TRIDIMENSIONAL PATTERN RECONSTRUCTION BY USING WEIGHTLESS ARTIFICIAL NEURAL NETWORKS

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1. ABSTRACT

This paper describes the structure and behavior of a system, composed by a set of weightless artificial neural networks, which is capable of learning different images and then reconstructing an image according to the closest learned pattern. This paper presents a technique which considers Hamming distance for pattern learning and reconstruction, therefore it is posible to study the mechanism for representing information inside weightless artificial neural networks.

2. INTRODUCTION

This system not only recognizes different types of pattern classes, but also manages each image or pattern as an independent item which is learned and then reconstructed from another pattern or image. There is a set of weightless artificial networks, each of them is associated to each point of the image or pattern. The learning phase is performed when the artificial network, which is associated to the point currently processed, classifies the whole image as the color of that point. The reconstruction phase is performed when a modified pattern is presented to the system and then each artificial neural network recognizes the correct color belonging to the point associated to it. This process is a sequence of operations in which each point of the image is recognized until the whole image is reconstructed to the closest pattern learned in the past by the system.

3. STRUCTURE AND PROCEDURE

Each pattern is stored in a data structure known as "Pattern Representation Array (W 3-D matrix)" which defines the maximum number of points (and also their position in space) that are associated to a tridimensional pattern. This model can be extended to a four dimensional pattern if the W matrix is a set of 3-dimensional matrixes. Each point belonging to the Pattern Representation Array has a weightless artificial network associated, each of them learns the color of its associated point from the pattern to be learned. Therefore, each weightless artificial neural network classifies each pattern according to the color that is present at the point associated to the neural network. The weightless artificial neural networks are indepent from each other, but they have the same structure. All of them are associated to the Pattern Representation Array and each network is associated to one point of the pattern when it is stored in the "W" array.

Each neural network has the following structure:

- Control matrixes and probability distribution functions for data sampling.
- Mapping Function.
- Learning/Recognition Array.

The following paragraphs explain each one of the elements of the system and its performance considering each network as an artificial neural network based on Hamming distances (Aleksander´s model)[1,2,5]. The performance of the whole system during the learning and reconstruction phases is also presented.

Each artificial neural network is capable of changing the way in which it receives external information. Patterns to be learned and/or reconstructed are sampled by each weightless artificial neural network by using different probability distribution functions. These probability distribution functions determine the way in which the first layer is activated.

3.1. Pattern Representation Array:

There is only one Pattern Representation Array in this system and it is intended for storing the patterns to be learned or reconstructed. Each cell stores the color for each pattern, this array is represented in case of a 3-D pattern by:

$$W[\,i\,,\,j\,,\,z\,]:=c$$

where "i", "j" and "z" represent the integer coordinates of a point "P(i,j,z)" and "c" represents the color code for point "P". There is a code for representing a set of colors , considering a maximum number of as "maxcod". This matrix can

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be viewed as a set of bidimensional matrixes $V_z[i , j]$ at different integer values of coordinate "z".

All of the bidimensional matrixes "V_z" have a maximum number of "m" rows for the coordinate (or index) "i", and a maximum number of "n" columns for the coordinate (or index) "j".

3.2. Control Matrixes and probability distribution functions for data sampling:

There are only two Control Matrixes in this system and they are required to perform the pattern learning and pattern recognition processes for each weightless neural network. As a set of weightless artificial neural networks, the process of pattern recognition of each network represents the process for reconstructing a previously learned pattern which has been altered and presented to this system. The points of a pattern that is stored in the Pattern Representation Array, are sampled by using the values stored in the Control Matrixes. Different probability distribution functions ("P(x)") compute these values. This paper also studies the behavior of the system accordingly with the values calculated with different probability distribution functions. For 3D patterns, there are 2 Control Matrixes ("MI_z" & "MJ_z") that are associated to the bidimensional matrixes that are part of the tridimensional matrix W at coordinate "z". The following expressions compute the values stored by Control Matrixes, at different integer values of the coordinate "z":

$$MI_z [i_{MI} , j_{MJ}] := INT ((m + 1) * P(X))$$
$$MJ_z [i_{MI} , j_{MJ}] := INT ((n + 1) * P(X))$$

where "P(X)" is a probability distribution function considering "X" as a random variable and therefore
$0 <= P(X) <= 1$.

The capacity of matrixes "MI" and "MJ" for any value for index "z" is "m*n" and:

$m_{MI} = m_{MJ} := m * 2$ where "m_{MI}" is the number of rows for matrixes "MI" and "MJ"

$n_{MI} = n_{MJ} := n / 2$ where "n_{MI}" is the number of columns for matrixes "MI" and "MJ"

3.3. Mapping Function:

The sampled elements from the Pattern Representation Array "W" (by using the Control Matrixes) are considered as inputs for the Mapping Function. This function calculates the address of an element that belongs to the Learning/Recognition Array and that is associated to the sampled point of the pattern.

