UTILIZING FUZZY RECOGNITION IN HOPFIELD NEURAL NETWORK IN RELATIVELY HIGH CORRUPTION SIGNAL TRANSMISSION

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Received 9 April 2013 Accepted 24 March 2014

ABSTRACT

This paper studies the utilization of fuzzy logic on pattern recognition sender after analyzing unknown pattern converged from associative. In order to specify the original patterns stored in memory. Results indicated that the addition of fuzzy stage to Hopfielf net to identify the unknown pattern called (FRS) was succeeded in differentiating and identifying unknown patterns were produced by "Hopfield neural network associative memory "(HNMAR) despite of the increasing in signal corruption to relatively high levels. It was demonstrated the possibility of rising the level of performance of memory type "Hopfield" where the signal corruption is at relatively higher percentage.

Key words: Fuzzy logic, linear associative Memory, Recurrent Neural Network, Hopfield Network, Corruption, Bipolar Transmission**.**

استخدام المنطق الضبابي في تحديد الأشكال التي لا يتم فيها التطابق عند تقارب شبكة الخلايا العصبية نوع ذاكرة الاقتران " هوبفيلد" في ظل تشوه عالي بالإشارة المرسلة نسبيا

الخلاصة

في هذا البحث يتم دراسة استخدام المنطق الضبابي في مرحلة الإخراج لشبكة الخلايا العصبية نوع ذاكرة الاقتران الخطي لغرض تحديد الشكل المستلم عندما تفشل الشبكة في إعادة تشكيل الشكل المرسل الأصلي المخزون ضمن الشبكة مع عدد آخر من الأشكال ,حيث تعمل المرحلة المضببة على تحليل الشكل الغريب المنتج من شبكة ذاكرة الاقتران وتقوم بإعطاء نسبة احتمالية لربط الرمز الغريب نسبتا لكل رمز من الأشكال المخزونة في الشبكة تبعا لقوانين مضببة يتم تصميمها بالاعتماد على الرموز والأشكال المخزونة، وقد ثبت من خلال النتائج نجاح المرحلة المضببة في معرفة وتحديد الرمز أو الشكل الغريب المرسل وتقريبه إلى إحدى الأشكال المخزونة داخل الشبكة وبشكل صحيح بالرغم من ارتفاع نسبة الضوضاء إلى الإشارة المرسلة نسبيا.

Nomenclature

Cl:	Column Index number
EP:	unknown pattern that produced at the output of Hopfield network after specific number of iteration when it received corrupted pattern with high percentage of noise
N	Number of the Bits
FRS:	The addition fuzzy stage that added to the Hopfield net to identify the unknown pattern
MF	fuzzy member ship relation
HD:	Humming Distance
HNRAM	Hopfield network recurrent associative memory
n	number of the neurons used in the network
p	number of the stored patterns in the study case
r:	the row index number in the patter
T	Fuzzy Value Of The Total Number Of Positive Ones In The Pattern
w	Weights connection matrix.

INTRODUCTION

There has been many studies on so-called Hopfield neural network and its variants **[1],[2].** The binary Hopfield network consists of N McCulloch-pitts neurons**[3]** t in which have two states : firing and quiescent, each neuron receives signals from its neighboring neurons and the signals are transmitted through synaptic weights, the neurons will be fired either if total input exceeds a threshold or remains quiescent otherwise **[4].** A hopfield network can be used as a content addressable memory (CAM). After asset of memory patterns are learned by the network, a presentation of a noisy in put causes the network to recall a memorized pattern in successful retrieval. Time independent sequences of spatial patterns **[5],[6],[7]** can also be stored and retrieved with Hopfield network.

Hopfield neural network is a form of recurrent artificial neural network. Hopfield nets serve as content –addressable memory system with binary threshold nodes **[8].**

They are guaranteed to converge to local minimum,-but amiss convergence to a false pattern rather than the stored pattern (expected local minimum) might be occurred. Furthermore, Hopfield networks provide a model for understanding human memory **[9,10].** Hopfield network is a suitable model for the associative memory of nervous system has a certain degree of vulnerability to noise and interference between stored patterns. The network fails to converge to a stored pattern when the initial state is deviated from the stored pattern by a certain degree of noise **[11].**

The corrupted initial state evolves to one of spurious patterns which are unintended stable state. The spurious patterns are a result of correlation between different stored patterns so it is questionable whether there is a relation between stored patterns and the noise effect. It is investigated how the noise tolerance changes when the number of stored patterns increases. It was demonstrated that the noise tolerance becomes poor. The percentage of correct convergence is highly decreased with increasing the percentage of corruption with fixed values of both HD and P, so that correct convergence rate drops about linearly with the amount of corruption on the key vector **[12].**

Therefore, it can be said that there is a tradeoff between the storage capacity and the noise tolerance in the Hopfield network. Seek how this tradeoff can be improved, and find that the orthogonally of stored patterns will guarantee the improvement **[13,14]**

SIMULATION OF THE SITUATION

A case investigated in this work different conditions of corruptions to converge to one of four stored prototype vectors represent the letters L,H,O,C as shown in **figure (1).**The number of the stored patterns and hamming distance will be will be constant.

Each litter is represented by 25 bipolar binary bits(+1.-1), and then the (FRS) has been design and implemented and then added in cascade with the (HNRAM) in order to recognize the output pattern where the (HNRAM) fails to converge to any of the stored patterns.

