'92 KACC 1992. 10. 19~21

# A Study on New Control Mechanisms of Memory

Haibin LIU and Yukinori KAKAZU

Department of Precision Engineering,Faculty of Engineering
Hokkaido University
N13-W8,Sappro,060,JAPAN

## Abstract

A physical phenomenon is observed through analysis of the Hodgkin-Huxley's model that is,according to Maxwell field equations a fired neuron can yield magnetic fields.The magnetic signals are an output of the neuron as some type of information,which may be supposed to be the conscious control information. Therefore,study on neural networks should take the field effect into consideration.Accordingly,a study on the behavior of a unit neuron in the field is made and a new neuron model is proposed. A mathematical Memory-Learning Relation has been derived from these new neuron equations,some concepts of memory and learning are introduced.Two learning theorems are put forward,and the control mechanisms of memory are also discussed. Finally,a theory,i.e. Neural Electromagnetic(NEM) field theory is advanced.

## 1 Introduction

In 1952 Hodgkin and Huxley analyzed the electric phenomena of excitation emergence and propagation of mono-neuron,and put them into mathematical form(Hodgkin-Huxleys equations)[Hodgkin&Huxley,1952].They thought of the brain as a giant network which consists of numerous neurons, and based on this view accounted for the dynamics of the electric phenomena of mono-neuron by physical and mathematical methods.Their research has made a great progress in neurobiology.

In this paper we make once more a further examination of their research, and find a physical phenomenon,i.e.a fired neuron can yield not only electric output signals but also magnetic output signals.We consider that the magnetic signals are also an important type of information distinct from the electric signals in information processing.The study on neural networks should take the effect of information of magnetic fields into consideration.According to this idea we propose a new neuron model,based on the McCulloch-Pitts' neuron model[McCulloch&Pitts,1943].With this model the mechanism of learning and memory is mathematically elucidated.Finally,Neural Electromagnetic Field Theory is suggested.

## 2 Two Types of Output Information of A Fired Neuron

### 2.1 Hodgkin-Huxley equations

In the paper[Hodgkin&Huxley,1952],Hodgkin and Huxley suggested that the electric behaviors of the membrane of a neuron may be represented by the network shown in Fig.1.

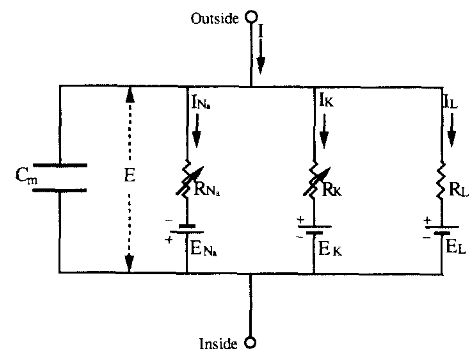


Figure 1. H-H's electric circuit representing membrane of mono-neuron, from the paper [Hodgkin& Huxley,1952].

The current can be carried through the membrane either by charging the membrane capacity or by movement of ions through the resistances in parallel with the capacity. They analyzed the properties of the membrane and divided the total membrane current into a capacity current and an ionic current.Thus a mathematical description of membrane current during a voltage clamp was made.The description was Hodgkin-Huxleys equations:

$$I = C_M \frac{dV}{dt} + \bar{g}_K n^4 (V - V_K) + \bar{g}_{Na} m^3 (V - V_{Na}) + \bar{g}_l (V - V_l) \quad (1)$$

where

$$\frac{dn}{dt} = \alpha_n(1-n) - \beta_n n \quad (2)$$

$$\frac{dm}{dt} = \alpha_m(1-m) - \beta_m m \quad (3)$$

$$\frac{dh}{dt} = \alpha_h(1-h) - \beta_h h. \quad (4)$$

where I is the total membrane current density,V is the displacement of the membrane potential from its resting value,$C_M$ is the membrane capacity,$V_{Na}$ and $V_K$ are the displacements of the sodium and potassium potentials from the resting values,$V_l$ is the displacement of the potential at which the 'leakage current' due to chlorde and other ions is zero from the resting value,the $\bar{g}'s$ are constants,the $\alpha's$ and $\beta's$ are functions of V but not t,and n,m and h are dimensionless variables which can vary between 0 and 1.

Their mathematical model properly accounted for the dynamics of electric phenomena of mono-neuron.

