B.E.

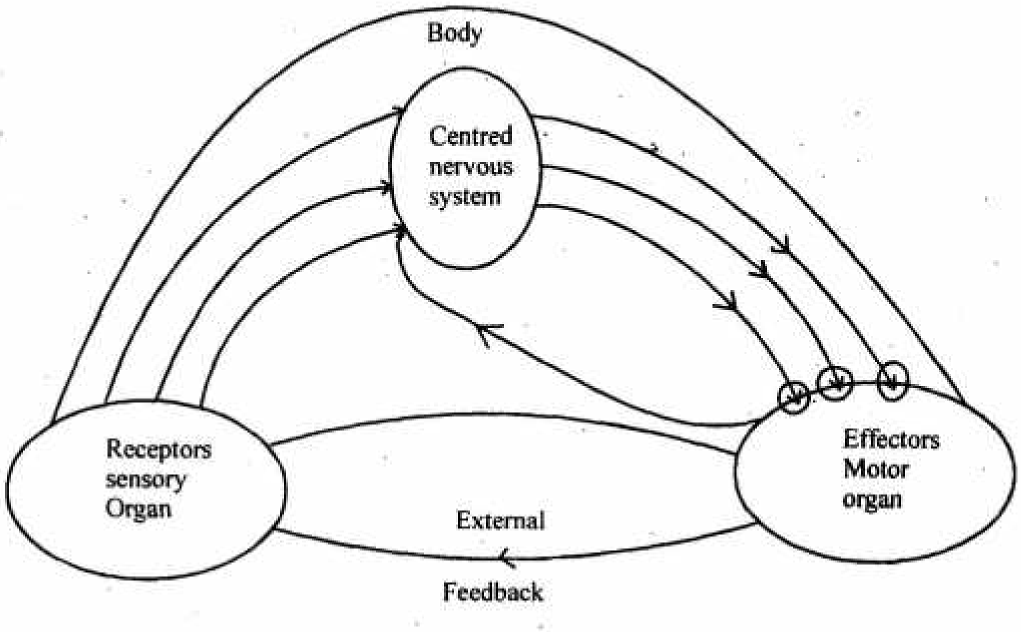
Seventh Semester Examination, May-2006

NATURAL NETWORK

Note : Attempt any five questions. All questions carry equal marks. Assume any missing data.

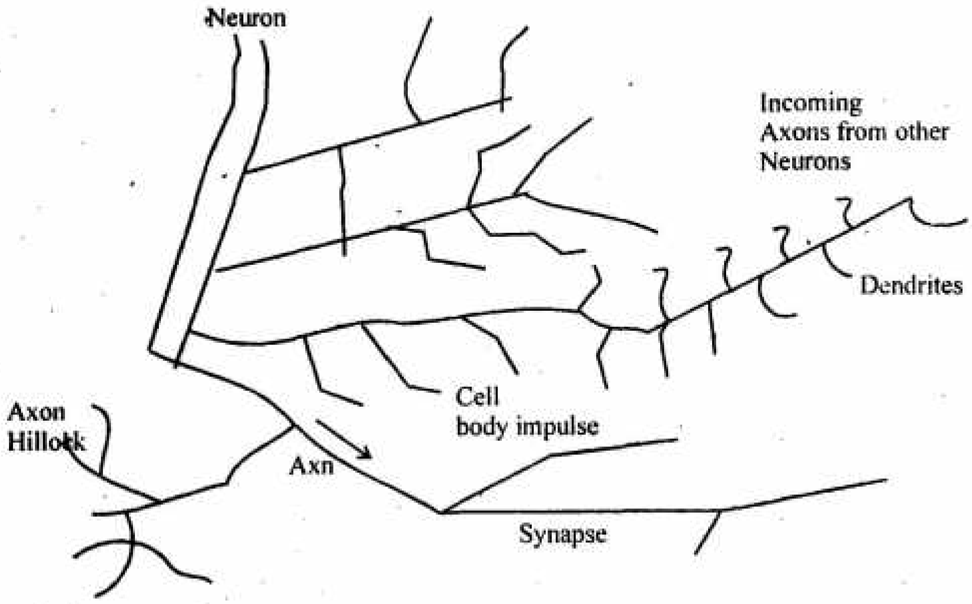
Q. 1. (a) How many neurons are there in an average human being's brain how many synoptic junctions? Are there any synoptic junctions in its brain when a child takes birth?