Construction of Traditional (HNRAM)

The proposed net consists of 25 bipolar threshold neurons since there is only one layer Hopfield recurrent net having number of neurons equal to a number of bits represents each stored pattern, the capacity of storage "P" for such net is given by $P \leq 0.14 \times 25$, $P \leq 3.75$

It is evidenced that the use this net to store four patterns stated before is slightly acceptable, the network contain 625 connection matrix (W).The network diagram is shown in **figure (2).**

Investigation Test -1

In this test the pattern L was transmitted under 24% of corruption the received corrupted pattern $\widetilde{L}$ as illustrated in **(fig 3-2)** then fed to (HNRAM), where

$\widetilde{L}$ =[-1+1-1-1+1-1+1-1-1-1-1-1-1+1+1+1+1-1-1-1-1+1+1-1+1], ………………………. (1)

After two iterations the (HNRAM) successfully give correct convergence to L stored pattern as shown in **(fig 3-3).** Pattern L is then re-transmitted but with higher percentage of corruption up to 36% as shown in (fig 4-2) where,

$\widetilde{L}$ = [+1+1-1-1+1-1+1+1-1-1-1-1-1+1+1+1+1-1+1-1-1+1+1-1+1]. ……………………………… (2)

When the corrupted pattern was presented at the input of (HNRAM) and after six iterations the net either it fails to converge the correct stored L pattern or the other three stored patterns It is attributed to high percentage of corruption. Instead of correct convergence the (HNRAM) produced at the output unknown pattern "EP" **(fig 4-3)**, and this pattern cannot be related to any one of the stored patterns yet, so that it is un useful where,

EP=[-1+1-1-1-1-1+1+1+1-1-1+1-1-1-1-1+1+1+1-1-1+1+1+1-1]. ………………………………..(3)

Investigation Test-2

The (HNRAM) in **(fig-2)** is again tested but with H pattern. In the same manner, **(fig 5-1)** shows the uncorrupted pattern whereas **fig (5-2)** presents the corrupted pattern $\tilde{\boldsymbol{H}}$ with percentage of corruption of 20%,

$\tilde{H}$= [+1-1+1-1+1-1-1-1-1-1+1+1-1+1+1+1-1-1-1+1+1-1+1-1+1] ……………………………….(4)

(HNRAM) was successfully recover the original stored H pattern shown in **(fig 5-3)** after 3 iterations

On the other hand, the same H pattern transmitted under higher percentage of corruption approach 32% as given in **(fig 6-2)** and presenting the corrupted pattern $\tilde{H}$ at input of the net, (HNRAM) failed to recover the stored H pattern or another stored one. However, after 6 iterations it converges to un known pattern (EP) shown in **(fig 6-3).**

EP=[+1-1+1+1+1+1-1-1-1+1+1-1+1+1+1+1-1-1-1+1+1-1-1-1+1]. …………………………….(5)

FUZZY RECOGNITION SOLUTION

The (EP) "unknown" recovered patterns given in test-1 and test-2 produced by the (HNRAM) shown in **fig (5-3)** and **fig (6-3)** when the transmitted patterns were corrupted with high degree of corruption 36% and 32% respectively. It is demonstrated that they cannot be related to any stored pattern or to be recognized. The objective of this work is to find a way that can make useful of these unknown patterns and recognize them by adding a fuzzy recognition stage (FRS) at the output of the (HNRAM) in order to reprocess these patterns and relate each one of them to the original stored pattern and finally make a correct recognition instead of correct convergence which (HNRAM) couldn't achieve. The (FRS) process mainly depends on the construction of the unknown pattern as it analyze the pattern into 11 element "inputs to the (FRS) system. These elements represent the total number of positive ones in hole pattern "the first input" and in each row "inputs 2,3,4,5,6" and in each column "inputs 7,8,9,10,11".The number of the outputs depends on the number of the stored patterns. In this case study four types are used "mamdani" fuzzy type and the centroid method will use to defuzzyfy output fuzzy values.

Realizing the Inputs for the (FRS)

The first input "input-T" represents the fuzz value of the total number of positive ones in hole pattern, from **(fig 1)** total **crisp** number of positive ones in each stored pattern is given by "L=8, H=13, C=13, O=16" so that the maximum and minimum limits are ~~is~~ given by: 8≤ total crisp number of positive ones in hole pattern≤16

Depending on that and with criteria by "4", **Fig (7)** shows the three proposed Gaussian fuzzy linguistic values to represent "input-T" given by

$4 \le T1 \le 12$ with crisp number=8, $9 \le T2 \le 17$ with crisp number=13, $12 \le T3 \le 20$ with crisp number=16.

Inputs 2,3,…..,6 represents the fuzzy value of total positive ones contained in each row "r1,r2,……,r5" in the pattern respectively .It is evidenced that in this work that each stored pattern consists of 5 rows and each row consists of 5 bits so that 0≤ crisp no. of total positive ones in the row "r"≤ 5 It is

suggested that six Gaussian fuzzy linguistic memberships"mf1,….,mf6" to represent rows inputs"r1,r2,r3,r4,r5", **(fig 8)** shows them for row1 and it is the same for other rows. Where: $0 \leq mf1 \leq 2$ with crisp number= 0, $0 \leq mf2 \leq 3$ with crisp number= 1, $0 \leq mf3 \leq 4$ with crisp number= 2, $1 \leq mf4 \leq 5$ with crisp number= 3, $2 \leq mf5 \leq 5$ with crisp number= 4, $3 \leq mf6 \leq 5$ with crisp number= 5, In the same manner inputs "7,8,…,11" for the (FRS) represents the fuzzy value of total number of positive ones in each column, here the patterns consists of 5 columns and each one has 5 bits so that :
0≤ crisp no. of total positive ones in the column "cl"≤ 5 and the same memberships shown in **(fig 8)** used before to represent rows will be used to represent the columns inputs "cl1,cl2,cl3,cl4,cl5".

