N93-18227

Membership Generation Using Multilayer Neural Network

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There has been intensive research in neural network applications to pattern recognition problems. Particularly, the back-propagation network has attracted many researchers because of its outstanding performance in pattern recognition applications. In this section, we describe a new method to generate membership functions from training data using a multilayer neural network. The basic idea behind the approach is as follows. The output values of a sigmoid activation function of a neuron bear remarkable resemblance to membership values. Therefore, we can regard the sigmoid activation values as the membership values in fuzzy set theory. Thus, in order to generate class membership values, we first train a suitable multilayer network using a training algorithm such as the back-propagation algorithm. After the training procedure converges, the resulting network can be treated as a membership generation network, where the inputs are feature values and the outputs are membership values in the different classes.

This method allows fairly complex membership functions to be generated because the network is highly nonlinear in general. Also, it is to be noted that the membership functions are generated from a classification point of view. For pattern recognition applications, this is highly desirable, although the membership values may not be indicative of the degree of typicality of a feature value in a particular class.

A. Typical Example

In this section we show an example of a membership network that can generate membership values for "shuttle" and "background". The network we used had one input unit, eight hidden units and two output units. Input data to the network were feature values and the observed activation values of the outputs after the network was trained with the back-propagation algorithm were considered as the degree of belonging to the particular classes. In this experiment, there were only two classes: object (shuttle) and background (space and earth). The training image is shown in Fig 1.

We generated membership functions corresponding to four texture features. These four feature images are shown in Fig 2. These features were contrast, difference, entropy, difference entropy, and homogeneity. They are defined by

$$\text{Contrast} = \sum_{n=0}^{N_g-1} n^2 \left\{ \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} p(i,j) \right\}.$$

$$\text{Entropy} = -\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} p(i,j) \log (p(i,j))$$

$$\text{Difference Entropy} = -\sum_{k=1}^{N_g} p_{x-y}(k) \log (p_{x-y}(k))$$

$$\text{Homogeneity} = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} \frac{1}{1+(i-j)^2} p(i,j)$$

where $p(i,j)$ is the (i,j)-th entry in the spatial gray level dependence matrix, and N_g is the number of gray levels. Also, $p_{x-y}(k)$ is defined by

$$p_{x-y}(k) = -\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} p(i,j) \quad \text{such that} \quad i| - j| = k$$

(See [1,2] for details.)

All feature values were normalized to lie between 0 and 255. The training sets were formed by manually picking samples from the object and background regions of all four texture feature images. There were 100 samples for each class. After the network was trained, we fed gray values (0-255) to the input unit and collected the activation values of output units to generate the membership functions. Fig 3.1 and Fig 3.2 show the histograms of the features for the background and the object, and the corresponding membership values for all four features.

B. Discussion

Fig 3.1 (c) shows the membership functions of object and background for contrast feature. The membership functions are very steep because only one or two gray level values overlap between the histograms of the background and the object. One the other hand, Fig 3.2 shows broader membership functions because of a broader overlapping area between the histograms for the entropy and homogeneity features. An interesting observation is that when histograms of object and background overlap, the network sets the crossover point at the middle of the overlapping area. This reveals the nice membership generation capability of the neural network.

C. Conclusion

This heuristic method of generating membership function has some merits compared to the probability-possibility transformation method described in our third quarterly report. The transformation method requires a precise estimation of a probability density function. In practice, this is difficult to achieve when the number of training samples is small. Also the resulting shape of the membership function is almost the same as the probability density function. In order words, membership functions generated by these methods seem to have a frequency interpretation of the data. Fig 4 and Fig 5 show examples of the transformation based membership functions obtained with 1,000 samples per feature per class. Even with this high number, the functions are rather noisy.

One short coming of this heuristic method is that the memberships do not represent "typicality". However, if the memberships are to be used subsequently in a pattern recognition algorithm then this method will provide better classification results.

REFERENCES

1. R. W. Conners and C. A. Harlow, "A Theoretical Comparison of Texture Algorithms", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 2, No. 3, May 1980, pp. 204-222.

