is large then the network takes a longer time to converge. On the other hand if the signature files are compressed to a very high state there is an inconsistency in the signature matching process. Hence an optimal value of the size of the signature is choosen after the image compression through wavelets. The overall procedure for signature matching system is indicated through a block diagram (Figure 4).

As shown in the block diagram of the proposed signature matching system (Figure 4) the different steps involved are image capturing and preprocessing, indexing each signature image through wavelets, thresholding and associative memory using DNN with reuse.

This section gives the results of the extensive experimentation carried out on wavelet transform for the signature image compression. The experimentation on wavelet compression has been done on approximately 100 images but the results only for a selected few are given here. As shown in figure 2 the compressed images are taken into consideration, each compressed image is subjected to thresholding procedure. Therefore after thresholding, each pixel in gray level signature image file of size 17x5 is replaced by 0's and 1's.

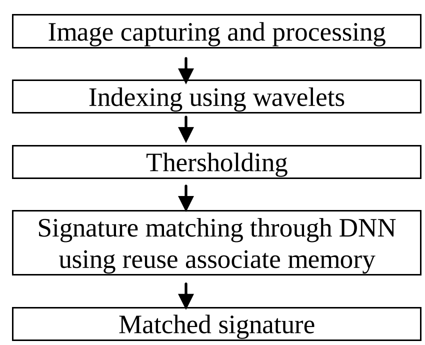

Figure 4 Block Diagram of the Proposed Signature Matching System

After arriving at series of 0's and 1's for each signature in the database the next step is to generate single binary string for each of the signature in the image database. Similarly the other compressed signature image files in the image database of 17x5 pixels is processed with the same procedure as explained below to obtain a single descriptor for each signature image in the database.

To obtain a single binary string (descriptor) for each of the signature images, by taking two rows at a time oring (Logical OR) is done, through which it becomes three rows and seventeen columns. These three rows thus obtained are concatenated to form a single binary string. Similarly, a descriptor (binary string) for each of the signature images in the signature image database file is obtained.

6. Results and Discussions

Let us consider a sample signature image database consisting of sixteen signatures. Descriptors for each of these sixteen signatures obtained are given below as S_i.

As already mentioned we have to make sure that for each person we have taken at least two signatures while creating signature image database. Form this, one set of signatures in each case we have obtained 51 bit binary string which will become the training set of the dynamical neural network with reuse, other set of signatures, for which a 51 bit of binary string is obtained, will become the test pattern (query signature) for which signature match is required from the trained set of signatures through the Dynamical Neural Network with reuse model. If the name of the person whose signature
is matched is same as that of the test signature person, it means that the signature is correctly recognized.

S_1= 1111111111110111110000000000000000000000000000000000

S_2= 1111111111111111100000000000000000010000010000000000

S_3= 1111111111111111101000000000000000000000000000000000

S_4= 11111110110110110001000000000000000100000000000000

S_5= 10001000000101101010010110010110100100000000000000000

S_6= 111011101110111110000000000000001010010000000000000000

S_7= 11101101101101101100010100100000000000000001000001000

S_8= 10100100110101111100111110010000100100000100000000100

S_9= 0100111000011110001010011111111111111011000000000000

S_{10}= 1110100101110100011000101100100011000100010000000000

S_{11}= 1111111111111111100000000100000000100000000000001000010

S_{12}= 0110110111111111111110010110110110101000000000000000

S_{13}= 1110110111111111110000000000000001000000000000000000

S_{14}= 1111111110110110100000001010010110110000000000000000

S_{15}= 1110110110111111111000000000000110100000100010000000001

S_{16}= 0110010110110110110111110111111111101001000001001000

Let us assume that the user wants to match the query signature whose descriptor is computed as explained above

X =
111111111111011111000000000000000000000110000 0000000

The step by step process of obtaining the closest pattern to the test pattern from the mouse movement database is explained with help of figures 5(a) to 5(e). Initially the descriptors or binary strings of the records in the database are presented as initial states or training patterns. Since the sample database has sixteen records, in the first iteration we have considered four basic nodes in the network to memorize sixteen records. That is each node H_i,i=1, …,4, is trained by set $\{S_{2j+1}, S_{2j+2}\}$,j=0, …,3, exemplar patterns. The query pattern X is presented to all the basic nodes H_i, i=1,…,4 (Figure 4.5(a)).

