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Short Paper

A Fast Winner-Take-All Neural Networks With the Dynamic Ratio

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In this paper, we propose a fast winner-take-all (WTA) neural network. The fast winner-take-all neural network with the dynamic ratio in mutual-inhibition is developed from the general mean-based neural network (GEMNET), which adopts the mean of the active neurons as the threshold of mutual inhibition. Furthermore, the other winner-take-all neural network enhances the convergence speed to become a decimal system. The proposed WTA neural networks statistically achieve the large ratio of mutual inhibition. The new WTA Neural Networks converge faster than the existing WTA neural networks for a large number of competitors based on both theoretical analyses and simulation results.

Keywords: winner-take-all, neural network, convergence speed, decimal system, mutual inhibition

1. INTRODUCTION

Neural networks have become a very popular field of research in cognitive science, neurobiology, computer engineering/science, signal processing, optics, and physics. This paper discusses a large variety of competitive learning networks, whose synaptic weights are adapted according to unsupervised learning rules. These models can learn in the absence of a teacher's guidance. One typical example of a lateral network is the winner-take all (WTA) circuit, which performs the important task of selecting the winner. In many well-known neural networks [1-10], the WTA process is required to select the nerve, which has the maximum activation or best correspondence to the input during learning or processing. These winner-take-all (WTA) neural networks [11-31] for selecting the largest element from a data set are key elements in competitive leaning. The MAXNET [26] which adopts heavy lateral inhibition is a famous winner-take-all (WTA) neural network. Recently, the general mean-based neural network (GEMNET) [30] with dynamically mutual inhibition has been developed based on the concept of the statistical mean to achieve fast convergence. The improved GEMNET [31] is a method to en-

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hance the convergence speed of GEMNET under the assumption of a known distribution of inputs. However, the convergence of the improved GEMNET [31] is not assured if the inputs don't belong to the class of the designated distribution.

In this paper, we propose a dynamic ratio winner-take-all neural network (DRNET) and a decimal speed winner-take-all neural network (DSNET) to further improve the convergence speed of mutually inhibited WTA networks. In section 2, the network structure of MAXNET [26], IMAXNET [27] and GEMNET [30] are briefly described. We will introduce the DRNET and the DSNET, which are theoretically designed to complete the WTA process, in section 3. In section 4, the convergence speed of DRNET and DSNET is discussed based on both theoretical analyses and simulation results. In addition, the convergence performance of DRNET and DSNET are compared with that of MAXNET [26], IMAXNET [27], and GEMNET [30].

2. MAXNET, IMAXNET AND GEMNET

2.1 MAXNET

If M competitive neurons with initial activations X_1, X_2, ..., and X_M are arranged in ascending order as $X_{<1>} \leq \ldots \leq X_{<M-1>} \leq X_{<M>}$, then $X_{<m>}$ is called the m^{th} least activation, where <m> carries the original index of the neuron. Thus, the first and second maximum activations can be expressed as $X_{<M>}$ and $X_{<M-1>}$, respectively. MAXNET [26] is a one-layer competitive architecture used to pick the winner, which is the one that has the maximum node value. MAXNET, depicted in Fig. 1, is a one-layer neural network with a feedback structure whose design mimics heavy use lateral inhibition of the human brain. In MAXNET, the connection weights between Node i and Node j are given by

$$W_{ij} = \begin{cases} 1 & i = j \\ -\varepsilon & i \neq j, \varepsilon < 1/M, and \quad 1 \leq i, j \leq M. \end{cases} \tag{1}$$

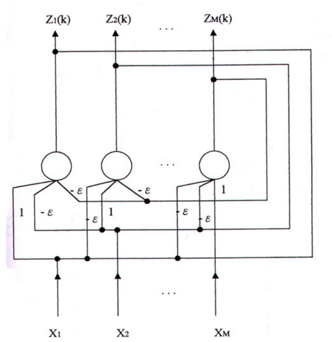

Fig. 1. The configuration of MAXNET.

