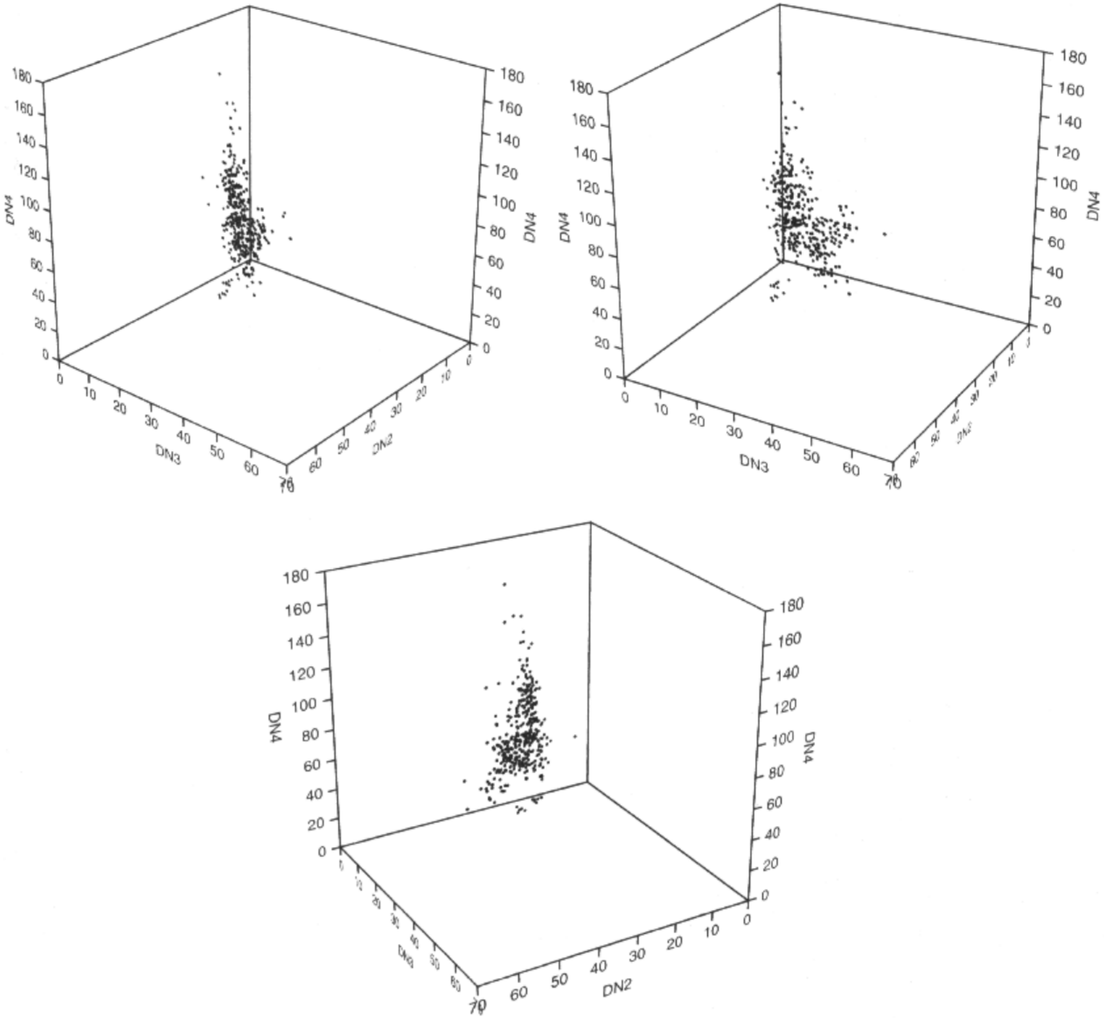


FIGURE 4-6. Three-band scatterplots of bands 2, 3 and 4 of a TM image, viewed from three different directions. Only every 20th sample and line of the image are used to calculate these scatterplots, so that they are not too dense. Every dot in the scatterplot represents one or more pixels with a particular spectral vector. Note that the image data occupies a small fraction of the total DN volume.