The dynamics of the Hopfield model stabilizes at a stable pattern ($O_{11}, O_{12}, O_{13}, O_{14}$) for each of the basic nodes H_i, i=1, …,4. Each basic node retrieves one of the memorized patterns that is close to the test pattern X (Figure5(a)). In the present example the outputs of H_1, H_2, H_3 and H_4 are S_1, S_3, S_5 and S_7 respectively. The outputs of H_1 and H_2 are fedback to H_1 and outputs of H_3 and H_4 are to H_3. The nodes H_2 and H_4 are ready for pruning.

In the second iteration, the nodes H_1 and H_3 with feedback patterns ($O_{11}, O_{12}, O_{13}, O_{14}$) and H_2 and H_4 with fresh set of exemplar patterns (S_9, S_{10}, S_{11} and S_{13}) are freshly trained. The query pattern X is presented as test pattern to all the nodes (Figure 5(b)). The dynamics of Hopfield model stabilizes at a stable pattern for each of the basic nodes ($O_{21}, O_{22}, O_{23}, O_{24}$). The outputs of H_1, H_2, H_3 and H_4 are S_1, S_9, S_5 and S_{11} respectively.

In the third iteration, the nodes H_1 and H_3 with feedback patterns (O_{21}, O_{22}, O_{23} and O_{24}) and H_2 and H_4 with fresh set of exemplar patterns (S_{13}, S_{14}, S_{15} and S_{16}) are freshly trained. The query pattern X is presented as test pattern (Figure 5(c)). The dynamics of Hopfield model stabilizes at a stable pattern for each of the basic nodes ($O_{31}, O_{32}, O_{33}, O_{34}$). The outputs of H_1, H_2, H_3 and H_4 are S_1, S_{13}, S_5 and S_{15} respectively.

In the fourth iteration, the nodes H_1 and H_3 are freshly trained with the feedback patterns ($O_{31}, O_{32}, O_{33}, O_{34}$). The nodes H_2 and H_4 are pruned as the sample database contains only sixteen exemplar patterns (sixteen records). The query pattern X is presented as test pattern (Figure 5(d)). The dynamics of the Hopfield model stabilizes at a stable pattern for each of the basic nodes H_1 and H_3 (O_{41} and O_{43}). The outputs of H_1 and H_3 are S_1 and S_5 respectively. In the fifth iteration, these S_1 and S_5 (O_{41} and O_{43}) are fedback to H_1. The node H_3 is pruned. The node H_1 is freshly trained with patterns S_1, S_5 and the test pattern X is presented (Figure.5(e)). Finally the node H_1 retrieves one among S_1 and S_5. Which intern closest pattern to X in the whole database. In the present case it is S_1 = 1111111111110111110000000000000000000000000 00000000. This is descriptor or binary string of the signature, which is required.

7. Conclusion

Signature matching has been attempted using a dynamical neural Network with reuse as an associative memory. The signature extraction from the digitized signature image database, indexing each signature using wavelets and thresholding of the image signature is clearly dealt with associative memory concept of the dynamical neural network with reuse has been explained. The procedure for obtaining a binary string for each signature in the image database is presented. The performance of the dynamical neural network with reuse using the learning strategy for signature matching is also discussed. Thus a complete comprehensive scheme, implemented for signature matching using dynamical neural network with reuse is presented.

References

[1] Rao, M.S., Arun K Pujari and sreenivasan. B. A New Neural Network architecture with associate memory, Pruning and order sensitive learning. International Journal of neural Systems 9, 4, 351-370, 1999.

[2] Falutsos, C. Access methods for text. ACM Computing Surveys, 17, 1, 49-74, 1985.

[3] Hall, P.A.V. Dowling. G.R. Approximate string matching. ACM Computing Surveys, 12, 4, 381-402, 1980.

[4] Rao, M.S., Arun K Pujari and sreenivasan. B. A New Neural Network architecture for efficient close proximity match of large databases. Proceedings of the Eighth International Workshop on DEXA, France, IEEE Computer Society Press, 444-449, 1997.

[5] Knuth, D.E., Morris, J.H., Pratt, V.R. Fast pattern Matching strings, SIAM Journal of Computing, 6, 2, 323-350, 1977.