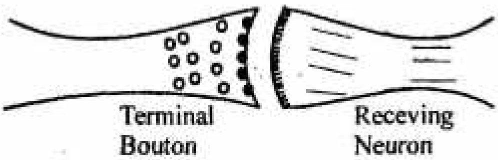
Ans. A human brain consists of approximately 10^{11} computing elements called newtons. They communicate through a connection network of axons and synopses having a density of approximately 10^4 synopses per neuron the hypothesis regarding the modelling of the natural nervous system is that neurons communicate with each other by means of electrical pulses. The neuron operates in a chemical environment that is even more important terms of actual brain be hair or. So we consider brain to be density conditioned largely by the biochemical processes. The input to network is provided by sensory respecters . Respecters deliver stimuli both from body as well as sense organs when the stimuli originate in external world. The stimuli are in the form of electrical pulses that convey information into the network of newtons. As result of information processing in central newtons system, the effectors are controlled and give human responses in form of diverse actions. So it has three stage system, consisting of receptions, neural networks and affections in control of the organism and its action. The diagram is shown.



Q. 1. (b) Draw a simple model of artificial neuron. Describe its working and explain the various terms used in it.

Ans. The elementary nerve cell called newtons, is the fundamental building block of biological neural network. Its diagram is shown below. A typical cell has three major regions : the cell body, which is also called the some the axon and the dendrites. Dendeites form a dendritic tree, which is a very fine bush of thin fivers around the neuron's body.





Dandifies receive information from neurons through axons-long fivers that serve as transmission lines. An axon is a long cylindrical connection that carries impulses from the neuron. The end part of an axon splits into a five arborization. Each branch of it terminates in a small end bulb almost touching the dendrites of neighbouring neuron. The axon-dendrite contact organ called synapse. The synapse is where the neuron introduces its signal to neighbouring neurons. The signal reaching a synapse and received by dendrites are electrical impulses.

Q. 2. (a) Describe Window-Hoff learning rule.

Ans. Window hoff learning rule is applicable for the supervised training of neural networks. It is independent of the activation function of neurons used since it minimizes the squared error between the desired output value di and the neuron's activation value $net_i = w_i^t x$. The learning signal for this rule is defined as follows :

$$r \triangleq d_i - w_i^t X$$

The weight vector increment under this learning rule is

$$\Delta w_i = c(d_i - w_i^t X)X$$

Or for the single weight the adjustment is

$$\Delta w_{ij} = c[d_i - w_i^t X]Xj$$

For j=1, 2.....n

This rule can be considered a special case of the delta learning rule. Indeed assuming in that $f(w_i^t x) = w_i^t x$ or the identify function f(net) = net, we obtain

$$f^1(\text{net}) = 1 \text{ and } r \stackrel{\Delta}{=} [di - f(w_i^t x)] f^1(w_i^t x)$$

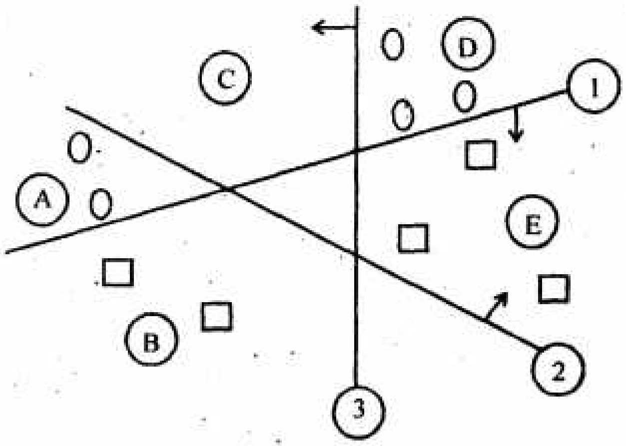
becomes identical to $r \stackrel{\Delta}{=} di - w_i^t x$. This rule is also called LMS (least mean square) learning rule. Weight all initialized at any value in this method.