For 3D patterns, the Mapping Function "f_z" is proposed as:

$$a_z := 1 + (k-1) * \max cod^{n_{MI}} + \sum_{l=0}^{n_{MI}-1} (V_z[MI_z[k,l], MJ[k,l]] * \max cod^{l})$$

where "k", "l" are coordinates of elements belonging to matrix "MI" & "MJ" at any value of index "z". "maxcod" represents the maximum number of color codes for representing patterns with colored points. "$V_z[MI_z[k,l], MJ_z[k,l]]$" is a sampled element from the "z^{th}" matrix V belonging to the Pattern Representation Array "W".

3.4. Learning/Recognition Matrix:

In this system there are as many Learning/Recognition Matrixes "B" as points belonging to the Pattern Representation Array. For each point from the pattern being analyzed, the Mapping Function is computed in such a way that the contents of the mapped elements of the corresponding Learning/Recognition Matrix (Matrix "B") will be updated. Each of these matrixes is composed by words containing a number of "maxcod" bits. Each bit does not represent a class for classifying the pattern to be learned, but in fact each bit represents a color in which the pattern is being classified by the current neural network under process. The color in which the pattern is clasified is the color associated to the point currently analized from the pattern.

3.5. Mechanism for pattern learning:

The pattern is stored in the Pattern Representation Array considering that the pattern should be represented as a set of points that are associated to their corresponding cells (from the Pattern Representation Array), storing the code for the color related to each point. In the phase for pattern learning, it is necessary to compute the coordinates for sampling points belonging to the pattern, through the selection and computation of a probability distribution function "P(X)".

These coordinates are stored in the Control Matrixes "MI_Z" & "MJ_Z" associated to any integer value of index "z". For each point belonging to the pattern, the whole pattern is analyzed and then some points and their color are sampled. These matrixes control the sampling of elements from the Pattern Representation Array. The sampled elements (considering their values as color codes stored in each of them) are used as inputs for the Mapping Function, so the addresses of elements belonging to the Learning/Recognition Arrays are computed. These computations are performed for each artificial neural network belonging to this system. For each artificial neural network the contents of the mapped elements are updated by setting "on" the associated bit to the color that is stored in the point associated to the current artificial neural network under process. In the case of 3D pattern learning, "p * n_{MI}" elements of the Learning/Recognition Array will be updated for each artificial neural network of this system. For 3D, this update is performed by:

$$B[a_z, z] := B[a_z, z] \, or \, 2^s$$

where "s" represents the code for the color that is associated to the point currently analyzed and "a_Z" represents the address of the element to be updated in the Learning/Recognition Array "B". The process for learning a pattern ends when all the points stored in the Pattern Representation Array "W" are analyzed following the described steps. In fact, analyzing all the cells of the Pattern Representation Array (or points of the pattern) is putting all the artificial neural network working together (at the same time).

3.6 Mechanism for pattern reconstruction:

The pattern to be reconstructed (that should be a pattern previously learned but which has been modified or has lost part of its information) by the system, is stored in the Pattern Representation Array. As in the learning phase, the reconstruction phase must process each point of the pattern (each cell of the Pattern Representation Array). The reconstruction consists of changing or preserving the color of each point depending on the output of each neural network of the system, considering that all of the artificial neural networks can be working at the same time. For each artificial neural network, the following process is performed:

Using the same Control Matrixes for data sampling ("MIz" & "MJz"), which were computed during the learning phase, the elements of the pattern are selected to be inputs for the Mapping Function. For each mapped element belonging to the Learning/Recognition Array, whose adddress is computed by the Mappping Function, its content is analyzed. This analysis consists of checking the bits which are set "on" in each mapped element. The number of bits of a given color class is counted. The following expression counts the number of bits set "on" for each color class (3D case):

$$count[s] := \sum_{z=1}^{p} \sum_{r=1}^{n_{MI}} \frac{B[a_{z,r}, r] \, and \, 2^s}{2^s}$$

For s = 0,1,2,.., maxcod-1

where "p" is the number of matrixes "V_Z" composing the Pattern Representation Array, and "B" is the Learning/Recognition array for the current artificial neural network under pattern reconstruction process. "$a_{Z,r}$" is the address of the mapped element which is computed by the Mapping Function "f_Z"

Once the count for each pattern class has been computed, the counts are compared with each other. The highest count for a given color class "k" implies that the weightless neural network reconstructs the color for its associated point from the pattern as being color "k". Color reconstruction may be measured by a score which ranges from 0 to 1. Each score is computed as a function of each count.