監督性全像素分類法

Distance measure

TABLE 9-3. Distance measures between two distributions in feature space. The city block, Euclidean, and angular measures ignore the covariances of the distributions. The normalized city block and MH measures are extensions that include covariance information for each class. The last five measures assume normal class distributions for a and b. All of these distance measures are scalars. Derivations of the normal distribution-based distance measures can be found in many books on statistical pattern recognition, including (Duda and Hart, 1973; Swain and Davis, 1978; Richards, 1993)

name	formula
city block	$L_1 = \lvert\mu_a - \mu_b\rvert = \sum_{k=1}^{K} \lvert m_{ak} - m_{bk}\rvert$
Euclidean	$L_2 = \lVert\mu_a - \mu_b\rVert = [(\mu_a - \mu_b)^T(\mu_a - \mu_b)]^{1/2} = \left[\sum_{k=1}^{K} (m_{ak} - m_{bk})^2\right]^{1/2}$
angular	$ANG = \mathrm{acos}\left(\frac{\mu_a^T \mu_b}{\lVert\mu_a\rVert \lVert\mu_b\rVert}\right)$
normalized city block	$NL_1 = \sum_{k=1}^{K} \frac{\lvert m_{ak} - m_{bk}\rvert}{(\sqrt{c_{ak}} + \sqrt{c_{bk}})/2}$
Mahalanobis	$MH = \left[(\mu_a - \mu_b)^T \left(\frac{C_a + C_b}{2}\right)^{-1} (\mu_a - \mu_b)\right]^{1/2}$
divergence	$D = \frac{1}{2}tr\left[(C_a - C_b)(C_b^{-1} - C_a^{-1})\right] + \frac{1}{2}tr\left[(C_a^{-1} + C_b^{-1})(\mu_a - \mu_b)(\mu_a - \mu_b)^T\right]$
transformed divergence	$D^t = 2[1 - e^{-D/8}]$
Bhattacharyya	$B = \frac{1}{8}MH + \frac{1}{2}\ln\left[\frac{\lvert(C_a + C_b)/2\rvert}{(\lvert C_a\rvert \lvert C_b\rvert)^{1/2}}\right]$
Jeffries-Matusita	$JM = \left[2(1 - e^{-B})\right]^{1/2}$