Realizing the Outputs for the (FRS)

Since having four stored patterns and as it was aforementioned the (FRS) has four outputs, one for each stored pattern and it determines how much the stored pattern responds in fuzzy value according to fuzzy factors presented at the inputs of the (FRS) as it was given in **Fig (3-1).** The fuzzy value produced by each output will measure the similarity between this output "one of the stored pattern" and the analyzed factors of the unknown pattern that presents at the inputs. **Fig (9)** states three fuzzy linguistic memberships to represent the fuzzy value degree of priority relation for each output "L, H, C, and O" given by:
0.55≤ good ≤1.0 with crisp degree =1, 0≤ medium ≤1.0 with crisp degree =0.5,
0≤ poor ≤0.45 with crisp degree =0, The (**FRS**) is completed now and **fig (10**) shows general block diagram.

Design Fuzzy Rules

In (**FRS**) the outputs responds to the input according to a group of fuzzy conditional rules, these rules in somehow govern the degree of effectiveness that appears in each output with respect to the input factors, and hence they decide which output has the strongest priority relation with the input pattern, Number of rules depends on the degree of accuracy needed in the output and the amount of deference between output in this work there will be four rules each pattern at the output has its own rule, which will be sufficient to make a correct recognition in case study.

The proposed fuzzy linguistic memberships must be examined and the relation between them and the stored patterns must be studied In order to design these rules. On the one hand, **table 1**" states the relation between fuzzy linguistic memberships that represents the total number of positive ones in hole pattern "input T" And the storied patterns that represents the four outputs. On the other hand, **Table (2)** states the relation between fuzzy linguistic memberships that represents the total fuzzy number of positive ones in each row and column *"inputs 2,3,………,11"* and the four output stored patterns. From **(table 1)** it is significant to observe that when input T takes a fuzzy value within linguistic membership T1, there is no pattern at the output can take on except pattern "L", while in the linguistic membership T2 all patterns at the output can be energized except pattern "L" but both "C"and "H" has the highest effectiveness because total number of positive ones in these patterns is located at crisp number of T2 ="13" , in T3 the same as in T2 but this time pattern "O" has the highest effectiveness due to same reason stated before . in **Table 2** it can be seen that when sum of positive ones of row1 "input2" for " FRS" is within fuzzy linguistic membership mf1, only "L and H" can take on in the output because r1 in these patterns is bounded within mf1, the same thing is happen when r1 is within mf2 but pattern L this time has the highest effectiveness since that sum of positive ones in r1 for pattern L is equal to "1" and that is located at the crisp number of mf2, when r1 goes mf3, again only L and H patterns can be energized because O and C patterns have sum of positive ones not bounded within mf3, H pattern now has the highest effectiveness since that sum of positive ones in r1 for pattern H is 2 and it is equal to the crisp value in mf3, in mf4 all patterns can be taken on the consideration but no one of them can take priority. As r1 goes mf5 pattern L cannot be effected in the output because of the number of positive ones for r1 in this patter is 1 and it is unbounded within mf5, no pattern at the output has a priority, as r1 extended to mf6 the same patterns still affected but with

Priority to O and C patterns comes from that sum of positive ones in r1 for these patterns is 5 and it located at the crisp of mf6. As seen before each row and column in all patterns has priority in one of the fuzzy membership in table2 and each pattern has apriority in fuzzy membership in table1, these priorities "+" will help us to design the fuzzy rules, so to design the " rule of L pattern " that make L pattern is the winner at the output all options that satisfies priority "high effectiveness" for L pattern must be taken in account, the options that colored with blue in **tables 1 and 2** satisfies all possible priorities for L pattern given by:

"*IF Input T is T1 and r1 is* mf_2 *and* r_2 *is* mf_2 *and* r_3 *is* mf_2 *and* r_4 *is* mf_2 *and* r_5 *is* mf_5 *and cl1 is mf1 and* cl_2 *is* mf_6 *and* cl_3 *is* mf_2 *and* cl_4 *is* mf_2 *and* cl_5 *is* mf_2
THEN Pattern "L" is good and Pattern "H" is poor and Pattern "O" is poor and Pattern "C" is poor"

The degree of L pattern at the output depends on how many the input factors for the presented unknown pattern satisfies the conditions given in L pattern rule stated before. In the same way it can be design the other three rules depending on the rest priorities in the tables as follow: "Rule of H pattern"

"*IF Input T is* T_2 *and r1 is* mf_3 *and* r_2 *is mf3 and* r_3 *is mf6 and* r_4 *is* mf_3 *and* r_5 *is* mf_3 *and cl1 is mf6 and cl2 is mf2 and cl3 is mf2 and cl4 is mf2 and cl5 is mf6*
THEN Pattern "H" is good and Pattern "L" is poor and Pattern "O" is poor and Pattern "C" is poor"

"Rule of C pattern"

"IF Input T is T_2 *and r1 is* mf_6 *and* r_2 *is* mf_2 *and* r_3 *is* mf_2 *and* r_4 *is* mf_2 *and* r_5 *is* mf_6 *and cl1 is mf6 and cl2 is mf3 and cl3 is* mf_3 *and* cl_4 *is* mf_3 *and* cl_5 *is* mf_3
THEN Pattern "C" is good and Pattern "H" is poor and Pattern "O" is poor and Pattern "L" is poor"

"Rule of O pattern"

"*IF Input T is T3 and r1 is mf6 and r2 is mf3 and r3 is mf3 and r4 is mf3 and r5 is mf6 and cl1 is mf6 and cl2 is mf3 and cl3 is mf3 and cl4 is mf3 and cl5 is mf6*
THEN Pattern "O" is good and Pattern "H" is poor and Pattern "C" is poor and Pattern "L" is poor"

TESTING AND EVALUATION

In the test of the performance of " FRS", both unknown patterns produced from (HNRAM) as it is illustrated in **(fig 4-3)** and **(fig 6-3)** which will be examined with the proposed " FRS" in order to recognize them and then detect the original stored pattern that was meant by the transmission in each case.