For 3D the following expression computes each score:

$$score[s] := \frac{count[s]}{p * n_{MI}} \quad \text{For s=0,1,.., maxcod-1}$$

The regenerated pattern may or may not be equal to the original pattern analyzed for reconstruction. The regenerated pattern is stored in an Auxiliary Pattern Representation Array and compared to the contents of the Pattern Representation Array. If there is any difference among them, the Pattern Representation Array is updated with the contents of the Auxiliar Pattern Representation Array and the reconstruction process is repeated. The reconstruction process ends when there is no difference between the Pattern Representation Array and the Auxiliary Pattern Representation Array or when a limit of iterations is reached by the system.

4. CONCLUSIONS AND DISCUSSION

The results from earlier works show in a very clear manner that different types of data sampling (used for activating the first layer of neural networks) have important and systematic effects on the global behavior of artificial neural networks. This paper shows the way a set of weightless artificial neural networks can work together at the same time for reconstructing patterns that were previously learned by the system and that require to be reconstructed due to an information loss, or that can be reconstructed to the closest pattern learned in the past by the system. Although the system analyzes each of the points belonging to a pattern, the artificial neural networks of the system only analyzes a reduced set of points due to the sampling of data performed by each network. Earlier works show the way in which experimental manipulation of the first layer affects and facilitates pattern recognition made by a neural network.

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Tridimensional Pattern Reconstruction by Using Weightless Artificial Neural Networks
Architecture and Procedure for Learning Phase