非監督性全像素分類法

K-means clustering

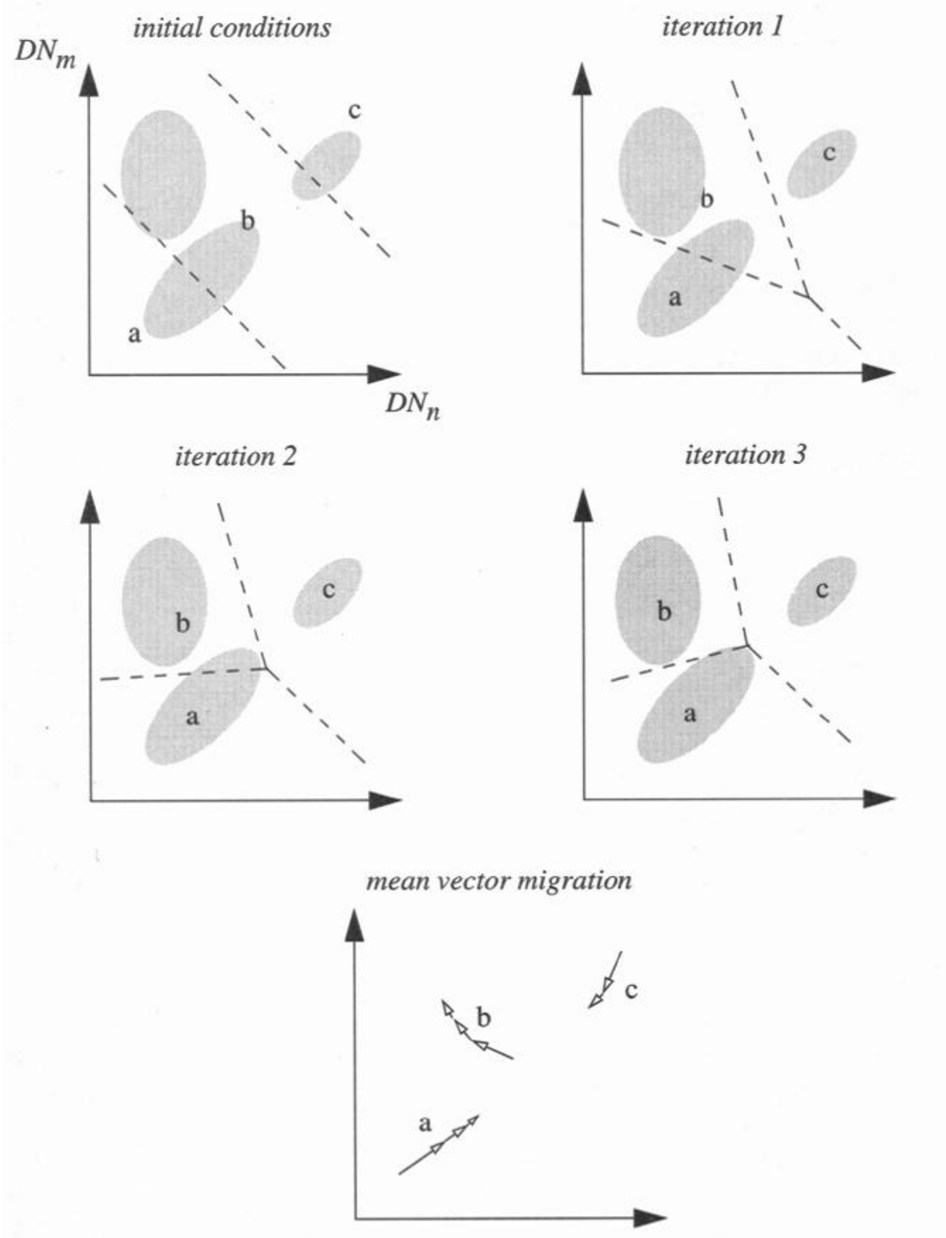


FIGURE 9-6. An idealized data distribution during three iterations of the K-means clustering algorithm with the nearest-mean decision criterion. The data is depicted as three distinct clusters, with the current, estimated mean vector for each class located at a, b and c. The initial "seed" locations are equidistant along the feature space diagonal. In the bottom figure, the movement of the estimated cluster means is shown.