Recognizing EP Pattern Given In Test-1

The unknown pattern given after convergence of (HNRAM) shown in (fig4-3) can be analyzed into factors

T =11, r1=1, r2=3, r3=1, r4=3, r5=3, cl1=0, cl2=5, cl3=3, cl4=3, cl5=0.

Presenting these inputs to "FRS" will produce results and priorities shown in **(fig 11)** and **(fig 12-a),** It is demonstrated that pattern" L" has the highest priority (75%), which means the original transmitted pattern was "L", and that is a correct truth .

Recognizing EP Pattern Given In Test-2

EP pattern is given in **fig (6-3)** to discover the original transmitted pattern. The factors of the pattern must be presented to " FRS",

T =14, r1=4, r2=2, r3=4, r4=2, r5=2, cl1=5, cl2=0, cl3=2, cl4=2, cl5=5.

Fig 13 and **fig 12-b** shows the results that state H pattern has the highest effectiveness priority (75%), means that original transmitted pattern was "H" and again the " FRS" succeeded to recognize the unknown recovered pattern.

CONCLUSIONS

It was concluded that Hopfield associative memory failed to recover the correct transmitted pattern when the transmission done under high percentage of corruption, However, adding fuzzy recognizing stage is possible to recognize the unknown pattern produced by (HNRAM), hence it improves the performance of (HNRAM) when the percentage of corruption about (32%-36%) by using "FRS". Consequently using such system will be more efficient in using with larger (HNRAM) that deals with larger number of stored patterns and larger number of bits that patterns consists of due to high number of uncovered patterns produced in such cases, so that using " FRS" lead to restore large number of distorted patterns.

FUTURE STUDIES

Recommendation for future works based on the investigations carried in this study can be drawn below

1- using more fuzzy rules in " FRS" and larger number of linguistic memberships, make it possible to increase the accuracy of performance and recognition given by fuzzy system, and lead to recognize patterns with larger percentage of corruption with higher accuracy.

2- In work" FRS", was succeeded in recognizing the unknown pattern with high corruption, but with modifications it can be study the possibility of " FRS" to help (HNRAM) recover the original transmitted pattern and not only recognize it in such Conditions of transmission

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Table (1): relation between fuzzy linguistic memberships that represents the total number of positive ones in hole pattern "input T" And the storied patterns that represents the four outputs.

Input T **Total fuzzy no. of positive ones**	**Output Storied pattern**
T1	L+
T2	C+ , H+ , O
T3	C , H , O+

Table (2): relation between fuzzy linguistic memberships that represents the total fuzzy number of positive ones in each row and column *"inputs 2, 3… 11"* and the four output stored patterns.

input index / fuzzy linguistic	Input 2 ROW1	Input 3 ROW2	Input 4 ROW3	Input 5 ROW4	Input 6 ROW5	Input 7 COLUMN1	Input 8 COLUMN2	Input 9 COLUMN3	Input 10 COLUMN4	Input 11 COLUMN5
MF1	L , H	C , O H , L	C , O L	C , O H , L	H	L+	C , O H	C , O H , L	C , O H , L	C , L
MF2	L+,H	C+,O H , L+	C+, O L+	C+, O H ,L+	H	L	C , O H+	C , O H+,L +	C , O H+,L +	C ,L+
MF3	L ,H+	C ,O+ H+, L	C ,O+ L	C ,O+ H+, L	H+,L	L	C+,O + H	C+,O + H , L	C+,O + H , L	C+, L
MF4	L , H C , O	C , O H , L	C , O H , L	C , O H , L	C , O H , L	C , O H	C , O H , L	C , O H , L	C , O H , L	C , O H , L
MF5	H , C O	O ,H	O , H	O , H	C , O H , L+	C , O H	C , O L	C , O	C , O	C , O H
MF6	H ,C+ O+		H+		C+,O + L	C+,O + H+	L+			O+,H +

