Image Encoding by Multi-Spectral Associative Memory Neural Network

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Summary

This work presents a new solution to overcome the obstacle of using Hopfield Neural Network with high level color images than binary images. This becomes a significant challenge in many applications with multi-spectral image recognition. Therefore, one may suggest adapting Hopfield model to perform high level image recognition by encoding the input data. The encoding will perform form all pixels in an image such that the rules of Hopfield model still valid and the output results should be agreed with converging. The important preliminary results of this work are represented by the advantages of using the new associative memory which based on Hopfield model for encoding high color images with any depth of pixels. In the encoding stage the number of colors can determine the proper level of the new technique. This leads to the ability of using the technique for compressing data easily along with the recognition operation.

Key words:

Hopfield Neural Network; Multi-Spectral images; High level Hopfield model; Oddness numerical system

1. Introduction

The Hopfield model faces an encumbrance of dealing with multi-spectral image which has more than 1-bit of pixel color depth. This becomes a significant challenge in many applications with multi-spectral image recognition. Therefore, one may suggest adapting Hopfield model to perform high level image recognition by developing for encoding the input data. The encoding will perform form all pixels in an image such that the rules of Hopfield model still valid and the output results should be agreed with converging requirements of this model.

2. Problem statement

The problem is that the Hopfield model with two values of bipolar, cannot achieve the need of multi- spectral image pattern recognition. Hence the developing of Hopfield model may achieve using a general model considering the Hopfield model as a first and special case in the new model.

3. Hopfield Traditional Model

An efficient model of HNN has been presented in [1] which uses the minimum size of the training vector and the net is consisted of n neurons with threshold values of Ti. The feedback input to the i'th neuron is equal to the weighted sum of neuron outputs vj, where j=1,2…n. Denoting wij as the weight value is connecting the output of the j'th neuron with the input of the i'th neuron. The total input neti of i'th neuron for m'th vector can be expressed by:

$$net_i^m = \sum_i^n \sum_j^n W_{ij}^m V_j^m + e_i^m - T_i^m \qquad (1)$$

for i=1,2, … n m=1,2,…M

where M is the total number of vectors. The external input to the i'th neuron of vector m has been denoted here as eim. Matrix W, sometimes called the connectivity matrix, is an (n×n) matrix containing network weights. The weight matrix W in this model is symmetric, i.e., wij= wji, and with diagonal entries equal explicitly to zero, i.e., wii= 0. In other words, no connection exists from any neuron back to itself. Physically, this condition is equivalent to the lack of the self-feedback in the nonlinear dynamical system. If the diagonal elements are not 0, the net would tend to reproduce the input vector rather than a stored vector [2, 3]. If an HNN model is given by weights and limited values, then the network will be in dynamic equilibrium when it creates a pattern and the total energy becomes minimum. This energy is a function that can be defined as follows [4]:

$$E^m = -\frac{1}{2}\left(\sum_i^n \sum_j^n W_{ij}^m V_i^m V_j^m \right) \qquad (2)$$

It is possible to calculate the energy function E for every input vector, which can be created in the network. However, for all possible input vectors, an energy landscape with maximums and minimums can be obtained. The point is that the minimum is taken when the input is a

Manuscript received May 5, 2013
Manuscript revised May 20, 2013

pattern. Considering n=3 as the minimum size of V_i, equations (1) and (2) are rearranged as follows:

$$net_i^{s,b,m} = \sum_i^3 \sum_j^3 W_{ij}^{s,b,m} V_j^{s,b,m} + e_i^{s,b,m} - T_i^{s,b,m} \qquad (3)$$

$$E^{s,b,m} = -\frac{1}{2}\left(\sum_i^3 \sum_j^3 W_{ij}^{s,b,m} V_i^{s,b,m} V_j^{s,b,m} \right) \qquad (4)$$

Equations (3) and (4) represent the general form of multi-spectral HNN as it may apply for all kinds of color-level images. Here s is the image number and b acts as the entire bit-planes (sub-binary images) of the image s. In the case of n=3 we found some properties of V_i.