[6] Hollar, L.A., Smith, K.F., Chow, W.H., Emrath, P.A., Haskin, R.L. Architecture and operation of large, full-text information retrieval system. Advanced Database Machine Architecture, D.K. Hsiao, Ed. Prentice Hall, Englewood Cliffs, New Jersey, 256-299, 1983.

[7] Lesk, M. Some applications of inverted indexes on the UNIX system. UNIX Programmers manual, Bell Laboratories, Marray Hill, New Jersey, 1978.

[8] Salton, G., Fox, E.A. Wu, H. Extended Boolean information retrieval Communication. ACM, 26, 11, 1022-1036, November, 1983.

[9] Tsichritzis, D., Christodoulakis, S. Message files, ACM Transactions on Office Information Systems, 1, 1, 88-98, 1983.

[10] Larson, P.A. A method for speeding up text retrieval. Proceedings of the ACM SIGMOD Conference, ACM, New York, 1983.

[11] Sack-Davis, R., Kent, A., K. Ramamohanarao. Multikey access methods based on superimposed coding technique. ACM Transaction on Database System, 12, 4, 655-696, 1987.

[12] M.J. Smith and T.P. Barnwell. Anew filter Bank theory for itme-frequency representation. IEEE Transaction on Acoustics, Speech and Signal Processing, 35, 314-327, March, 1987.

[13] Lippman, R. An introduction to computing with neural nets, IEEE ASSP magazine 4-22, 1987.

[14] McEliece, R.J., Posner, E.C., Rodemich, E.R. and Venkatesh, S.S. The capacity of the Hopfield associative memory, IEEE Trans on Inform Theory 33, 641, 1987.

[15] M Swamy Das, D Sandhya Rani, C R K Reddy, A Govardhan""Script Identification from Multilingual Telugu, Hindi and English Text documents", International Journal of wisdom Based Computing, Vol. 1(3), December 2011

[16]B.M Sagar, Dr.G.Shoba, Dr. P.Ramakanth Kumar," Character Segmentation algorithms for kannada optical character Recognition",
Proceedings of the 2008 International Conference on Wavelet Analysis and Pattern Recognition