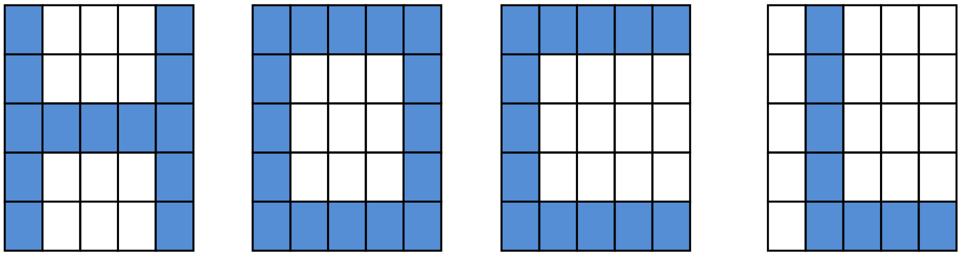


Figure (1): prototype patterns

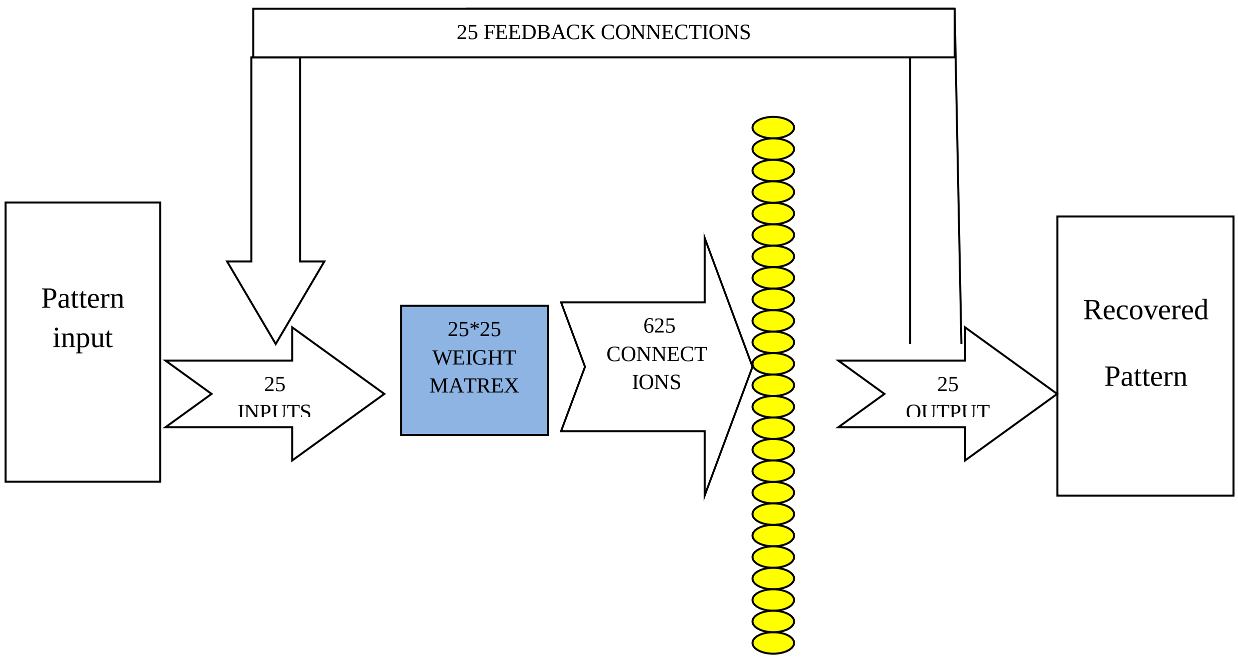
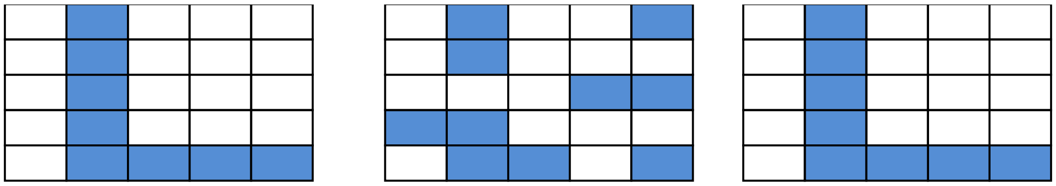


Figure (2): proposed Hopfield associative memory neural network.

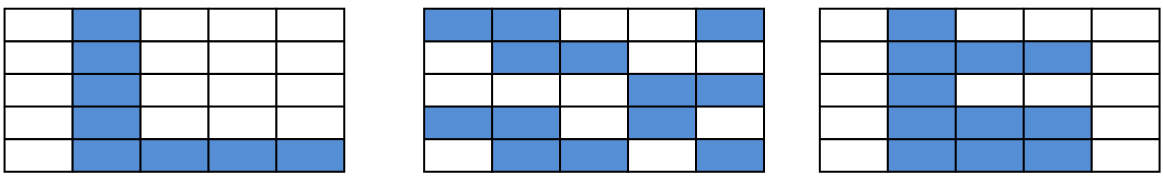
1 2 3



1- Transmitted "L" pattern
2- Received corrupted "$\widetilde{L}$" pattern with percentage of corruption =24%
3- The recovered pattern at the output of the Hopfield associative memory net after two iterations.

Figure (3): Reconstruction of Transmitted Prototype "L" under corruption with 24%

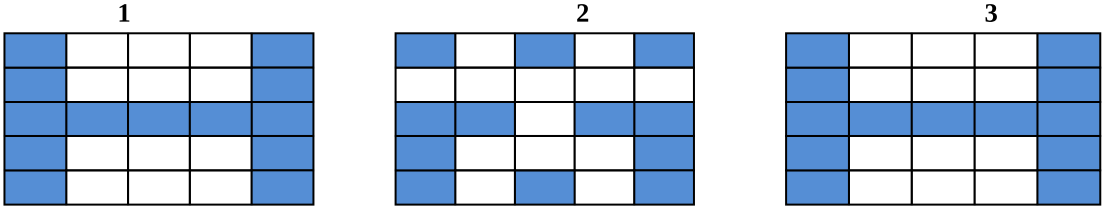
1 2 3



1- Transmitted "L" pattern
2- Received corrupted "$\widetilde{L}$" pattern with percentage of corruption =36%
3- The recovered unknown pattern (EP) at the output of the Hopfield associative memory net after six iterations.