### 2.2 A Fired Neuron Can Yield Magnetic Fields

Hodgkin-Huxleys' electric network can be made an equivalent change shown in Fig.2.In this network we let J be an ionic current,$\boldsymbol{j}$ be a capacity current or displacement current,$\boldsymbol{D}$ be electric flux density of the capacity.When the neuron is fired(whether passive or active), the variation of the electric potential is about 100mv during about 1ms.The variation is so great that we can not ignore the magnetic field yielded by the electric field.According to Maxwell field equations the electric circuit can yield a magnetic field,and the magnetic field strength will be $\boldsymbol{H}$:

$$rot\boldsymbol{H} = \boldsymbol{j} + \frac{\partial \boldsymbol{D}}{\partial t} \tag{5}$$

However,if the neuron is not fired,the magnetic field strength is so small that we can ignore it.From the analysis above we can conclude that when a neuron is fired,together with the electric field,a magnetic field will be yielded.It means that a fired neuron can yield two distinct types of output,i.e.one type is electric signals,the other is magnetic signals. As two types information,we think their function is different in information processing.Therefore,we should reconsider the study of neural networks and take these two distinct types information together into consideration.

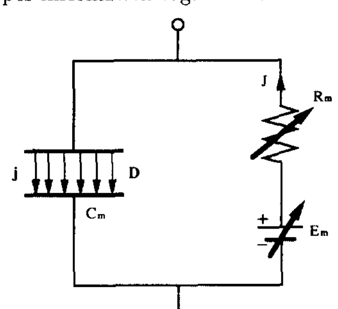


Figure 2. An equivalently transformed circuit of H-H's electric circuit of mono-neuron. **J** is an ionic current, **j** is a capacity current, **D** is electric flux density of the capacity. Cm is the membrane capacity,Rm is the membrane resistence ,Em is the membrane potential.

## 3 Neuron Model

### 3.1 Features of the Behavior of a Neuron

(1) Input signals

The input signals can be divided into electric input signals and magnetic input signals.The electric input signals are electric impulses through the synapses from other fired neurons.The magnetic input signals are magnetic impulses from other fired neurons.

(2) Excitation

When the input signals arriving at the neuron, the membranous electric potential and membranous magnetic potential will be changed by the effect.If the membranous electric potential exceeds some specific value(threshold value,about -55mv), the neuron is fired and electric potential will automatically and rapidly rise up during about 1 ms. After that,the electric potential will quickly decrease and return to the resting state.At the same time, with the changing of the electric potential the membranous magnetic potential is also changed.This changing process described above is called Excitation of the neuron.

(3) Threshold

If the membranous electric potential exceeds a specific value,the neuron can yield electric output signals.Otherwise the neuron can not.The specific value is defined as Threshold.However,for magnetic output signals there is no threshold.

(4) Output signals

The output signals can be divided into electric output signals and magnetic output signals.When a neuron fired, it can yield eletric output signals and magnetic output signals. But evenif a neuron is not fired, it also can yield magnetic output signals.

(5) Fatigue

When a neuron is continualy made be excited,the threshold is gradually getting bigger, and it will be difficult for the neuron to be fired again in a short time.This phenomenon is called Fatigue.

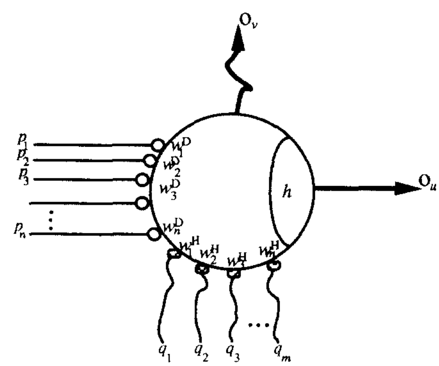


Figure 3. A conceptual neuron model.[$p_1$ ,$p_2$ ,...,$p_n$] are electric input signals;$w_i^D$ is synaptic efficiency, [$q_1$,$q_2$,...,$q_m$] are magnetic input signals; $w_j^H$ is hebbian efficiency;$O_u$ is electric output signals; $O_v$ is magnetic output signals; h is threshold.