Q. 2. (b) What do you mean by learning in the context of ANNs.

Ans. Learning is a relatively permanent change in behaviour brought about by experience bearing in human being and animals is an inferred process; and we can not see it happening directly learning in neural networks is a more direct process and we can capture each learning step in district cause - effect relationships . Designing an associator cab be based on learning relationship that transforms input into outputs given a set of examples of input output pairs.

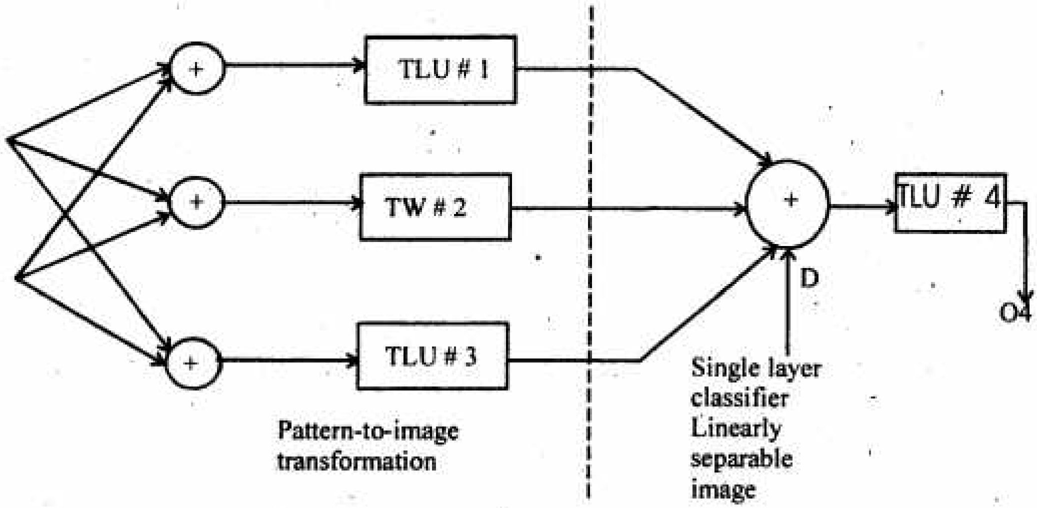
Q. 3. What are linearly inseparable problems? What kind of perception is required to handle such problems. Describe a training algorithm for such a perception.

Ans.

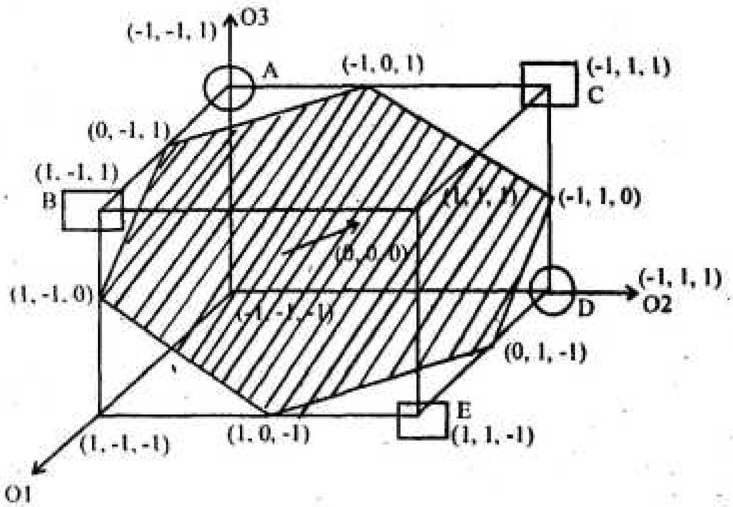


Assume two training sets $y_1 \& y_2$ of augmented pattern are available if no weight vector w exists such that $y^t w > 0$ for each $y \in y_1$ and $y^t w < 0$ for each $y \in y_2$ then the pattern such that $y_1 \& y_2$ are linearity non-separate. Let us now see how the original pattern space can be mapped into the so called image space so that a two layer network can eventually classify the pattern that are linearly non separable in original pattern space.