Figure (4): Transmitting and Recovering "L" prototype under Corruption of 36%

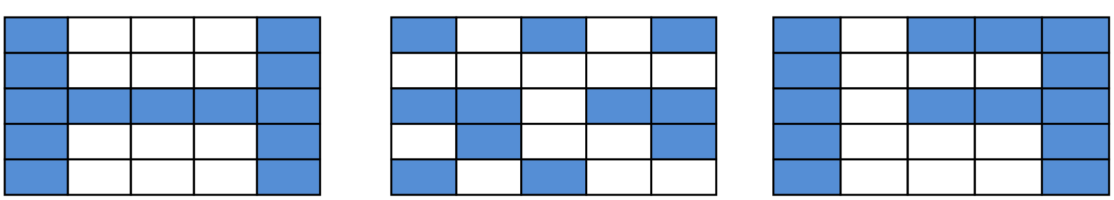
1 2 3



1- Transmitted "H" pattern
2- Received corrupted "$\widetilde{H}$" pattern with percentage of corruption =20%
3- The recovered pattern at the output of the Hopfield associative memory net after three iterations.

Figure (5): Transmitted and Recovery of "H" under corruption of 20%.

1 2 3



1- Transmitted "H" pattern
2- Received corrupted "$\widetilde{H}$" pattern with percentage of corruption =32%
3- The unknown pattern (EP) at the output of the Hopfield associative memory net after six iterations.

Figure (6): Transmitted and Recovery of "H" under Corruption of 32%.

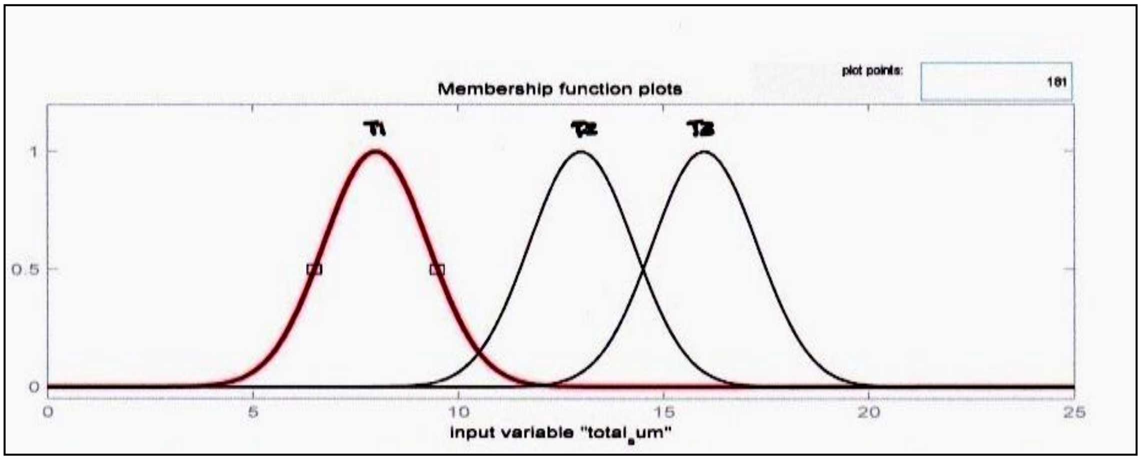


Figure (7): Proposed Gaussian fuzzy linguistic Values to represent "input-T".

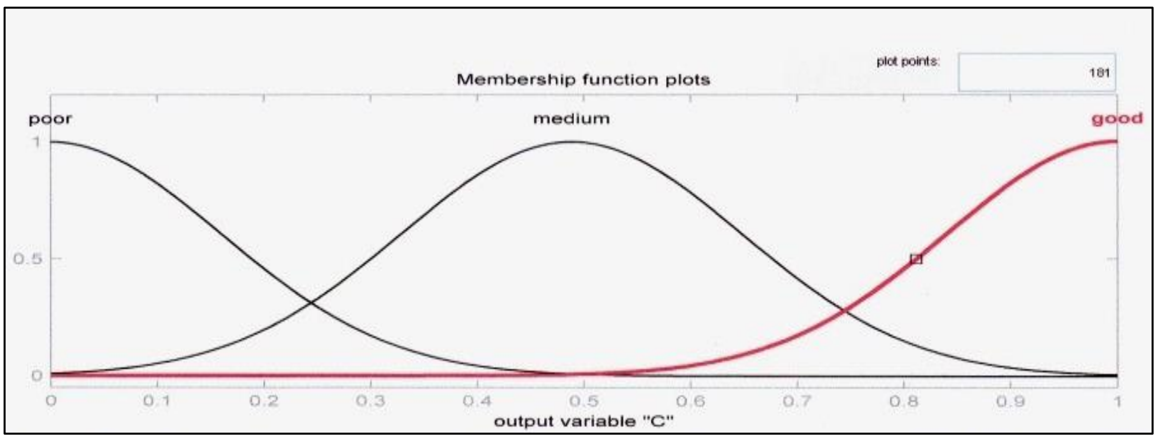


Figure (8): Gaussian fuzzy linguistic memberships to represent rows inputs"r1,r2,r3,r4,r5".

