Patterns and Pattern Classes:

A **pattern is an arrangement of descriptors**,

The name *feature is* used often in the pattern recognition literature to denote a descriptor. A *pattern class is a family* of patterns that share some common properties. Pattern classes are denoted ω1,ω2,…………,ωW, where W is the number of classes. Pattern recognition by machine involves techniques for assigning patterns to their respective classes— automatically and with as little human intervention as possible. Three common pattern arrangements used in practice are vectors (for quantitative descriptions) and strings and trees (for structural descriptions). Pattern vectors are

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ . \\ . \\ . \\ . \\ . \\ x_n \end{bmatrix}$$

represented by bold lowercase letters, such as **x, y**, and **z**, and take the form where each component, x_i, represents the ith descriptor and n is the total number of such descriptors associated with the pattern. Pattern vectors are represented as columns (that is, n x 1 matrices). Hence a pattern vector can be expressed in the form shown in Eqn. (1) or in the equivalent form x = (x1, x2, , xn)T, where ***T*** indicates transposition. The nature of the components of a pattern vector x depends on the approach used to describe the physical pattern itself. Let us illustrate with an example that is both simple and gives a sense of history in the area of classification of measurements. In our present terminology, each flower is described by two measurements, which leads to a 2-D pattern vector of the form

$$X=\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

where x_1 and x_2 correspond to petal length and width, respectively. The three pattern classes in this case, denoted ω1, ω2, and ω3, correspond to the varieties *setosa, virginica,* and *versicolor, r*espectively. Because the petals of flowers vary in width and length, the pattern vectors describing these flowers also will vary, not only between different classes, but also within a class. The above Figure shows length and width measurements for several samples of each type of iris. After a set of measurements has been selected (two in this case), the components of a pattern vector become the entire description of each physical sample. Thus each flower in this case becomes a point in 2-D Euclidean space. We note also that measurements of petal width and length in this case adequately separated the class of *Iris setosa* from the other two but did not separate as successfully the *virginica* and *versicolor* types from each other. This result illustrates the classic *feature selection* problem, in which the degree of class seperability depends strongly on the choice of descriptors selected for an application.

RECOGINITON BASED ON MATCHING:

Recognition techniques based on matching represent each class by a prototype pattern vector. An unknown pattern is assigned to the class to which it is closest in terms of a predefined metric. The simplest approach is the minimum distance classifier, which, as its name implies, computes the (Euclidean) distance between the unknown and each of the prototype vectors. It chooses the smallest distance to make a decision. We also discuss an approach based on correlation, which can be formulated directly in terms of images and is quite intuitive.

MINIMUM DISTANCE CLASSIFIER

Suppose that we define the prototype of each pattern class to be the mean vector of

$$m_j = \frac{1}{N_j}\sum_{x \epsilon \omega_j} x_j \qquad j = 1,2,\ldots\ldots\ldots\ldots\ldots,W.$$

the patterns of that class:

where *NJ* is the number of pattern vectors from class ωj and the summation is taken over these vectors. As before, W is the number of pattern classes. One way to determine the class membership of an unknown pattern vector x is to assign it to the class of its closest prototype, as noted previously. Using the Euclidean distance to determine closeness reduces the problem to computing the distance measures.

$$d_{ij}\ (x) = d_i\ (x) - d_j\ (x)$$

The decision boundary between classes ωi , and ωj for a minimum distance classifier is

$$= x^T(m_i - m_j) - \frac{1}{2}(m_i - m_j)^T(m_i + m_j) = 0$$

The surface given by the above equation is is the perpendicular bisector of the line segment joining m_i and m_j. For n = 2, the perpendicular bi-sector is a line, for n = 3 it is a plane, and for n > 3 it is called a hyper plane. The two classes, Iris versicolor and Iris setosa, denoted ω1 and ω2, respectively, have sample mean vectors m1 = $(4.3, 1.3)^T$ and m2 = $(1.5, 0.3)^T$. The decision functions are

$$d_1\ (x) = x^T m_1 - \frac{1}{2} m_1^T m_1$$

$$= 4.3\ x_1 + 1.3\ x_2 - 10.1$$

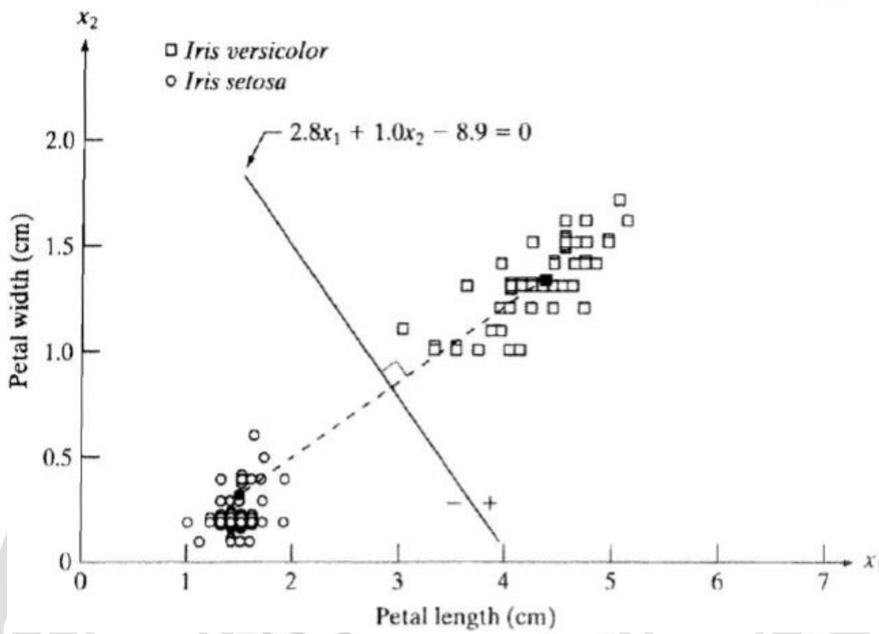

Fig.5.4.1 plot of this boundary

(Source: Rafael C. Gonzalez, Richard E. Woods, ‗Digital Image Processing', Pearson, Third Edition, 2010. - Page – 862)

The above figure shows a plot of this boundary (note that the axes are not to the same scale). Substitution of any pattern vector from class ω1 would yield d12(x) > 0.

- Conversely, any pattern from class ω2would yield d12(x) < 0.
- In other words, given an unknown pattern belonging to one of these two classes, the sign of d12(x) to one of these two classes, the sign of d12(x) would be sufficient to determine the pattern's class membership.