Assume initially that the two salt of pattern $x_1 \& x_2$ should be classified into two categories. Example pattern shown in following diagram. Three arbitrary selected partitioning surfaces 1, 2 and 3 have been shown in the pattern space x. The petitioning has been done in such a way that pattern space now has compartments containg only patterns of a single category. More over, the partitioning surfaces are hyper planes in pattern space E^n. The partitioning shown in figure 1 is non redundant i.e. implemented with minimum number of lines. It corresponds to mapping n-dimensional original. Pattern space x into the 3D image space 0 . Recognizing that each of the decision hyperplanes 1, 2, or 3 is implemented by a single discrete preceptors with suitable weights that transformation of the pattern space to image space can be performed by network as shown in following diagram.

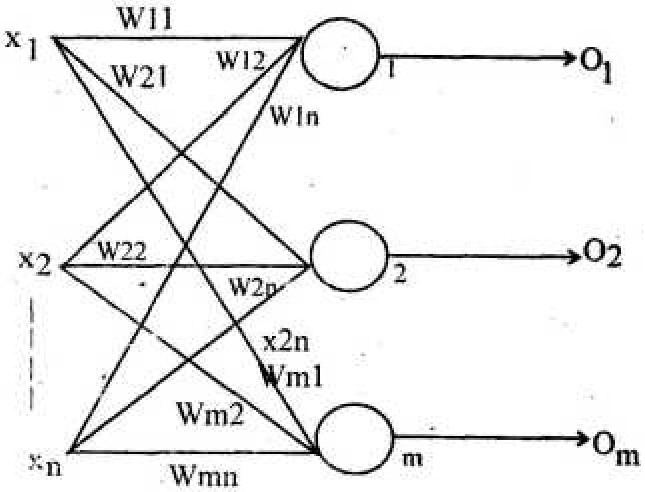


The result of the mapping pattern from the figure is depicted in figure 3 showing cube in image space $0_1, 0_2$ and 0_3 with corresponding labels at corners.

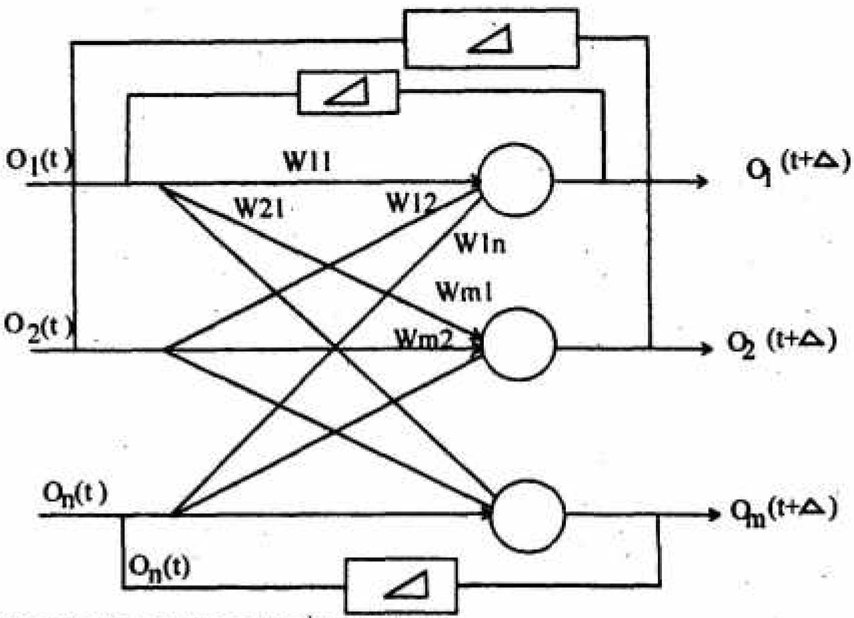


Q. 4. (a) What is the basic principle of feedback networks.

Ans. A feedback network can be obtained from the feed forward network. Shown in figure (1) by connecting the neuron's outputs to their input. The result is depicted in figure (2)



The essence of closing the feedback loop is to enable control of output 0_i through outputs 0_j for $j = 1, 2, \ldots, m$. Such control is especially meaningful of the present output say 0(t) control the output at the following instant $D(t + \Delta)$.