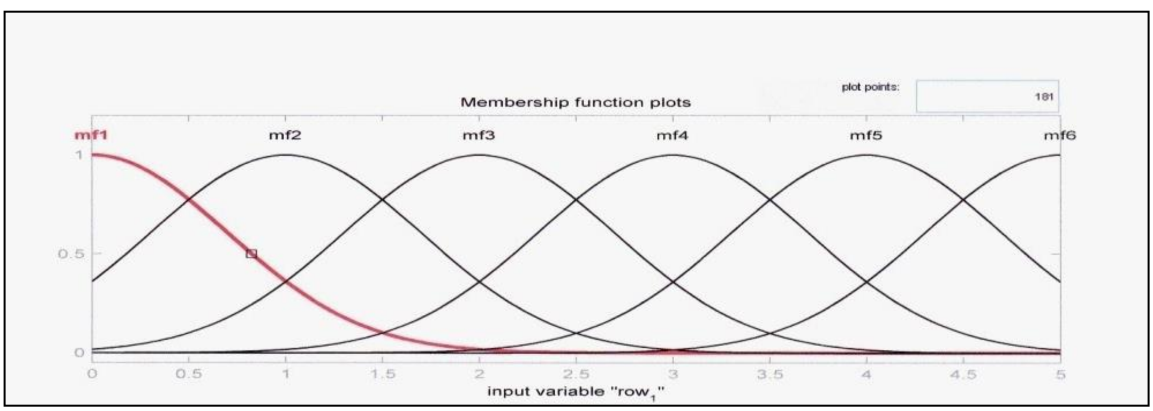


Figure (9): States Three Fuzzy Linguistic memberships to represent the fuzzy Value Degree of priority Relation for each output "L, H, C, and O"

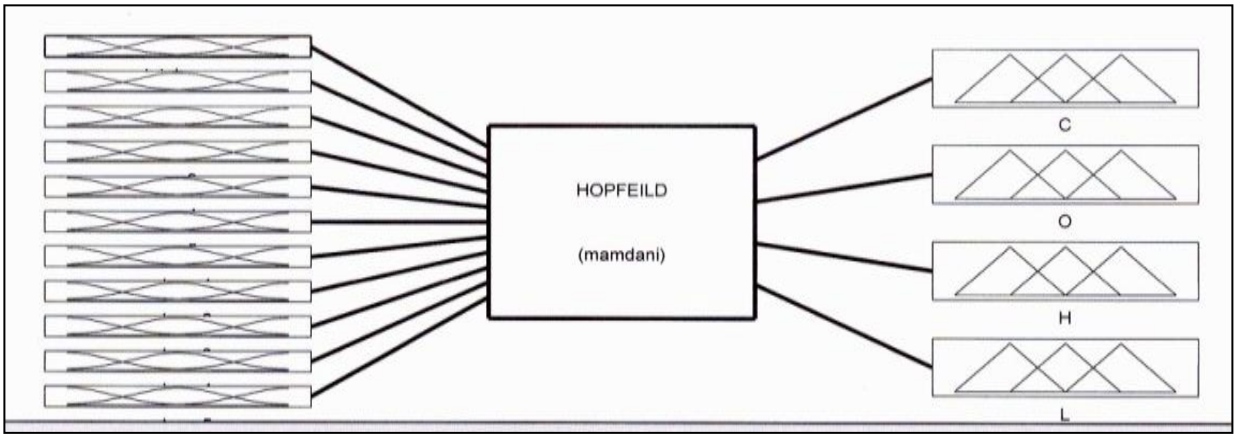


Figure (10): Complete Fuzzy identification stage.

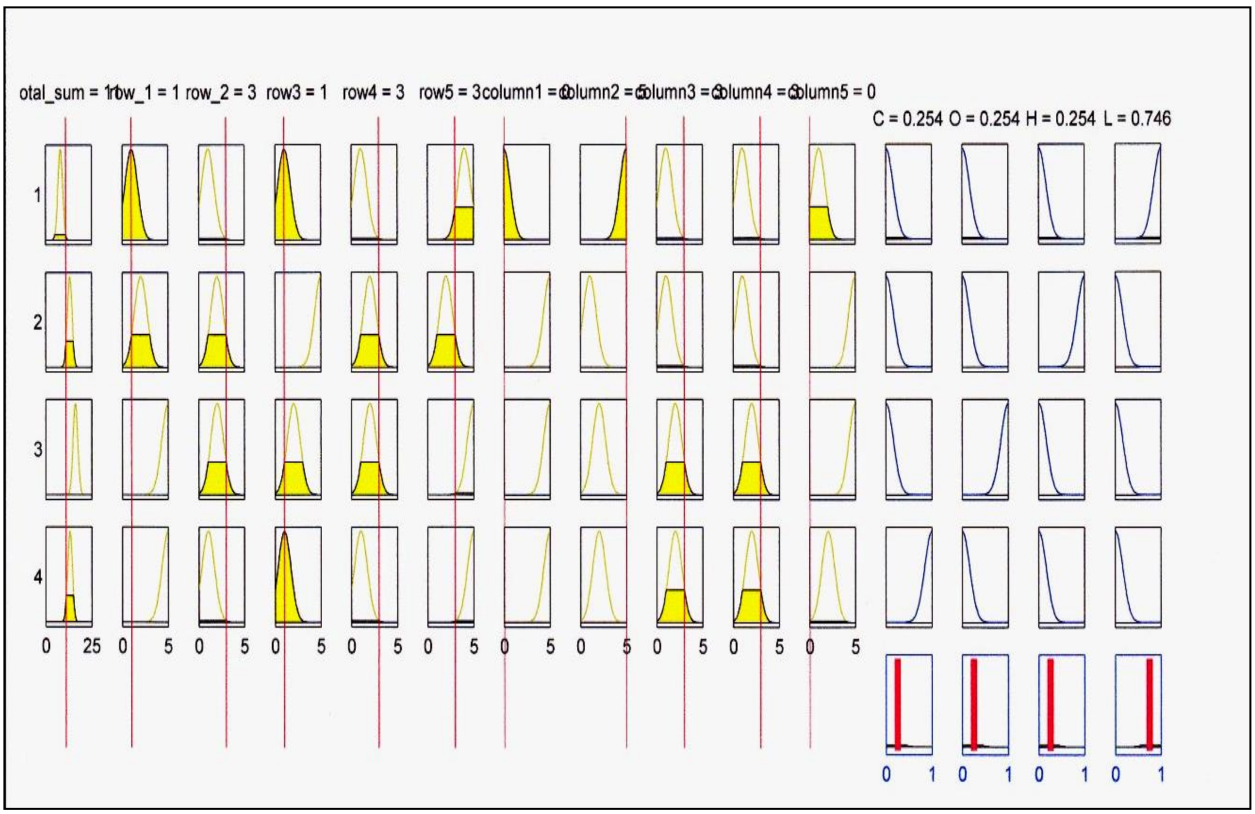


Figure (11): inputs to the "FRS" and priorities produced at the output of the system in the case of (fig4-3) "L" pattern.