The inputs of MAXNET [26] are initialized by X_1, X_2, ..., and X_M, and then iterate until only one node is positive. When ε is less than 1/M, it can be proven that MAXNET will converge. The most important advantage of MAXNET is its simple one-layer structure. However, its slow convergence speed, which largely depends on the distribution of activations and the number of competitors, is the main weakness of MAXNET.

2.2 IMAXNET

IMAXNET [27], shown in Fig. 2, can succeed when MAXNET values of the output decrease, then each other inhibitory will cause the decrease. The result will cause convergence to be slow. IMAXNET can get the effect of inhibition each other easily, and the output of the IMAXNET will decrease quicker than the MAXNET. Therefore, IMAXNET will achieve convergence more quickly than MAXNET. The connection weights of IMAXNET between node i and node j are as follows:

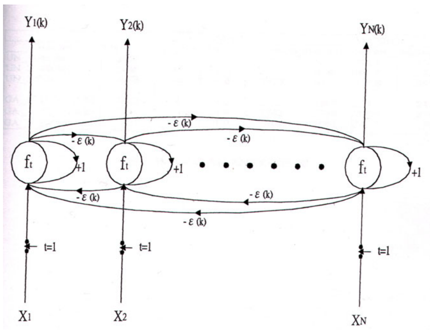

Fig. 2. Network model of IMAX.

$$W_{ij}(k) = \begin{cases} 1 & \text{if } i = j \\ -\dfrac{1}{M_I(k)} & \text{if } i \neq j \end{cases} \qquad 1 \le i, j \le M \tag{2}$$

where $M_I(k)$ denotes the number of active neurons in IMAXNET.

The main disadvantage of IMAXNET is that when the number of competitors is very large, the convergence speed of IMAXNET will be slow.

2.3 General Mean-Based WTA Neural Network (GEMNET)

The *ge*neral *m*ean-based WTA neural network (GEMNET) [30] has the same one-layer competitive neural network based on the concept that the maximum is always greater than the mean of activations. Thus, the connection weights between node i and node j in GEMNET, depicted in Fig. 3 are expressed as

$$W_{ij}(k) = \begin{cases} 1 & i = j \\ \dfrac{-1}{M_G(k) - 1} & i \neq j, 1 \leq i, j \leq M \end{cases} \tag{3}$$

where $M_G(k)$ denotes the number of active neurons in GEMNET. GEMNET with built-in dynamic thresholding outperforms MAXNET, which only uses fixed mutual inhibition. It is also obvious that the convergence speed is slow in GEMNET when there are many competitors. Thus, we will propose a fast WTA neural network to conquer a very large number of competitors.

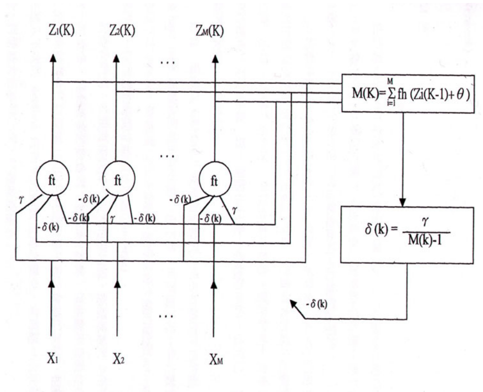

Fig. 3. The configuration of GEMNET.