4. The Idea

The significance of length of V is when using minimum size of 3 elements (pixels) that segmented from the image under processing. Then there are only 8 vectors and 8 weights overall existing vectors and weights. The summation of the any 3 elements of each of the 8 cases is limited within values of -3, -1, +1, +3. Hence, the idea is to build any level based on the previous one. Accordingly, the next level then is the summation of the 3 elements of V and limited to -9, -7, -5, -3, -1, +1, +3, +5, +7, +9 values. And so on.

Table 1. Oddness levels and the corresponding number of possible colors in an image that may covered and encoded.

Oddness Level	Coding Scheme of Odits	Possible Covered Color Level	Number of Colors	Tolerance/Surplus
#0	-1, +1	1-bit	2	0
#1	-3, -1, +1, +3	2-bit	4	0
#2	-9, … , -1, +1, … , +9	3-bit	8	2
#3	-27, … , -1, +1, … , +27	4-bit	16	12
#4	-81, … , -1, +1, … , +81	6-bit	64	18
#5	-243, … , -1, +1, … , +243	7-bit	128	116
#6	-729, … , -1, +1, … , +729	9-bit	512	218

5. Bits verses Odits:

Throughout this work the researcher will use the term Odit to refer to a single odd digit, in other words, (Odd digit) as Odit, same as Binary Digit which in short called Bit.

6. The model

One may start from the original algorithm with keeping the main ideas of learning and converging in the new model. Since the networks on two values only, i.e. bipolar values ±1, it is very convenience to consider the net as levels according to the number of colors that an image may have, as shown below:

Figure1. Oddness levels

As shown in Fig. 1, the amount of possible encoding colors is more than binary scheme. Therefore, it is possible to deal with any color level by encoding the available colors with the proper level or according the number of colors in an image. Table 1 illustrates the Oddness levels and the corresponding number of possible colors in an image that can be covered and encoded. See also the pixel depth that can be covered by this scheme.

The coding scheme is produced here from the summation of the vector elements, for example level #0 has the first classical model of HNN with only two values of bipolar (±1), while level #1 is derived from the possible values of #0 by performing the summation of vector elements of length 3.

Hence, #1 takes four values of pixel depth (±3, ±1), i.e. there are four possible colors can be encoded in this level. Level #2 has 10 values for encoding ten different colors. Extra levels are shown in Table 1. In addition, number of possible vectors and weights will also increase according to:

Number of vectors/weights = b3 (5)

For example level #0 has 2^3=8 possible cases of V and then for W, which agreed with the classical algorithm of

HNN. Level #1 possesses 4^3=64 cases of both of V and W, and so on. These numbers of levels at each level, make it is possible to expect the capability of the level to perform the learning and converging operations, and then one can cover all cases of V and W in each level with systematic regulation. To jump from lower level into higher one, the maximum and minimum probabilities can be taken to each level, for instance,

For all V of length 3,

Level #0 → ±1 then level#1 → ± 3, ± 1 and level#2 → ±9, ±7, ±5, ±3, ±1 and so on.

The architecture of Oddness associative memory is similar to the Hopfield model, as shown in Fig. 2.

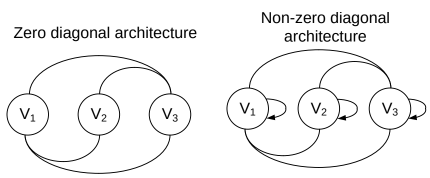

Figure 2. Oddness architectures

Generally, the distribution of odits can be achieved in two ways. The first is by knowing the depth of original image in binary. Hence the distribution follows the normal scheme in which the lower pixel value represents the lower value in the chosen level, as can be seen from Fig. 3. Note that the 4-bit, 16 colors take only a part of level #2. Whereas, the remaining odits are never used.