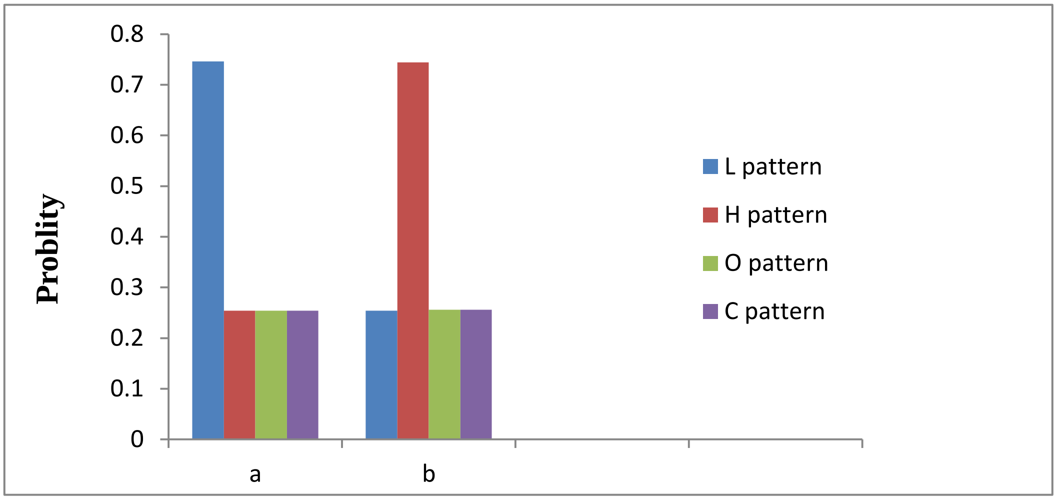


Figure (12): priority of identification at the FRS

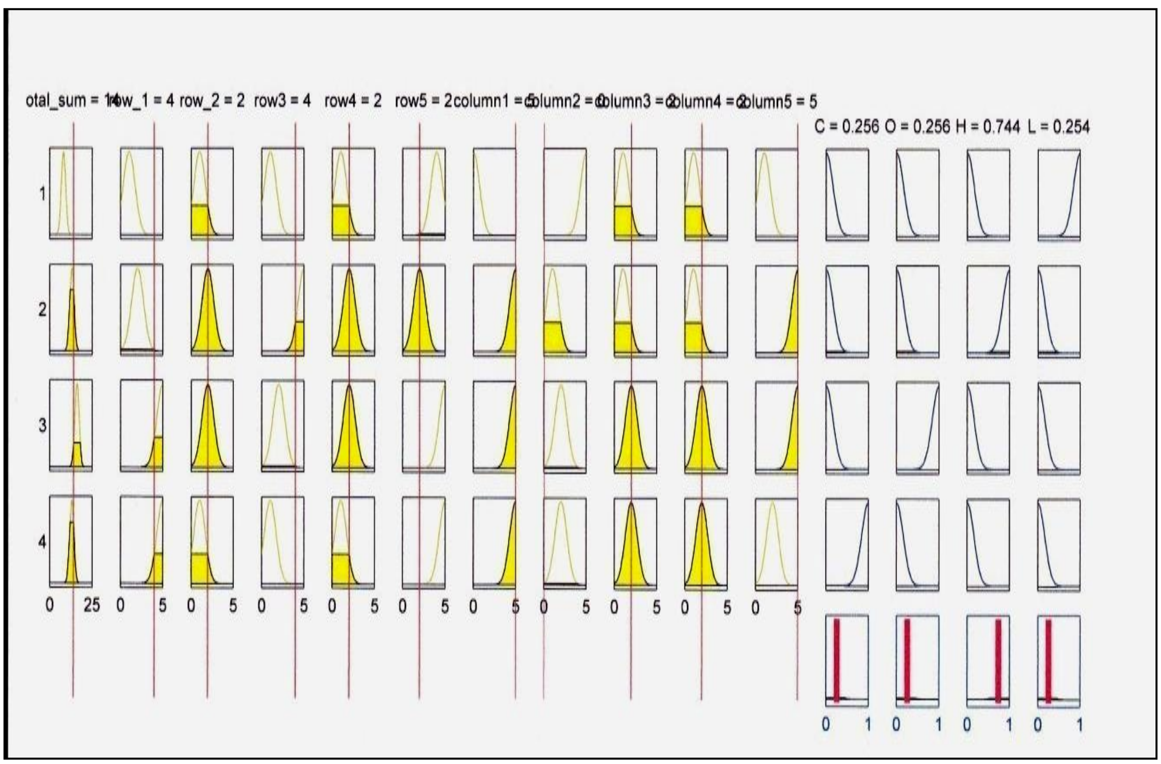


Figure (13): inputs to the "FRS" and priorities produced at the output of the system in the case of (fig6-3) "H" pattern.