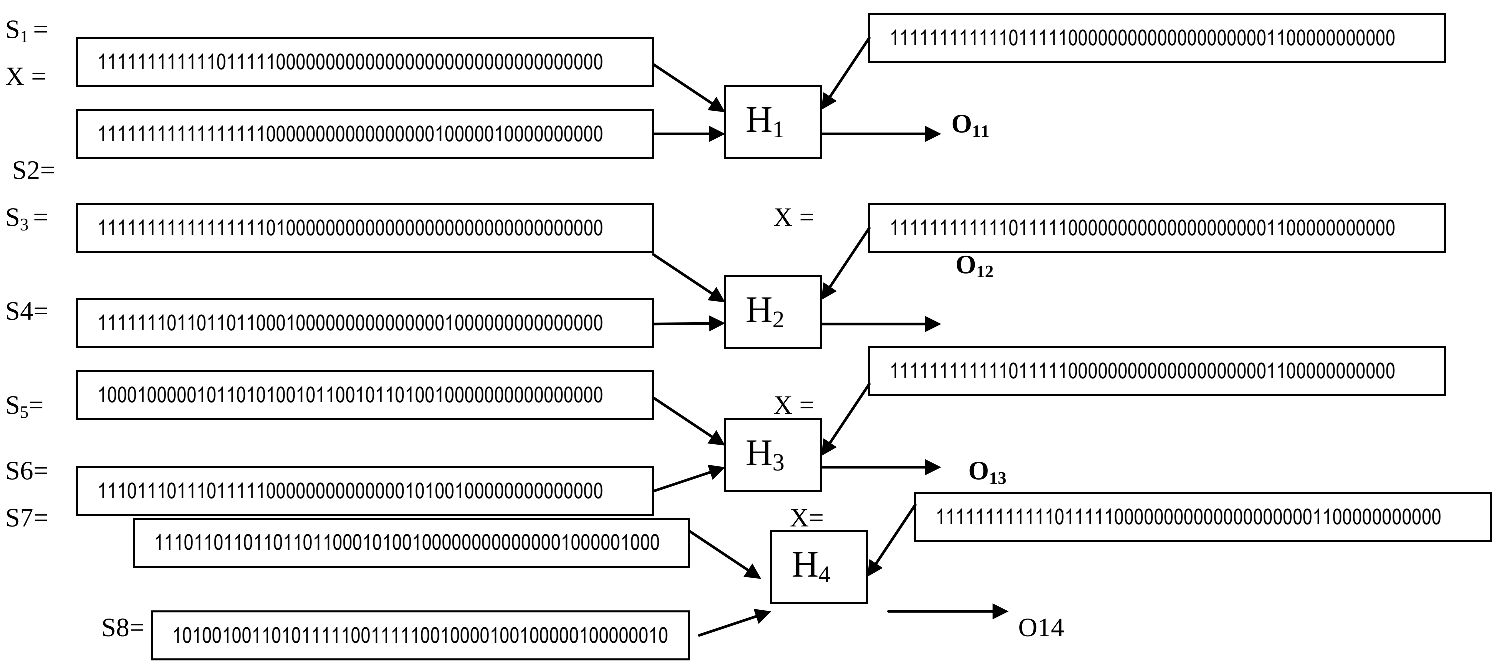

Figure 5(a) Iteration 1: Initialization with Training, Test Pattern and exemplar patterns

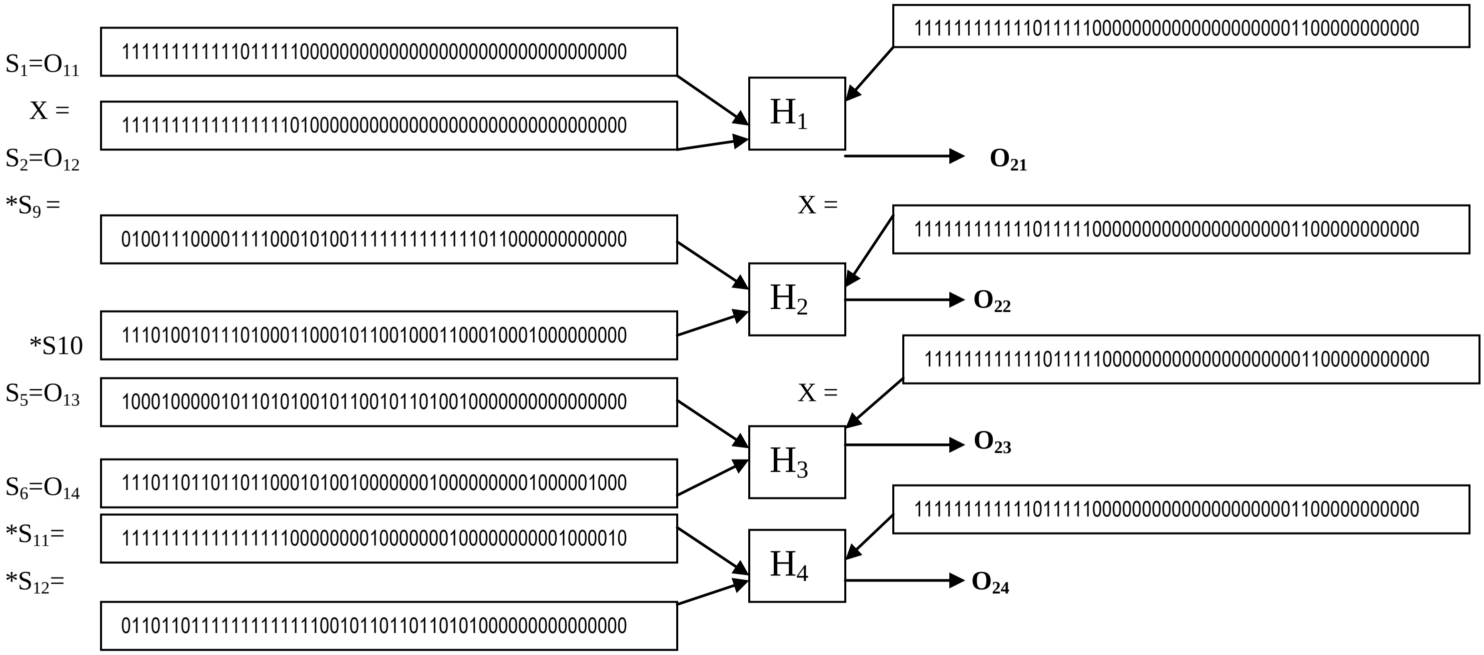

Figure 5(b) Iteration 2: Hopfield Stable States Reutilization of Pruned Nodes and Feedback patterns
X = TEST PATTERN, H_i = HOPFIELD NETWORK
** Fresh set of exemplar patterns are presented by reutilization of pruned nodes.*