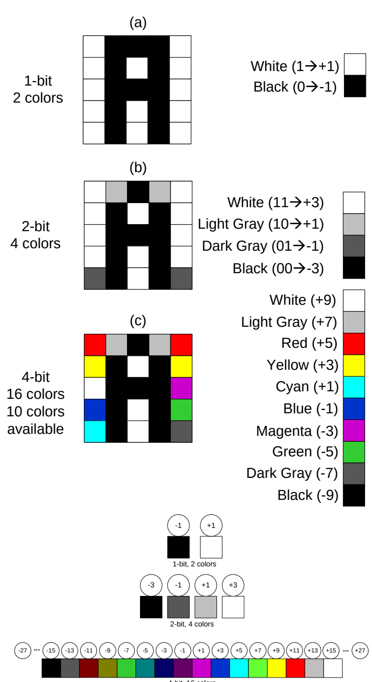

Figure 3. Examples of color encoding with odits, (a) level #0, (b) level #1, and (c) level #2, it has only 10 colors (d) color encoding based on pixel depth for levels #0, #1, and #2

The second way is to calculate the number of colors in the image rather than taking the pixel depth, this because not all images has covering all available colors. The advantage of this way is to allow the lower levels to be more reliable and convenience according to the nature of resented image. In addition, only the determined odits will be function which make the operations very simple and limited without losing in undesired iterations, see Figure 3 (b). In this work, the researcher will adopt the second way as empirically it is more efficient than the first one.

7. Encoding Algorithm

The encoding algorithm is given by

Algorithm *1*. Image bipolarization and quantization

Step 0 Read image I(x, y) where x=0,1,2,… is the width with length of m and y=0,1,2,… is the height with length of n.

Step 1 Read pixel depth in bits

Step 2 Read number of colors in the image

Step 3 Select Oddness level according to the number of colors

Step 4 Rearrange the pixels colors values in ascending order

Step 5 Set the values of pixels colors to the selected Oddness level

Figure 4 is an example showing the transformation from original sample of an image into Oddness encoding.

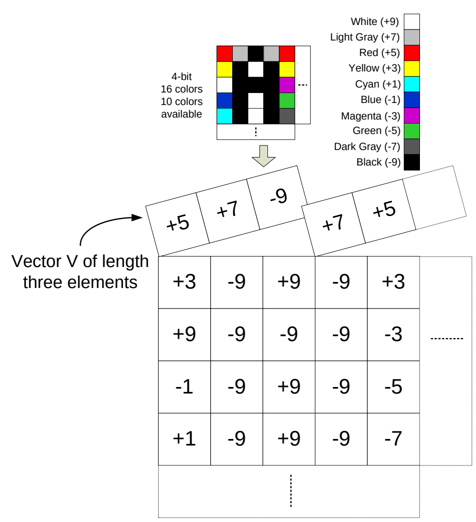

Figure 4. Color encoding of the example in Figure 3 (c)

8. Learning operation

This operation is same as level #0, hence, all levels in Oddness will use Heb rule to achieve the learning operation. For vector V of length 3 elements, the learning rule is:

$$W_{ij}^k = \sum_i \sum_j V_i^k V_j^k \qquad (6)$$

Table 2 shows the learning operation for the first seven levels of Oddness with modifications on each level. (Number of elements in V is 3).

9. Converging operation

This operation also uses the same procedure of Hopfield model. For vector V with length 3, the converging can be done by:

$$V_{out}(t+1) = \sum W_{ij} V_{out}(t) \qquad (7)$$

10. Conclusions

The important preliminary outcomes of the current work are represented by the advantages of using the new associative memory which based on Hopfield model for encoding high color images with any depth of pixels. In the encoding stage the number of colors can determine the proper level of the new technique. This leads to the ability of using the technique for compressing data easily along with the recognition operation.

Table 2. Learning in Oddness levels and the corresponding number of possible V and W

Level	Number of V	Learning formula	Number of W
#0	8	$W_{ij}^k = \sum_i \sum_j V_i^k V_j^k$	8
#1	64	$W_{ij}^k = \sum_i \sum_j V_i^k V_j^k$	64
#2	1000	$W_{ij}^k = \sum_i \sum_j V_i^k V_j^k$	1000
#3	21952	$W_{ij}^k = \sum_i \sum_j V_i^k V_j^k$	21952
#4	551368	$W_{ij}^k = \sum_i \sum_j V_i^k V_j^k$	551368
#5	14526784	$W_{ij}^k = \sum_i \sum_j V_i^k V_j^k$	14526784
#6	389017000	$W_{ij}^k = \sum_i \sum_j V_i^k V_j^k$	389017000

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