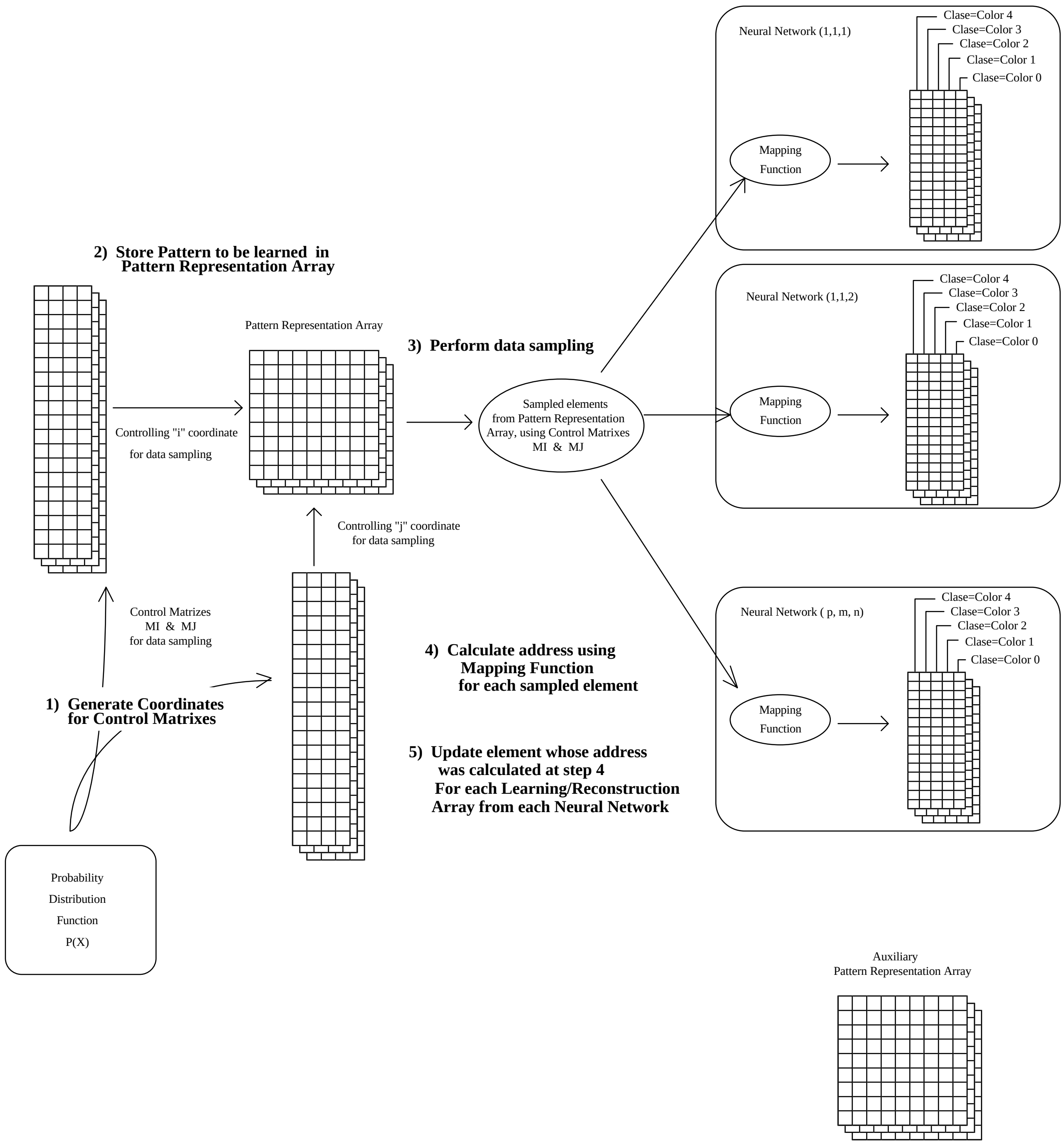

Figure 1

Tridimensional Pattern Reconstruction by Using Weightless Artificial Neural Networks
Architecture and Procedure for Reconstruction Phase

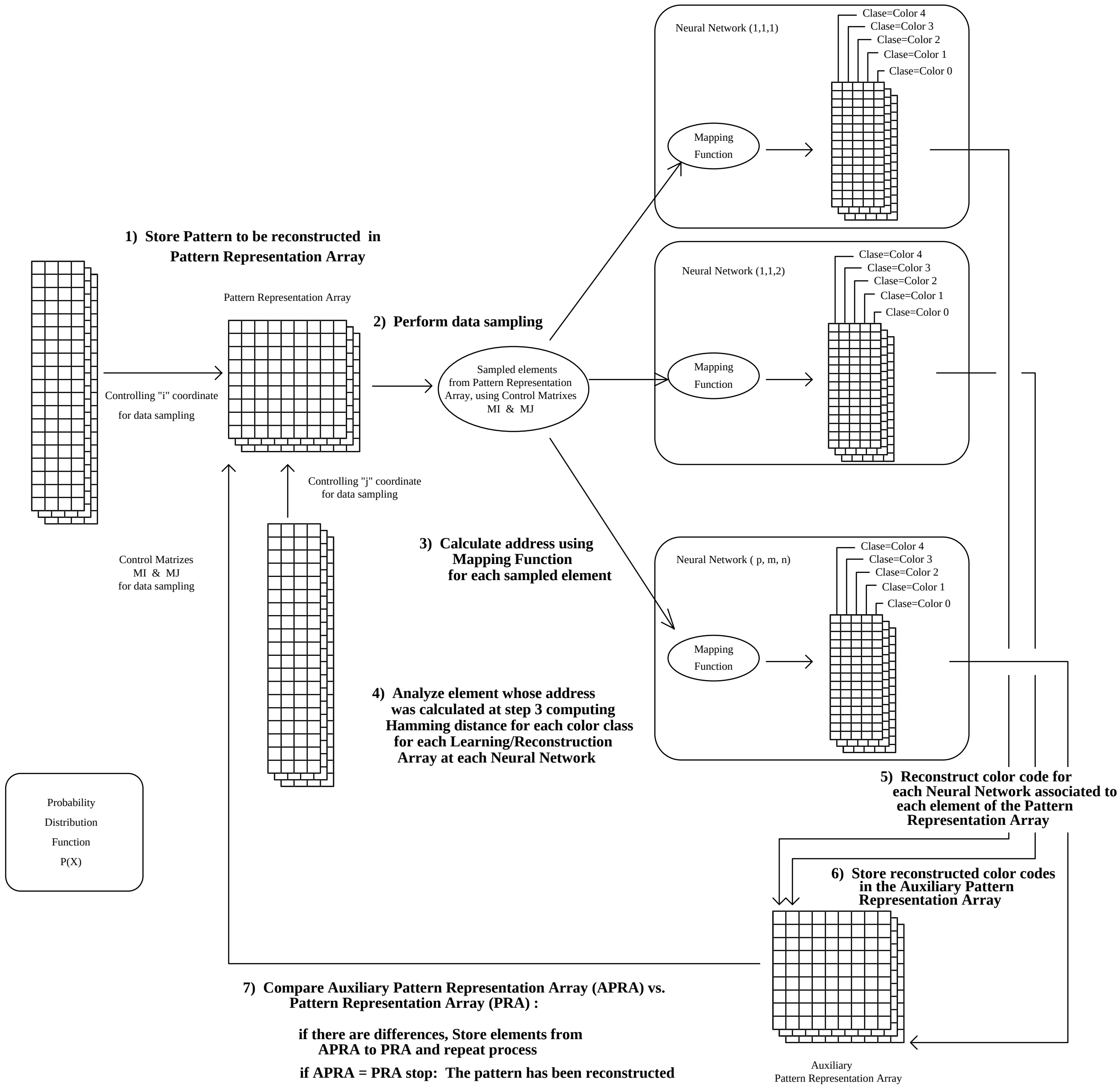

Figure 2