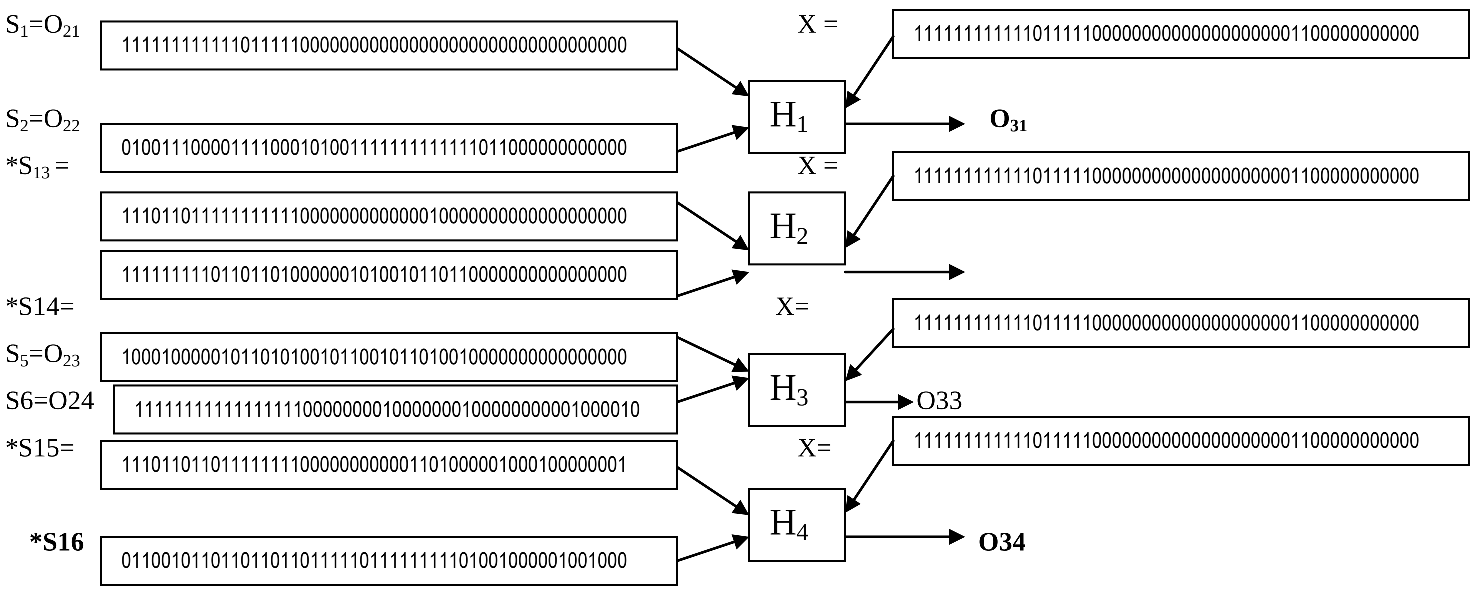

Figure5(c) Iteration 3: Hopfield Stable States, Reutilization of Pruned Nodes for fresh set of Exemplar Patterns and Feedback Patterns