Q. 4. (b) Describe the training of Hop field network.

Ans. Following the postulates of hop field the single layer feedback neural network is shown below :

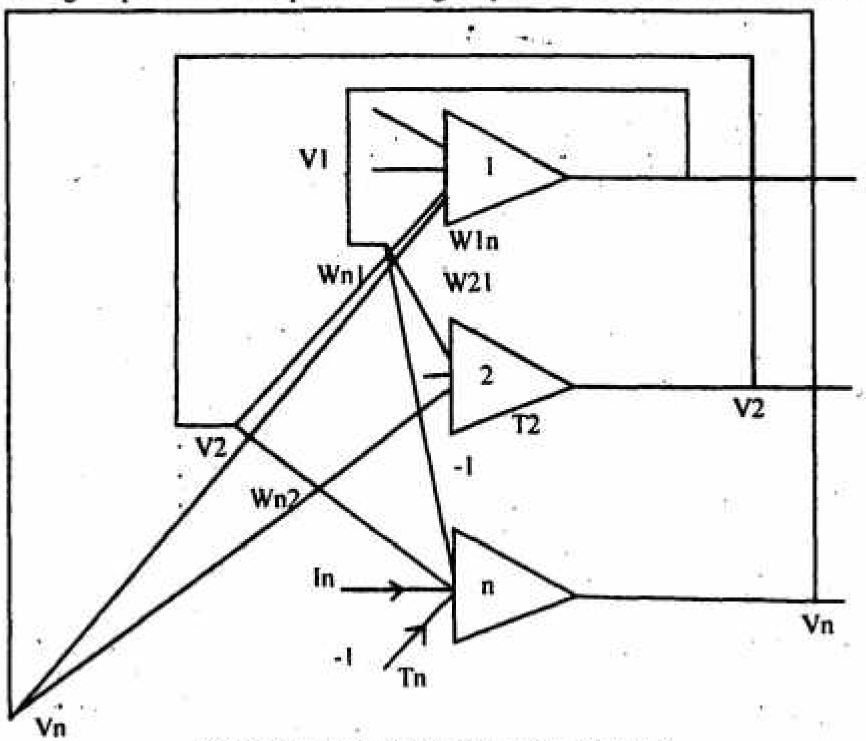


Fig Single payer feedback neural network

In consists n neurons end T_i valves

$$neti = \sum_{j=1}^{n} wij\forall j + ij - T_i \text{ for } i = 1,2-n \quad j \neq i$$

Weight value

Total i/p of ith neutron

$$net_i = w_i^! 0i_1 - T_i \text{ for } i = 1,2....n$$

Where $$w_i \triangleq \begin{bmatrix} w_{i1} \\ w_{i2} \\ \vdots \\ w_{in} \end{bmatrix}$$

weight vector is v : $$\triangleq \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_n \end{bmatrix}$$

$$net = w_v + i - t$$

where net $$\triangleq \begin{bmatrix} net_1 \\ net_2 \\ \vdots \\ net_n \end{bmatrix} i \triangleq \begin{bmatrix} i_1 \\ i_2 \\ \vdots \\ i_n \end{bmatrix}$$

The threshold vector t is $$t \triangleq \begin{bmatrix} T_1 \\ T_2 \\ \vdots \\ T_n \end{bmatrix}$$

Matrix W_1 sometime called Connectivity

Q. 6. Explain unsupervised learning of clusters. Take a typical example to illustrate the process.

Ans. The tearing is based on clustering of input data. No a prior knowledge is assumed to be available regarding an input's membership in a particular class. Rather gradually detected characteristics and a history of training will be used to assist the network in define classes and possible boundaries between them be followed by labelling clusters with appropriate category names or numbers. This process of providing the category of objects with a label is usually termed as calibration.

Q. 7. (a) What are the guidelines with regard to choice of neurons in different layers and the choice of no. of hidden layers?

Ans. The size of hidden layer is one of the most important consideration when solving actual problems using multilayer feed forward network. The problem of the size choice is under intensive study with no conclusive answer available. The exact analysis of the issue is rather difficult because of the complexity of the mapping and due to the non deterministic nature of many successfully completed training procedure. Single hidden layer networks can form arbitrary decision regions in n dimensional input pattern space. There exist certain useful solutions as to the number J of hidden neurons needed for the network to perform properly. The solution also determine the lower bound on the number of different pattern P required in the training set. As well will be shown, the number of hidden neurons depends on the dimension n of the input vector and on the number of separable regions in n-dimensional declined input space.