### 3.2 Neuron Equations

First,based on McCulloch-Pitts' neuron model [McCulloch&Pitts,1943] we describe the main features analyzed above as a conceptual model shown in Fig.3. Second,by using Maxwell field equations and Faraday's rule we put the conceptual model into mathematical form.The mathematical neuron model is proposed as follows:

$$\tau_u \frac{du(t)}{dt} = -u(t) + \sum_{i=1}^{n} w_i^D p_i - \mu \sum_{j=1}^{m} \frac{d(w_j^H q_j)}{dt} - \mu \frac{dv(t)}{dt} - h \quad (6)$$

$$\tau_v \frac{dv(t)}{dt} = -v(t) + \epsilon \sum_{i=1}^{n} w_i^D p_i + \sum_{j=1}^{m} w_j^H q_j + \epsilon u(t) \quad (7)$$

$$O_u = f_u[u(t)] \quad (8)$$

$$O_v = f_v[v(t)] \quad (9)$$

where

$p_1, p_2, \ldots, p_n$ are electric input signals through the synapses from n fired neurons;

$q_1, q_2, \ldots, q_m$ are magnetic input signals from m fired neurons in wave forms;

u(t) is variation of the membranous electric potential in terms of time;

v(t) is variation of the membranous magnetic potential in terms of time;

$O_u$ is electric output signals of the neuron,and propagates through the axons of the neuron to other neurons;

$O_v$ is magnetic output signals of the neuron,and travels in wave forms;

h is threshold;

$w_i^D$ is synaptic efficiency or synaptic weight connected with i neuron;

$w_j^H$ is hebbian efficiency or learning weight connected with j neuron;

$\mu$ is magnetoelectric coefficient;

$\epsilon$ is electromagnetic coefficient;

$\tau_u$ is constant in terms of time;

$\tau_v$ is constant in terms of time;

t is excited time of the neuron.

This new neuron model is an information processing model and implies the relation between memory and learning.In the following,the input electric signals are assumed to be perception information,and the output electric signals to be action information.And also the magnetic signals are assumed to be conscious information.The action information has a direct concern in the learning target.However,the conscious information,which is regarded as control information,has an indirect concern in the learning target.In fact the model is a three-dimensional model as well. $q_j$ and v(t) are potential functions in a three-dimensional field.However,since $p_i$ and u(t) are carried through the nets,it is unnecessary to express them as field form.Therefore,the neuron equations also can be represented as:

$$\tau_u \frac{du(t)}{dt} = -u(t) + \sum_{i=1}^{n} w_i^D p_i - \mu \sum_{j=1}^{m} \frac{\partial[w_j^H q_j(x,y,z,t)]}{\partial t} - \mu \frac{\partial v(x,y,z,t)}{\partial t} - h \quad (10)$$

$$\tau_v \frac{\partial v(x,y,z,t)}{\partial t} = -v(x,y,z,t) + \epsilon \sum_{i=1}^{n} w_i^D p_i + \sum_{j=1}^{m} w_j^H q_j(x,y,z,t) + \epsilon u(t) \quad (11)$$

The neuron equations can be regarded as the basis of Neural Electromagnetic Field Theory.

# 4 Memory–Learning Relation

## 4.1 Derivation of Memory–Learning Relation

We can convert $\sum_{i=1}^{n} w_i^D p_i$ and $\sum_{j=1}^{m} w_j^H q_j$ in the neuron equations into vector form.Thus,the neuron equations will be

$$\tau_u \frac{du}{dt} = -u + \boldsymbol{PW}^D - \mu \frac{d(\boldsymbol{QW}^H)}{dt} - \mu \frac{dv}{dt} - h \quad (12)$$

$$\tau_v \frac{dv}{dt} = -v + \epsilon \boldsymbol{PW}^D + \boldsymbol{QW}^H + \epsilon u \quad (13)$$

where

$\boldsymbol{P} = [p_1, p_2, \ldots, p_n]$;

$\boldsymbol{Q} = [q_1, q_2, \ldots, q_m]$;

$\boldsymbol{W}^D = [w_1^D, w_2^D, \ldots, w_n^D]^T$;

$\boldsymbol{W}^H = [w_1^H, w_2^H, \ldots, w_m^H]^T$.