3. FAST WTA WITH DYNAMIC RATIO AND DECIMAL SPEED

3.1 Fast WTA With Dynamic Ratio

It is noteworthy that the convergence performance of GEMNET is mainly governed by the important parameter $M_G(k)$. Theoretically, the mean threshold approach, which inhibits about one half of the currently active neurons, is too conservative to achieve fast WTA performance for a large number of competitors. Therefore, we can properly reduce $M_G(k)$ to increase the level of inhibition. Then, the convergence speed of mutual inhibition depicted in (3) will be further improved. The larger the threshold is, the more the inhibited neurons will be. To assure that the WTA process is alive, however, we should limit the threshold to a certain bound to keep the winning neuron active. DRNET actually performs thresholding as follows:

$$X_i(k) = \begin{cases} X_i(k-1) - \mu_F(k-1) & \text{if } X_i(k-1) - \mu_F(k-1) \geq 0 \\ 0 & \text{if } X_i(k-1) - \mu_F(k-1) < 0 \end{cases} \tag{4}$$

where

$$\mu_F(k) = \frac{1}{M_F(k) - N + 1} \sum_{i=active} X_i(k) \cdot \quad (5)$$

In order to enhance the convergence speed, it is obvious that the threshold of mutual inhibition should be given as $X_{<M-1>} \leqq \mu_F(k) < X_{<M>}$ so that we can inhibit all competitors except for the maximum one. To achieve the fastest possible convergence and avoid over-estimation, therefore, we suggest that $\mu_F(k) = E(X_{<M-N>})$. The threshold $\mu_F(k)$ should be equal to $E(X_{<M-N>})$ to avoid over-inhibition. Selecting a proper value of N is necessary to avoid over-inhibition.

According to order statistics [32], the expected of $X_{<K>}$ with M competitors is expressed as follows:

$$E[X_{<m>}] = M\binom{M-1}{m-1}\int_{-\infty}^{\infty} x[P(x)]^{m-1}[1-P(x)]^{M-m}\, dP(x), \quad (6)$$

where P(x) is the cumulative distributed function of activations. If activations are uniformly distributed between 0 and 1, the expectation for $X_{<m>}$ is

$$E[X_{<m>}] = M\binom{M-1}{m-1}\int_0^1 x x^{m-1}(1-x)^{M-m}\, dx = \frac{M\binom{M-1}{m-1}}{(M+1)\binom{M}{m}} = \frac{m}{M+1}. \quad (7)$$

The threshold of mutual inhibition can be obtained in the average sense by replacing $X_{<M-N>}$ with $E[X_{<M-N>}]$. At the first iteration, the proper selection for the ratio implies that the inhibition threshold is exactly equal to $\frac{M-N}{M+1}$. The probability of the neuron being inhibited is $p=\frac{M-N}{M+1}$. On the other hand, the probability of each neuron becoming active is $q=\frac{N+1}{M+1}$. For M neurons, the number of active neurons after the first DRNET process includes M+1 cases, which are $M_F(1) = i$ for i = 0, 1, 2, .., M-1, M. Based on Bernoulli's theorem, the probability that i neurons will remain active after the first DRNET iteration is equal to

$$P_i = \frac{M!}{i!(M-i)!}\left(\frac{M-N}{M+1}\right)^{M-i}\left(\frac{N+1}{M+1}\right)^{i} \quad (8)$$

When i = 0, it is

$$P_0 = \left(\frac{M-N}{M+1}\right)^M = \left(1 - \frac{N+1}{M+1}\right)^M \approx e^{-N} \quad \text{if } M >> N \quad (9)$$

Now, we will discuss the probability of over-inhibition when DRNET performs the complete WTA process with M-competitors. According to (8), it is obvious that P_0 denotes the probability of over-inhibition. If N = 1 and M = 1000, we find that the probability of over-inhibition in the first iteration is equal to 0.3679. When N is selected as 1, it is obvious that the probability of over-inhibition is very large. When N = 7 and M = 1000, we have $P_0 = 9.11*10^{-4}$. If N = 20 and M = 2000, we have $P_0 = 2.06*10^{-9}$. When N = 50 and M = 1000, we obtain $P_0 = 1.93*10^{-22}$. It is obvious that

When N = 50 and M = 1000, we obtain $P_0 = 1.93*10^{-22}$. It is obvious that the probability of over-inhibition depends on the parameter N and is independent of the parameter M in DRNET. If N is selected as 23, the probability of over-inhibition is less than 10^{-10}. We suggest that N should be larger than 23 to prevent DFRNET from encountering over-inhibition.