Assume that the n-dimensional non augmented input space is linearity séparable into M-disjoint regions with boundaries being part of hyperplanes. Each of the M reclusion the input space can be labelled as belonging to one of the R classes where $R \leq M$.

The maximum number of regions linearly separable using J hidden neurons in n-dimensional input space is given by relationship

$$M(J,n) = \sum_{k=0}^{n} \binom{J}{K} \text{ where } \binom{J}{K} = 0 \text{ for } J < K.$$

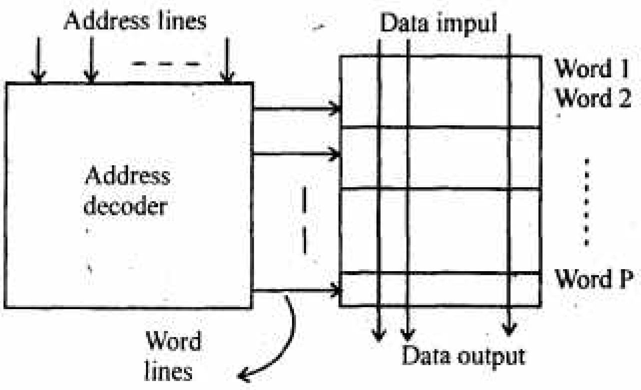
Q. 7. (b) What is the architecture of associative memory?

Ans. Associative memory belongs to a class of NN that teams according to a certain recording algorithm. They usually require information a prior and their connectivity matrices most often need to be formed in advance. Writing into memory produces changes in neural in Fel connection Associative memories usually enables a parallel search with in a stored data cite. The purpose of the search is to output either one or all store items that match the given search argument and to retrieve it either entirely or partially. It is also believed that biological memory principles. No memory location have addresses; storage is distributed over a large density inter connected ensemble of neurons.

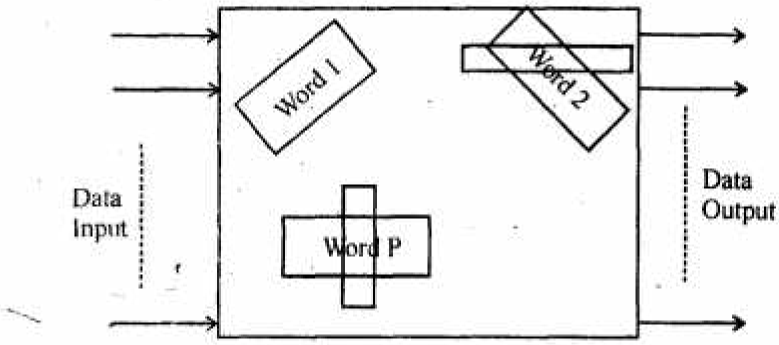
Addressing Modes of Memories are :

(a) Address addressable memory.

(b) Content addressable memory.



(a)



(b)

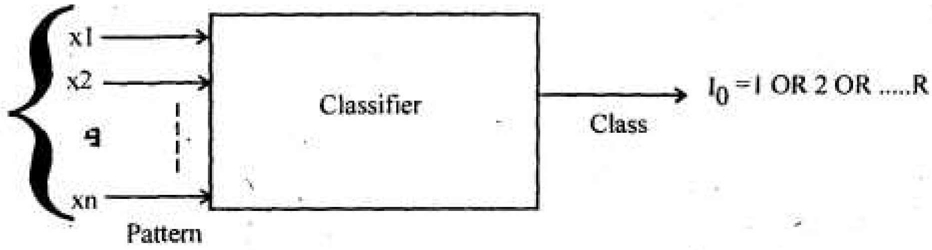
Q. 8. Write short technical notes on :

(a) Decision regions for single layer perception.

(b) Hebbian learning rule.

Ans. (a) Classification can often be conveniently described in geometric terms. Any pattern can be represented by a point in n dimensional euclidean space E^n called the pattern space. Points in that space corresponding to the members of the pattern set are n-tuple vector X. A pattern classifier maps sets of points in E^n space into one of the numbers $i_0 = 1, 2, \ldots R$ are denoted here by $n_1, n_2 \ldots n$ respectively.