Assuming that u is definite and does not vary with time,eqns.(12) and (13) can be changed as

$$0 = -u + \boldsymbol{PW}^D - \mu \frac{d(\boldsymbol{QW}^H)}{dt} - \mu \frac{dv}{dt} - h \quad (14)$$

$$\tau_v \frac{dv}{dt} = -v + \epsilon \boldsymbol{PW}^D + \boldsymbol{QW}^H + \epsilon u \quad (15)$$

Solving the two eqns.(14) and (15)we can obtain an equation

$$(\tau_v - \epsilon\mu)\boldsymbol{PW}^D = (\tau_v + \epsilon\mu)u - \mu v + \tau_v \mu \frac{d(\boldsymbol{QW}^H)}{dt} + \mu \boldsymbol{QW}^H + \tau_v h \quad (16)$$

Let $\tau_v - \epsilon\mu = \alpha$ and $\tau_v + \epsilon\mu = \beta$ ,we get

$$\tau_v = \frac{1}{2}(\beta + \alpha) \quad (17)$$

$$\epsilon\mu = \frac{1}{2}(\beta - \alpha) \quad (18)$$

Eqn.(16) may be written as

$$\alpha \boldsymbol{PW}^D = \beta u - \mu v + \tau_v \mu \frac{d(\boldsymbol{QW}^H)}{dt} + \mu \boldsymbol{QW}^H + \frac{1}{2}(\alpha + \beta)h \quad (19)$$

By differentiation with respect to eqn.(19),we can get the differential form:

$$\alpha \boldsymbol{P} \frac{d\boldsymbol{W}^D}{dt} = -\mu \frac{dv}{dt} + \mu \frac{d(\boldsymbol{QW}^H)}{dt} + \tau_v \mu \frac{d^2(\boldsymbol{QW}^H)}{dt^2} \quad (20)$$

Equation(20) can be defined as Memory-Learning Relation(MLR). In the MLR $\alpha$ is memory factor($\alpha > 0$),$\mu$ is learning factor($\mu > 0$),and $\tau_v \mu$ is confusing factor($\tau_v > 0$). From the MLR we can conclude that the relation between memory and learning is expressed through the neurons magnetic fields and a neuron has learning abilities.The MLR can be called Learning Rule in the NEM field theory.

An attention should be paid to the condition assumed that u is definite and does not vary with time.This means that when learning target is decided in the learning process,variable u,which has a direct relation with the learning target,can be made as a fixed function which has no concern with time.v and $O_v$ have an indirect relation with the learning target as mentioned above.

### 4.2 Concepts

(1). Memory is the synaptic plasticity or the modification of synaptic efficiencies of a neuron.And therefore memory is a time-dependent process structure;

(2). Memory Consolidation Rate is the variation rate of synatic efficiencies of a neuron;There are no long-term memory or short-term memory;

(3). Memory Capacity is the number of synaptic connections which a neuron has;

(4). Learning is a process that is caused by the input signals and attempts to make the synaptic efficiencies of a neuron change.Learning consists of Reflex learning,Associative learning,and Union learning;

(5). Reflex learning is a process that is caused only by the electric input signals and attempts to make the synaptic efficiencies of a neuron change;

(6). Associative learing is a process that is caused only by the magnetic input signals and attempts to make the synaptic efficiencies of a neuron change;

(7). Union learning is a process that is caused by the electric input signals and magnetic input signals and attempts to make the synaptic efficiencies of a neuron change;

(8). Learning is a medium,a process; Memory is a result,a state;the state is a process record;

(9). A neuron has learning abilities,and the nervous system has the parallel distributed processing functions.

(10). Remembering Process is a process that even when a neuron is fired,the synaptic efficiencies($w_i^D$)have not any changes;i.e.a process that existent information which the neuron has is reproduced.

(11). Memorizing Process is a process that when a neuron is fired,the synaptic efficiencies($w_i^D$)are changed;i.e.a process that for the neuron an existent information state is changed into a new information state;

## 5 Learning Theorem

### 5.1 Reflex learning theorem

**Definition 5.1** *Reflex learning is a process that is caused only by perception information (the electric input signals) and attempts to make the synaptic efficiencies of a neuron change.*