3.2 Decimal Speed WTA

In DSNET, if $M_D(k)$ denotes the number of the active neurons, we can design a ratio factor, N, which is equal to $\alpha M_D(k)$ to modify the connection weights as follows:

$$W_{ij}(k) = \begin{cases} 1 & \mathrm{i = j} \\ -\dfrac{1}{M_D(k) - N - 1} & \mathrm{i \neq j, 1 \leq i, j \leq M} \end{cases} \tag{10}$$

In other words, DSNET actually performs thresholding as follows:

$$X_i(k) = \begin{cases} X_i(k-1) - \mu_D(k-1) & \textit{if} \ \ \mathrm{X_i}(k-1) - \mu_D(k-1) \geq 0 \\ 0 & \textit{if} \ \ \mathrm{X_i}(k-1) - \mu_D(k-1) < 0 \end{cases} \tag{11}$$

where

$$\mu_D(k) = \frac{1}{M_D(K) - N} \sum_{i=active} X_i(k) \tag{12}$$

The parameter α plays an important role in controlling the convergence speed. When α is selected as 0.444, the convergence speed of DSNET is very close to that of the decimal system. At the first iteration, the proper selection for the decimal speed factor implies that the threshold for inhibition is exactly at $\frac{0.5M}{M-N}$. The probability of the neuron being inhibition is p = $\frac{0.5M}{M-N}$. On the contrary, the probability of each neuron of being active is only q = $\frac{0.5M-N}{M-N}$. For M neurons, the number of active neurons after the first DSNET includes M+1 cases which are $M_D(1)$ = i for I = 0, 1, 2, ..., M-1, M. According to the Bernoulli's theorem, the probability of i neurons being active is

$$P_i = C_i^M (p)^{M-i} (q)^i = \frac{M!}{i!(M-i)!} (\frac{0.5M}{M-N})^{M-i} (\frac{0.5M-N}{M-N})^i \tag{13}$$

When i = 0, it is

$$P_0 = (\frac{05M}{M-N})^M = (1 - \frac{0.5M-N}{M-N})^M \tag{14}$$

The natural logarithmic function of P_0 is

$$\ln P_0 = \ln(1-\frac{0.5M-N}{M-N})^M = M\ln(1-\frac{0.5M-N}{M-N}) \tag{15}$$

Since

$$\ln(1+x) = x - \frac{x^2}{2} + \frac{x^3}{3} - \frac{x^4}{4} + \ldots + (-1)^{n-1}\frac{x^n}{n} + \ldots, \tag{16}$$

we choose N = 0.444M_D(k) to set their connection weights in DSNET. Then, we can rewrite (15) as follows:

$$\ln P_0 = M\ln(\frac{-0.056M}{0.556M}) \cdot \tag{17}$$

If the decimal fraction is too small (i.e. $(0.01)^A$, A > 4), then we can further simplify (17) as follows:

$$\begin{aligned}\ln P_0 &= M\left\{(-\frac{0.056M}{0.556M}) - \frac{1}{2}(-\frac{0.056M}{0.556M})^2 + \frac{1}{3}(-\frac{0.056M}{0.556M})^3 + \ldots + (-\frac{1}{n})^{n-1}(-\frac{0.056M}{0.556M})^n + \ldots\right\}\\ &\approx M\left\{(-\frac{0.056M}{0.556M}) - \frac{1}{2}(-\frac{0.056M}{0.556M})^2 + \frac{1}{3}(-\frac{0.056M}{0.556M})^3\right\}\end{aligned} \tag{18}$$

It is obvious that we can approximately obtain

$$P_0 \approx \exp M\left\{(-\frac{0.056M}{0.556M}) - \frac{1}{2}(-\frac{0.056M}{0.556M})^2 + \frac{1}{3}(-\frac{0.056M}{0.556M})^3\right\} \approx \exp^{-0.10608M} . \tag{19}$$

Now, we will discuss the probability of over-inhibition when the practical DSNET attempts to achieve complete WTA with M-competitors. Based on (19), it is obvious that P_0 represents the probability of over-inhibition. When M = 200, we have P_0 = 6.1095*10^{-10}. If M = 1000, then we have P_0 = 8.5121*10^{-47}. If M = 2000, then we obtain P_0 = 7.2457*10^{-93}. If M is selected as 200, then the probability of over-inhibition is less than 10^{-10}.