監督性次像素分類法

An example of spatial mixing

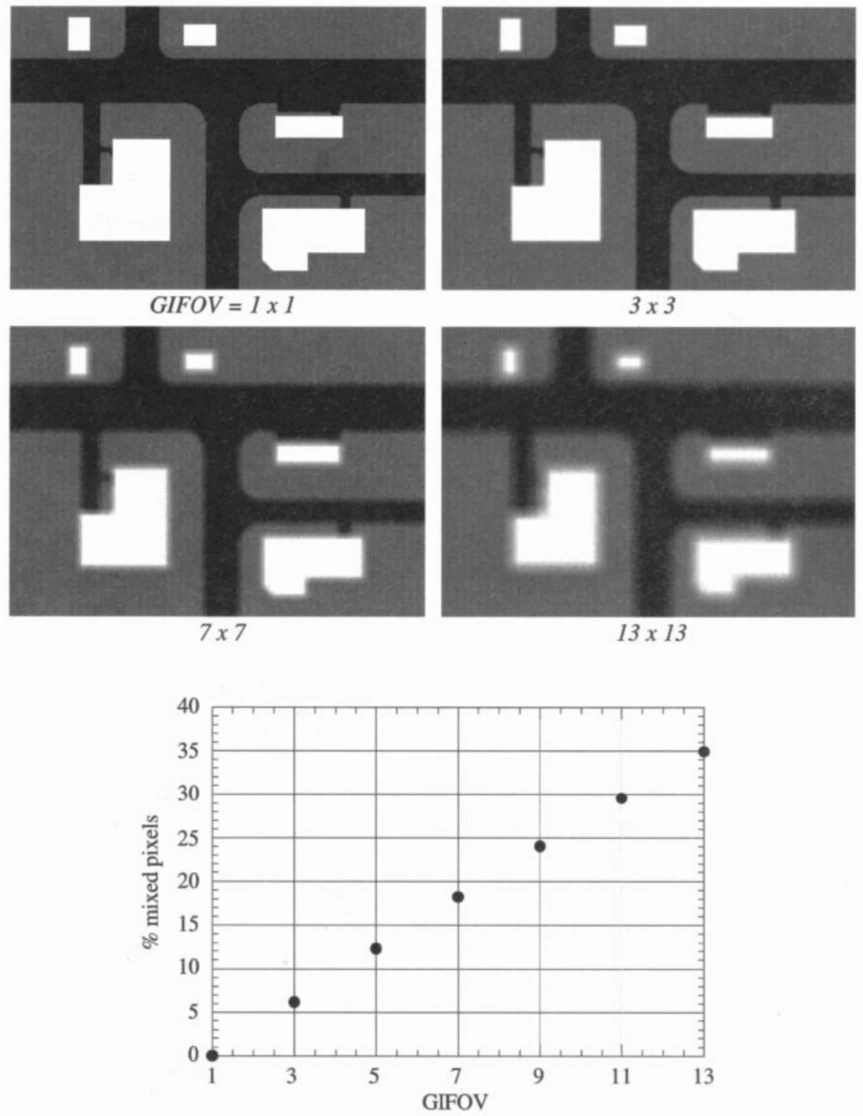


FIGURE 9-39. Simple example to illustrate spatial mixing. A synthetic scene consisting of three types of objects was created at a pixel size of one (upper left). Simulated images were then generated by spatial averaging over a range of GIFOVs. The percentage of mixed pixels for various GIFOVs is shown in the bottom graph.

監督性次像素分類法

- *Linear Spectral Mixture Analysis*

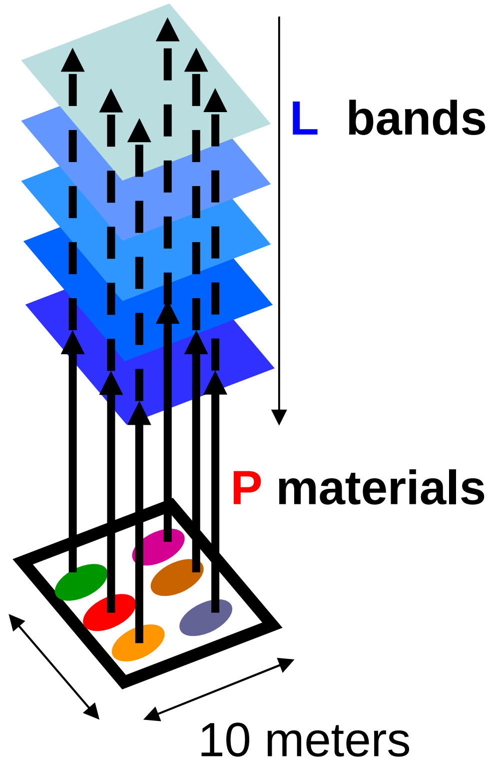
$$r \quad = \quad M \quad \cdot \quad \alpha \quad + n$$