By this definition,in case of Reflex learning the neuron equations will be

$$\tau_u \frac{du}{dt} = -u + \boldsymbol{P}\boldsymbol{W}^D - \mu\frac{dv}{dt} - h \tag{21}$$

$$\tau_v \frac{dv}{dt} = -v + \epsilon \boldsymbol{P}\boldsymbol{W}^D + \epsilon u \tag{22}$$

and the Learning Rule be

$$\alpha \boldsymbol{P}\frac{d\boldsymbol{W}^D}{dt} = -\mu\frac{dv}{dt} \tag{23}$$

**Theorem 1** *For a neuron if the learning target A is decided,according to the Reflex learning Rule $\alpha \boldsymbol{P}\frac{d\boldsymbol{W}^D}{dt} = -\mu\frac{dv}{dt}$,for Reflex learning which has the learning result A to exist it is necessary and sufficient that the Memory function be*

$$\boldsymbol{P}\boldsymbol{W}^D(t) = (h+A)(1-e^{-\frac{t}{\alpha}}) + M_e e^{-\frac{t}{\alpha}},$$

$$\left(\boldsymbol{P}\boldsymbol{W}^D(t)\big|_{t=0} = M_e\right).$$

*where:*
*A:learning target;*
*h:threshold;*
$\boldsymbol{P} = [p_1, p_2, \ldots, p_n]$*: perception information;*
$\boldsymbol{W}^D = [w_1^D, w_2^D, \ldots, w_n^D]^T$*: synaptic efficiencies;*
$M_e$*: memory consolidation function;*
*n: memory capacity;*
$\alpha$*: memory factor;*
$\mu$*: learning factor;*
*t: excited time of the neuron.*

In general,after learning the output information of the neuron is
action information:

$$O_u = A + (M_e - h - A)e^{-\frac{t}{\alpha}} \tag{24}$$

conscious information:

$$O_v = \epsilon(2A+h) + \epsilon(M_e - h - A)e^{-\frac{t}{\alpha}} \tag{25}$$

learning error:

$$e = \left|(M_e - h - A)e^{-\frac{t}{\alpha}}\right| \tag{26}$$

memory consolidation function:

$$M_e(t) = (h+A)(1-e^{-\frac{t}{\alpha}}) + M_e e^{-\frac{t}{\alpha}} \tag{27}$$

where $\alpha$ is memory factor($\alpha > 0$),and $\epsilon$ is electromagnetic coefficient.

The expressions above are called Reflex learning Formulas.

DISCUSSION 1

Memory consolidation function $M_e$ is a state function.It shows the current state of the MEMORY,and has a close relation to the learning time.Based on Theorem 1,we understand that the contents of the memory can be updated in a learning process.The change of memory is controlled by a new control mechanism different from the traditional control theory,such as feedback control theory. The control mechanism lies in that the unit neuron itself has two different types information as stated above,which have different function in information processing,so that the neuron has a self-control (or autonomous) function.In fact,the mechanism of traditional control theory is an "external" control mechanism,i.e.the state of controlled object is changed only by the external control information,and the controlled system or object itself has no self-control function or autonomous function. We think this is the difference between this new control mechanism and the traditional control theory.In a sense,the study of artificial intelligence depends on the development of the control theory.

**Definition 5.2** *If Memory consolidation function is $M_e = h + A$,Reflex learning which has the learning result A is defined as Self-remembering process.*

## 5.2 Union learning theorem

**Definition 5.3** *Union learning is a process that is caused by perception information(the electric input signals) and conscious information(the magnetic input signals) and attempts to make the synaptic efficiencies of a neuron change.*

By this definition,in case of Union learning the neuron equations will be

$$\tau_u \frac{du}{dt} = -u + \boldsymbol{P}\boldsymbol{W}^D - \mu \frac{d(\boldsymbol{Q}\boldsymbol{W}^H)}{dt} - \mu \frac{dv}{dt} - h \tag{28}$$

$$\tau_v \frac{dv}{dt} = -v + \epsilon \boldsymbol{P}\boldsymbol{W}^D + \boldsymbol{Q}\boldsymbol{W}^H + \epsilon u \tag{29}$$

and the Learning Rule be

$$\alpha \boldsymbol{P} \frac{d\boldsymbol{W}^D}{dt} = -\mu \frac{dv}{dt} + \mu \frac{d(\boldsymbol{Q}\boldsymbol{W}^H)}{dt} + \tau_v \mu \frac{d^2(\boldsymbol{Q}\boldsymbol{W}^H)}{dt^2} \tag{30}$$