4. CONVERGENCE ANALYSES

4.1 Fast WTA With Dynamic Ratio

In this section, we will discuss the convergence speed of DRNET and DSNET. As in the case of GEMNET, DRNET is entirely controlled by M_F(k-1), the number of active neurons. In other words, the neural updating process for the k^{th} step is completely dependent on the previous step M_F(k-1). It has been proven that GEMNET on average requires [30]

$$K = \mathrm{Log}_2(M) \tag{20}$$

iterations to achieve convergence for uniformly distributed competitors. If the initial activations are assumed to be uniformly distributed uniform in [0, 1], then we can also analyze the convergence performance of DRNET. If the threshold of DRNET is selected as E [$X_{<M-N>}$], then we can analyze the convergence speed of DRNET conservatively. The performance analysis is based on the statistical average of the first iteration. Then, after the first iteration, DRNET returns to perform GEMNET process to achieve stable WTA convergence. Now, we can discuss the average number of iterations required for the DRNET to complete the WTA process with M-competitors. It is obvious that DRNET on average requires

$$K = 1 + \mathrm{Log}_2(N) \tag{21}$$

iterations. Comparing (20) with (21), since N is much less than M, the result shows that the convergence speed of DRNET is higher than that of GEMNET if the number of competitors is very large. In other words, when M is much greater than N, the convergence speed of DRNET is superior to that of GEMNET.

4.2 Decimal Speed WTA

As DSNET, when M < 1000, the process of DSNET returns to perform GEMNET process in order to achieve stable WTA convergence. When the number of competitors is very large (M > 1000), DSNET requires

$$K_1 = \log_{10}(M)-\log_{10}(\gamma) \qquad \text{if } M \geqq 1000 \tag{22}$$

iterations. We assume that the number of remaining active neurons in DSNET is γ. Then after the K_1 iteration, when the number of competitors is smaller than 1000, DSNET returns to perform GEMNET for stable convergence. The remaining number of iterations required by DSNET to complete the WTA process is

$$K_2 = \log_2(\gamma) \qquad \text{if } \gamma < 1000 \tag{23}$$

iterations. In DSNET, we combine (22) and (23) to compute the convergence speed. Now, we can discuss the average number of iterations required by DSNET to complete the WTA process with M-competitors. It is obvious that DSNET on average requires

$$K = K_1 + K_2 = \log_{10}M- \log_{10}\gamma + \log_2\gamma \tag{24}$$

iterations. Comparing (20) with (24), if the number of competitors, M, is greater than 1000, then DSNET exhibits better convergence behavior than does GEMNET. DSNET has a faster decimal speed is faster than GEMNET in the case of distributed inputs.

5. SIMULATION

Various numbers of inputs with uniform distribution in [0,1] and normal distribution in [0,1] were randomly generated as the competitors to evaluate the WTA behavior of DRNET and DSNET. For different choices of N, Table1 shows the average number of iterations for 1000 WTA cases performed by DRNET in simulations. When the parameter N was less than 7, over-inhibition occurred in DRNET. Similar to Table 1, Table 2 shows the average number of iterations for 1000 WTA cases performed under different N factors by DRNET in simulations with normal distribution in [0, 1]. It is obvious that when N was greater than 15, the over-inhibition did not happen. Table 3 shows the average number of iterations required in GEMNET, MAXNET, IMAXNET, DRNET, and DSNET for completion of the WTA process with uniform distribution in [0, 1]. Table 4 shows the average number of iterations required in GEMNET, MAXNET, IMAXNET, DRNET, and DSNET for completion of the WTA process with normal distribution in [0, 1]. Table 3 and Table 4 show that DRNET achieved better convergence performance among others WTA when there was a large number of competitors. In additions, Table 3 and Table 4 show that the convergent rate of DSNET is higher than that of GEMNET, MAXNET and IMAXNET. In other words, Table 3 and Table 4 also show that DSNET achieves better convergence performance among others WTA when there was a large number of competitors.