$$r_1 = m_{11}\alpha_1 + m_{21}\alpha_2 + \cdots + m_{P1}\alpha_P + n_1$$

$$r_2 = m_{12}\alpha_1 + m_{22}\alpha_2 + \cdots + m_{P2}\alpha_P + n_2$$

$$\vdots \qquad \vdots \qquad \vdots \qquad \vdots \qquad \vdots$$

$$r_L = m_{1L}\alpha_1 + m_{2L}\alpha_2 + \cdots + m_{PL}\alpha_P + n_L$$



$L < P \Rightarrow$ infinitely number of solutions

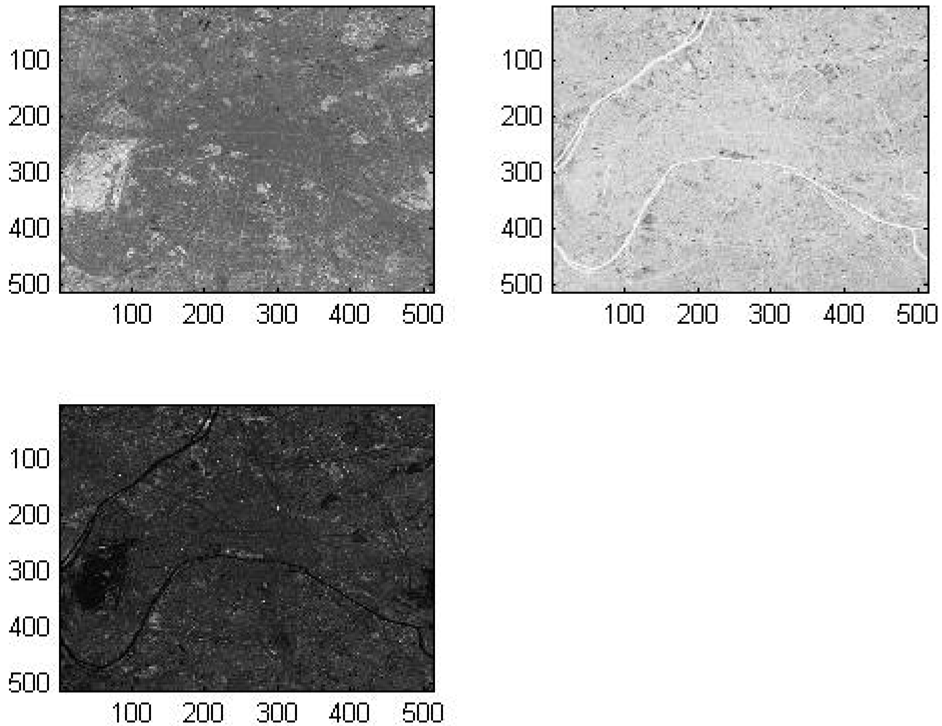
$L = P \Rightarrow$ only one solution

$L > P \Rightarrow$ least square error solution

Least square error $\hat{\alpha}_{LS} = \left(M^T M\right)^{-1} M^T r$

監督性次像素分類法

最小方差法




```
for i=1:512
    for j=1:512
        abd(i,j,:)=inv(M'*M)*M'*shiftdim(Cub(i,j,:));
    end
end
figure
for i=1:3
    subplot(2,2,i)
    imagesc(abd(:,:,i))
end
colormap(gray)
```