**Theorem 2** *For a neuron if the learning target A is decided,according to the Union learning Rule $\alpha \boldsymbol{P}\frac{d\boldsymbol{W}^D}{dt} = -\mu\frac{dv}{dt} + \mu\frac{d(\boldsymbol{Q}\boldsymbol{W}^H)}{dt} + \tau_v\mu\frac{d^2(\boldsymbol{Q}\boldsymbol{W}^H)}{dt^2}$, for Union learning which has the learning result A to exist it is necessary and sufficient that the Memory function be*

$$\boldsymbol{P}\boldsymbol{W}^D(t) = (h + A)(1 - e^{-\frac{t}{\alpha}}) + \left[M_e + \tfrac{\mu}{\alpha}\textstyle\int H(t)e^{\frac{t}{\alpha}}dt\right]e^{-\frac{t}{\alpha}},$$

$$(\boldsymbol{P}\boldsymbol{W}^D(t)|_{t=0} = M_e,\ H(t)|_{t=0} = 0,$$

$$\lim_{t\to\infty} \frac{\int H(t)e^{\frac{t}{\alpha}}dt}{e^{\frac{t}{\alpha}}} = 0).$$

*where:*
*$H(t) = 2\frac{d(\boldsymbol{Q}\boldsymbol{W}^H)}{dt} + \tau_v\frac{d^2(\boldsymbol{Q}\boldsymbol{W}^H)}{dt^2}$: Hebbian function;*
*$A$: learning target;*
*$h$: threshold;*
*$\boldsymbol{P} = [p_1, p_2, \ldots, p_n]$: perception information;*
*$\boldsymbol{W}^D = [w_1^D, w_2^D, \ldots, w_n^D]^T$: synaptic efficiencies;*
*$\boldsymbol{Q} = [q_1, q_2, \ldots, q_m]$: conscious information;*
*$\boldsymbol{W}^H = [w_1^H, w_2^H, \ldots, w_m^H]^T$: hebbian efficiencies;*
*$M_e$: memory consolidation function;*
*$n$: memory capacity;*
*$m$: learning capacity;*
*$\alpha$: memory factor;*
*$\mu$: learning factor;*
*$t$: excited time of the neuron.*

In general,after learning the output information of the neuron is
action information:

$$O_u = A + \left[M_e - h - A + \frac{\mu}{\alpha}\int H(t)e^{\frac{t}{\alpha}}dt\right]e^{-\frac{t}{\alpha}} \tag{31}$$

conscious information:

$$O_v = \epsilon(2A + h) + \epsilon\left[M_e - h - A + \frac{\mu}{\alpha}\int H(t)e^{\frac{t}{\alpha}}dt\right]e^{-\frac{t}{\alpha}} + C_e(t) \tag{32}$$

learning error:

$$e = \left|\left[M_e - h - A + \frac{\mu}{\alpha}\int H(t)e^{\frac{t}{\alpha}}dt\right]e^{-\frac{t}{\alpha}}\right| \tag{33}$$

memory consolidation function:

$$M_e(t) = (h + A)(1 - e^{-\frac{t}{\alpha}}) + [M_e + \frac{\mu}{\alpha}\int H(t)e^{\frac{t}{\alpha}}dt]e^{-\frac{t}{\alpha}} \tag{34}$$

where: $C_e(t) = \boldsymbol{Q}\boldsymbol{W}^H$ is Conscious control function,$\alpha$ is memory factor($\alpha > 0$),and $\epsilon$ is electromagnetic coefficient.

The expressions above are called Union learning Formulas.

DISCUSSION 2

The same as Reflex learning,we have another definition as follows.

**Definition 5.4** *If Memory consolidation function $M_e = h + A - \frac{\mu}{\alpha}\int H(t)e^{\frac{t}{\alpha}}dt$,Union learning which has the learning result A is defined as Compound remembering process.*

The meaning of Memory consolidation function is $M_e$ of Union learning is similar to that of Reflex learning.The discussion of $M_e$ is omitted.

Then the important effect of Hebbian function H(t) will be discussed in detail.

1.Learning Effectiveness

If H(t) is satisfied with $\lim_{t\to\infty}\frac{\int H(t)e^{\frac{t}{\alpha}}dt}{e^{\frac{t}{\alpha}}}=0$,Union learning is an Effective learning.This means that if $t\to\infty$(ideally),it is certain that the learning target can be achieved.