Table 1. The average number of iterations required by DRNET under different N factors to complete the WTA process in U (0, 1).

DRNET	**N = 6**	**N = 7**	**N = 8**	**N = 15**
Distribution M	Uniform U(0,1)	Uniform U(0,1)	Uniform U(0,1)	Uniform U(0,1)
1000	OVER-inhibition	3.7465	3.9390	4.7490
2000	3.5170	3.7230	3.8760	4.7060
3000	OVER-inhibition	3.6710	3.8830	4.7480
4000	3.4670	3.6590	3.9030	4.7050
5000	3.4320	3.6530	3.8050	4.6980

Table 2. The average number of iterations required DRNET under different N factors to complete the WTA process in N (0, 1).

DRNET	**N = 13**	**N = 15**	**N = 20**	**N = 23**
Distribution M	Normal N(0,1)	Normal N(0,1)	Normal N(0,1)	Normal N(0,1)
1000	3.566	3.789	4.194	4.390
2000	OVER-inhibition	3.817	4.192	4.427
3000	OVER-inhibition	3.791	4.306	4.433
4000	3.612	3.843	4.306	4.444
5000	3.653	3.875	4.313	4.482

Table 3. Average number of iterations after 1000 independent runs required by GEMNET, HOSNET, MAXNET, IMAXNET, DRNET, and DSNET to achieve convergence under various distributed input (Uniform with (0, 1)).

WTA NETS	**GEMNET**	**MAXNET**	**IMAX-NET**	**DRNET N = 7**	**DSNET N=0.444M**
DISTRIBU-TION M	Uniform U(0,1)	Uniform U(0,1)	Uniform U(0,1)	Uniform U(0,1)	Uniform U(0,1)
1000	9.966	1000*	26.35	3.7465	7.418
2000	10.97	2000*	41.37	3.7230	8.398
3000	11.55	3000*	63.30	3.6710	9.026
4000	11.97	4000*	71.36	3.6590	9.418
5000	12.29	5000*	88.43	3.6530	9.698

*The number of iterations is more than M, the number of inputs.

Table 4. Average number of iterations after 1000 independent runs required by GEMNET, HOSNET, MAXNET, IMAXNET, DRNET, and DSNET to achieve convergence under various distributed input (Normal with (0, 1)).

WTA NETS	**GEMNET**	**MAXNET**	**IMAXNET**	**DRNET N = 15**	**DSNET N=0.444M**
DISTRI-BUTION M	Normal N(0,1)	Normal N(0,1)	Normal N(0,1)	Normal N(0,1)	Normal N(0,1)
1000	6.90	1066	8.42	3.789	5.011
2000	7.60	2000*	9.16	3.817	6.072
3000	8.04	3000*	9.60	3.791	6.689
4000	8.42	4000*	9.96	3.843	7.167
5000	9.19	5000*	10.28	3.875	7.533

*The number of iterations is more than M, the number of inputs.

6. CONCLUSIONS

Based on a fast ratio, we have developed DRNET and DSNET to improve the convergence performance of GEMNET, which is based on the mean-threshold WTA process. DRNET and DSNET, which obtain the highest threshold in mutual inhibition, show their superiority in the WTA process. Results of both theoretical analyses and simulation show that the convergence speeds of DRNET and DSNET are higher than that of the existing WTA structure if the number of competitors is very large.

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