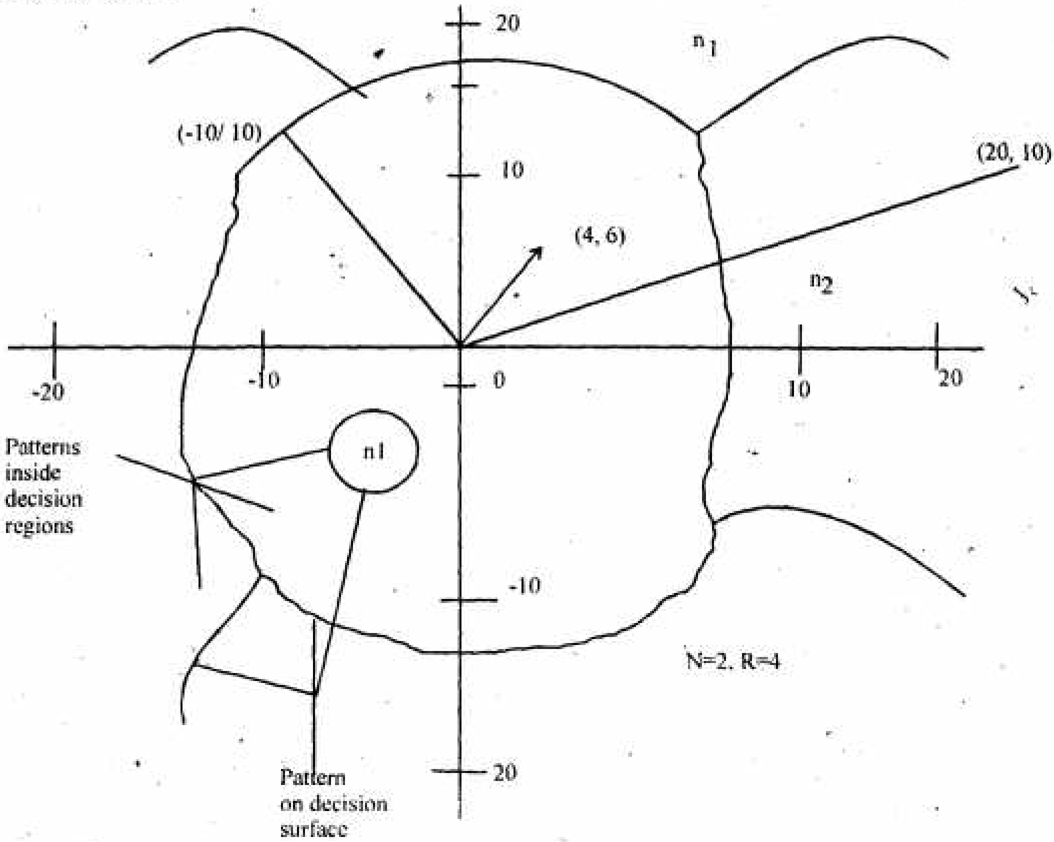
- An example case for n = 2 and R = 4 is illustrated in figure showing disjoint regions $\eta_1 ..... \eta_4$. Let us postulate for simplicity that the classifier response as in figure (1) should be the class number.



We now have the decision functions for a pattern of class j yielding the following results :

$$i_0(x) = j \text{ for all } x \in x_j, j = 1, 2, 3, 4.$$

Thus the example vector $x = [20\ 10]^t$ belongs to n_2 and is of class 2, vector $x = [4\,6]^t$ belongs to n_3 and is of class 3; etc.



The region denoted n_i is called decisions regions. Regions n_i are separated from each other by so called decision surface. The figure is below showing decision region examples.

(b) Hebbian Learning Rull : For Hebbian learning rule the learning signal is equal simply to the neuron's output. We have :

$$r \underline{\underline{\Delta}} f\left(w_i^t x\right)$$

The increment Δw_i of weight vector becomes

$$\Delta w_i = cf\left(w_i^t X\right) X$$

The single weight w_{ij} is adopted using the following increment

$$\Delta w_{ij} = cf\left(w_i^t x\right) x_j$$

This can be written briefly as

$$\Delta w_{ij} = CO_i x_j \text{ for } j = 1, 2, \ldots.. n$$

This learning rule requires the weight initialization at small random values around $w_i = 0$ prior to learning. The hebbian learning represents feed forward learning.