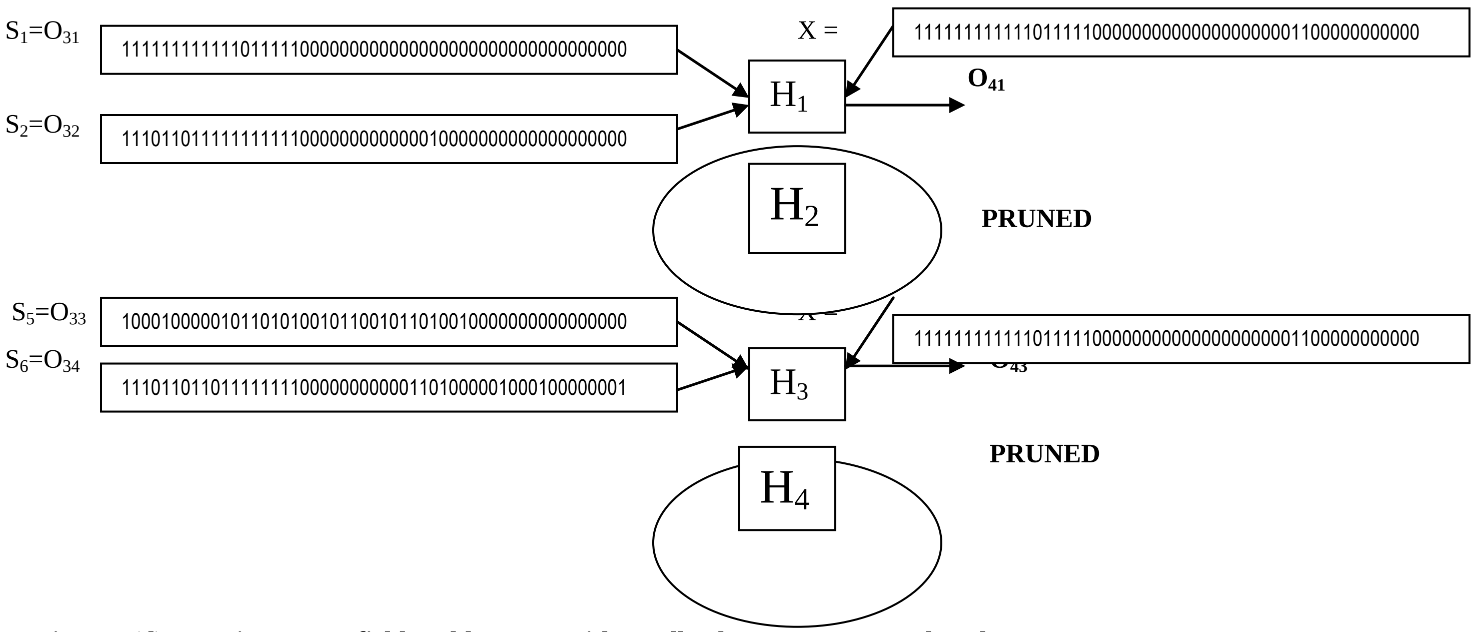

Figure 5(d) Iteration 4: Hopfield Stable States with Feedback Patterns, Pruned Nodes

X = TEST PATTERN, H_i = HOPFIELD NETWORK

** Fresh set of exemplar patterns are presented by reutilization of pruned nodes.*

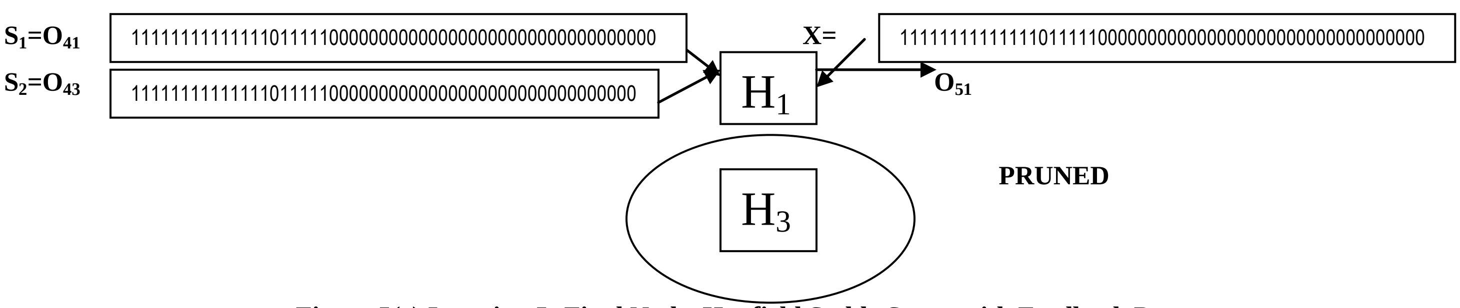

Figure 5(e) Iteration 5: Final Node, Hopfield Stable States with Feedback Pattern

X = TEST PATTERN, H_1 = HOPFIELD NETWORK