If H(t) is not satisfied with $\lim_{t\to\infty}\frac{\int H(t)e^{\frac{t}{\alpha}}dt}{e^{\frac{t}{\alpha}}}=0$,Union learning is an Uneffective learning.This means that even if $t\to\infty$(ideally),the learning target can not be achieved.

Reflex learning is an Effective learning.In the Effective learning,if

$$\left|M_e-h-A+\frac{\mu}{\alpha}\int H(t)e^{\frac{t}{\alpha}}dt\right|<|M_e-h-A|$$

(as t is increasing), the learning is Active learning,if

$$\left|M_e-h-A+\frac{\mu}{\alpha}\int H(t)e^{\frac{t}{\alpha}}dt\right|>|M_e-h-A|$$

(as t is increasing),the learning is Passive learning.

2. Learning Time($T_l$)

It should be noted that the learning time $T_l$ and the excited time t are different.The learning time is $T_l=t\times L_e$,where t is excited time and $L_e$ is learning times(or excited times).Generally,the sequence of the Learning Time $T_l$ from short to long is Active learning,Reflex learning,and Passive learning.

In this section,the mechanism of learning and memory of a neuron is analyzed by mathematical methods.

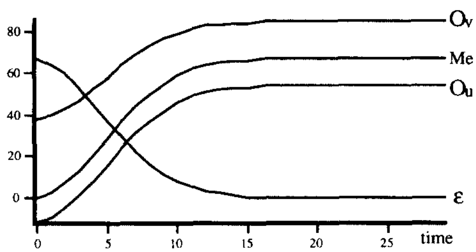


Figure 4. A simulation result of memorizing process of a neuron. Learning target A=54.6, threshold h=12.8,memory factor $\alpha$=26,limit of learning error E=0.000001,$p_1$=32.6,$p_2$=-25.32, $p_3$=8.46,Ou=54.6,Ov=85.4,Me=67.4,$w_1$=-1.251,$w_2$=-5.0042, $w_3$=-2.1893,learning error $\varepsilon$=0.0000008,learning time t=31.

## 6 Computer Simulation

Based on the learning theorems,some computer simulations were carried out as shown in Fig.4 and Fig.5.

## 7 Conclusion

In this paper we present a new control mechanism of memory for the study of memory.The control mechanism also suggests an approach to understanding the mechanism of human information processing.The neuron model proposed in this paper is a new kind of information processing model which introduces the effect of magnetic fields into the traditional neuron model. The neuron model is able to solve the black-box problem of automata and has an autonomous function. To bring to light the mechanisms of learning,memorizing,thinking,reasoning and creating with the neuroscience some new theories should be put forward.Based on the new information processing principle,we advance a theory of Neural Electromagnetic(NEM) field theory.

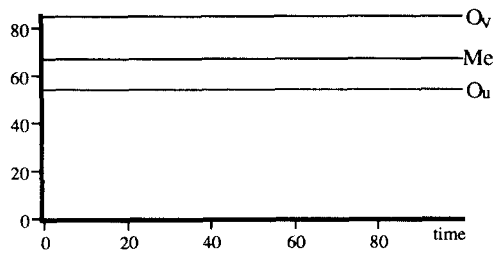


Figure 5. A simulation result of Self-remembering process of a neuron . Ou=54.6,Ov=85.4,Me=67.4,excited time t=100.

## References


[1] Hebb,D.O.(1949):The Organization of Behavior.New York:Wiley.

[2] Hodgkin,A.L.,&Huxley,A.F.(1952):A quantitative description of membrane current and its application to conduction and excitation in nerve.J.Physiol.,117,500-544.

[3] McCulloch,W.S.,&Pitts,W.H.(1943):A logical calculus of the ideas immanent in nervous activity.Bull.Math.Biophys.,5,115-133.

[4] Minsky,M.,&Papert,S.(1969):Perceptons—an introduction to computational geometry.The MIT Press.

[5] Rosenfield,I.(1988):The invention of memory:a new view of the brain.New York.

[6] Rumelhart,D.E.,McCleland.J.L.,&The PDP Research Group,(1986):Parallel distributed processing.The MIT Press.