監督性次像素分類法

最大似然法

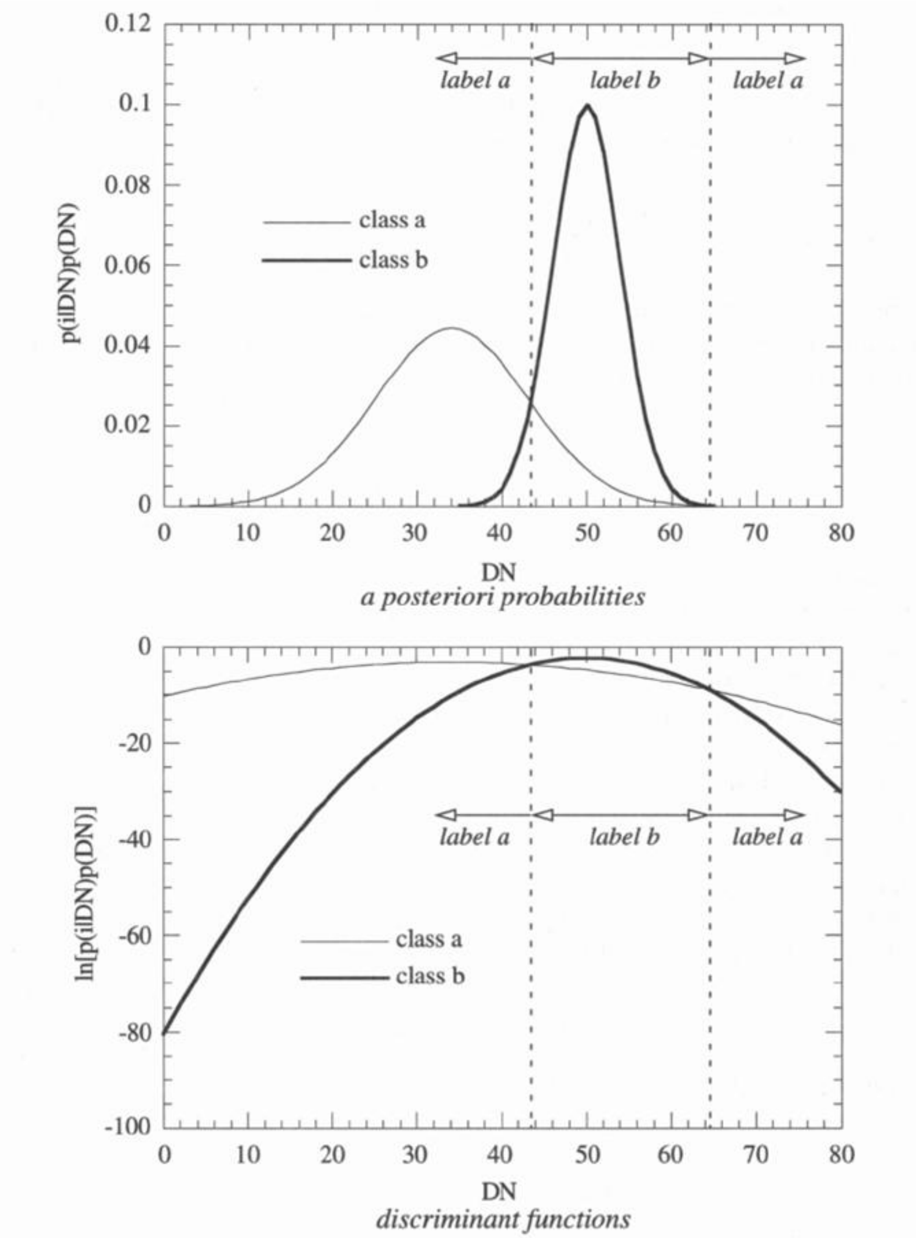


FIGURE 9-22. Maximum-likelihood decision boundaries for two Gaussian DN distributions in one dimension. The class statistics are: $\mu_a = 34$, $\sigma_a = 9$, $\mu_b = 50$, $\sigma_b = 4$. Note the decision boundary on the right is not visible in the upper graph because of the ordinate scale, but becomes clear in the discriminant function graph below.

非監督性次像素分類法

Unsupervised Remote Sensing Method

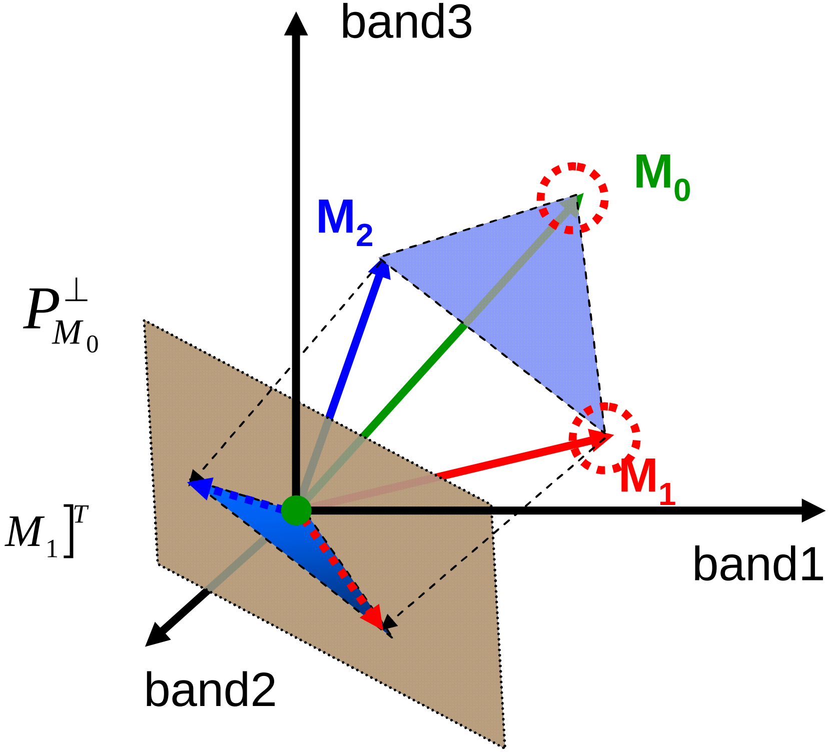
- **Step 1** Search Endmember
- **Step 2** Unmixing (Least square error)

Choose largest as M_0

$$P_{M_0}^{\perp} = I - M_0 \cdot (M_0^T \cdot M_0)^{-1} \cdot M_0^T$$

Choose largest as M_1

$$P_{M_0 M_1}^{\perp} = I - [M_0 M_1] \cdot ([M_0 M_1]^T \cdot [M_0 M_1])^{-1} \cdot [M_0 M_1]^T$$



Least square error $\hat{\alpha}_{LS} = \left(M^T M\right)^{-1} M^T r$