2. R. M. Haralick, K. Shanmugam, and I. Dinstein, "Textural Features for Image Classification", IEEE Transactions on SMC, Vol. 3, No. 6, Nov. 1973, pp. 610-621.

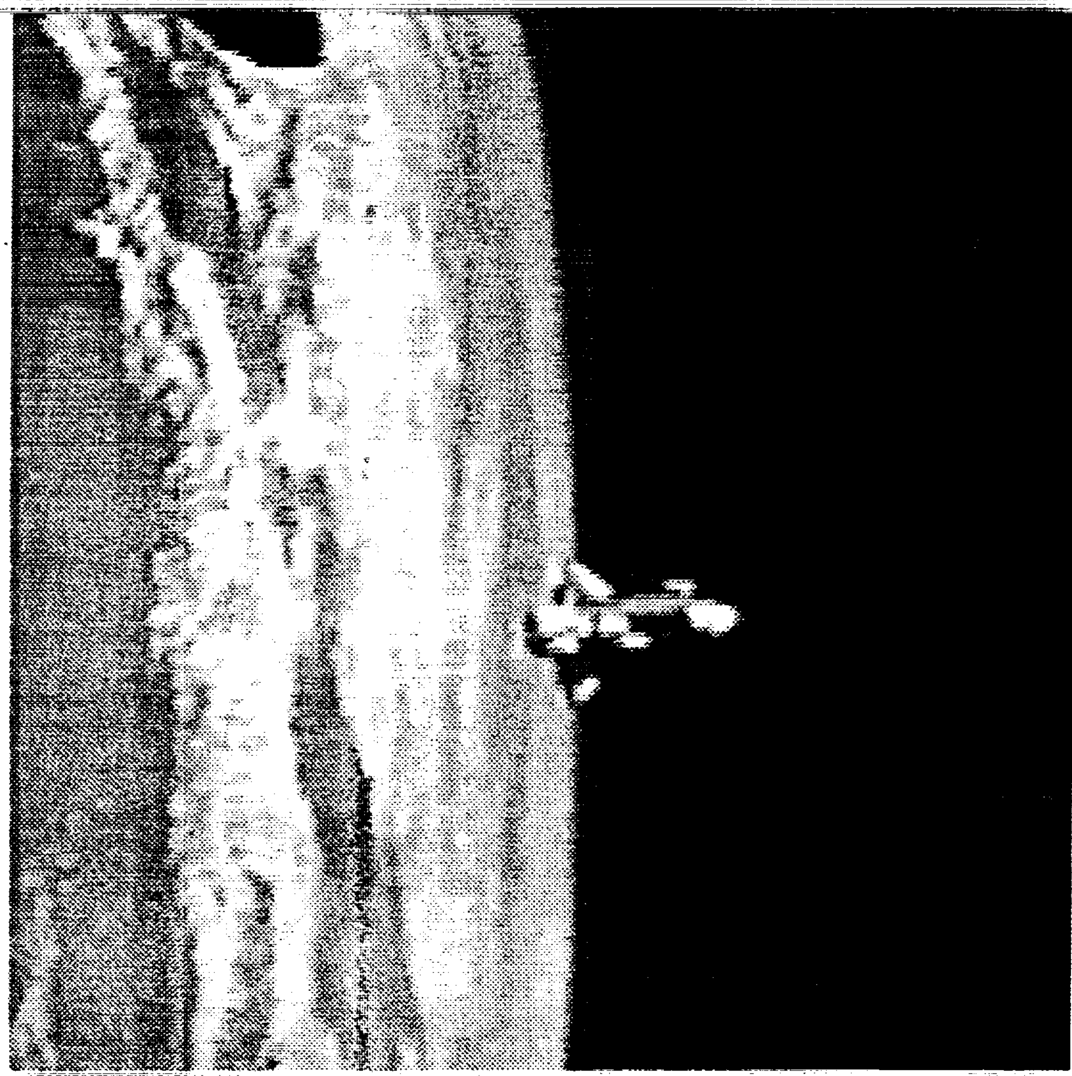


Fig.1 Space shuttle image

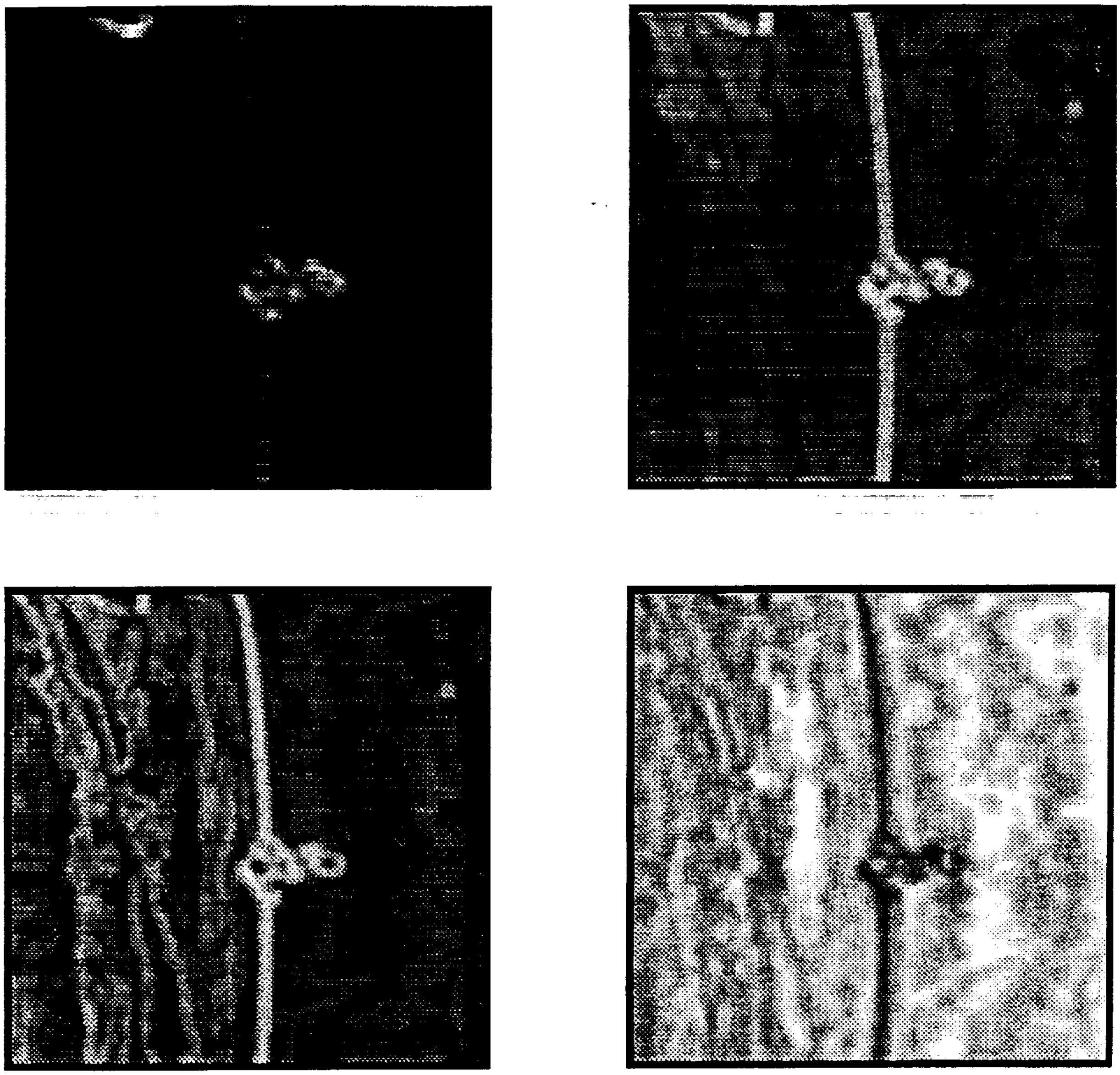
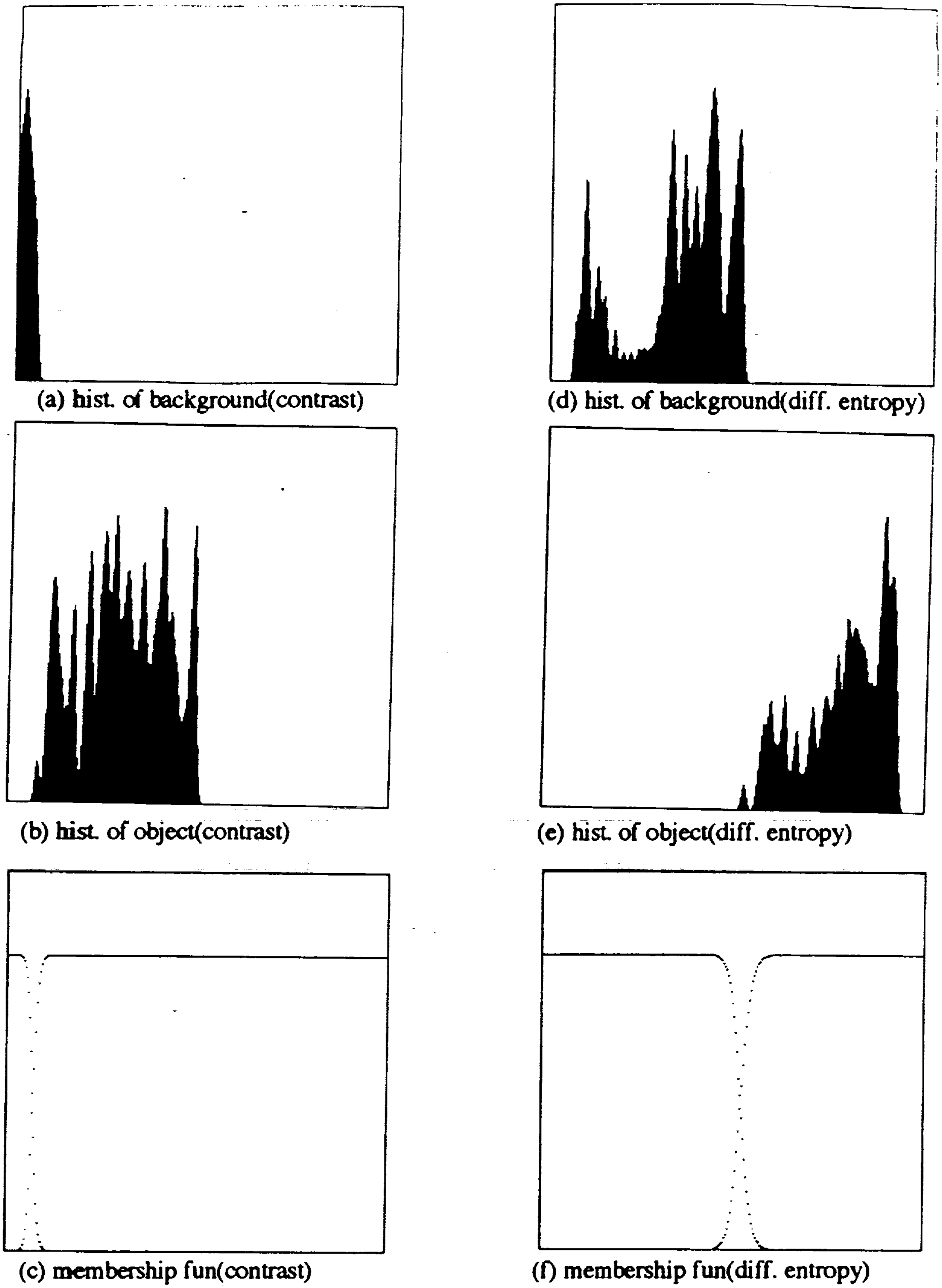


Fig 2. text features : in clockwise, contrast, difference entropy,entropy, and homogeneity.



(a) hist. of background(contrast)

(d) hist. of background(diff. entropy)

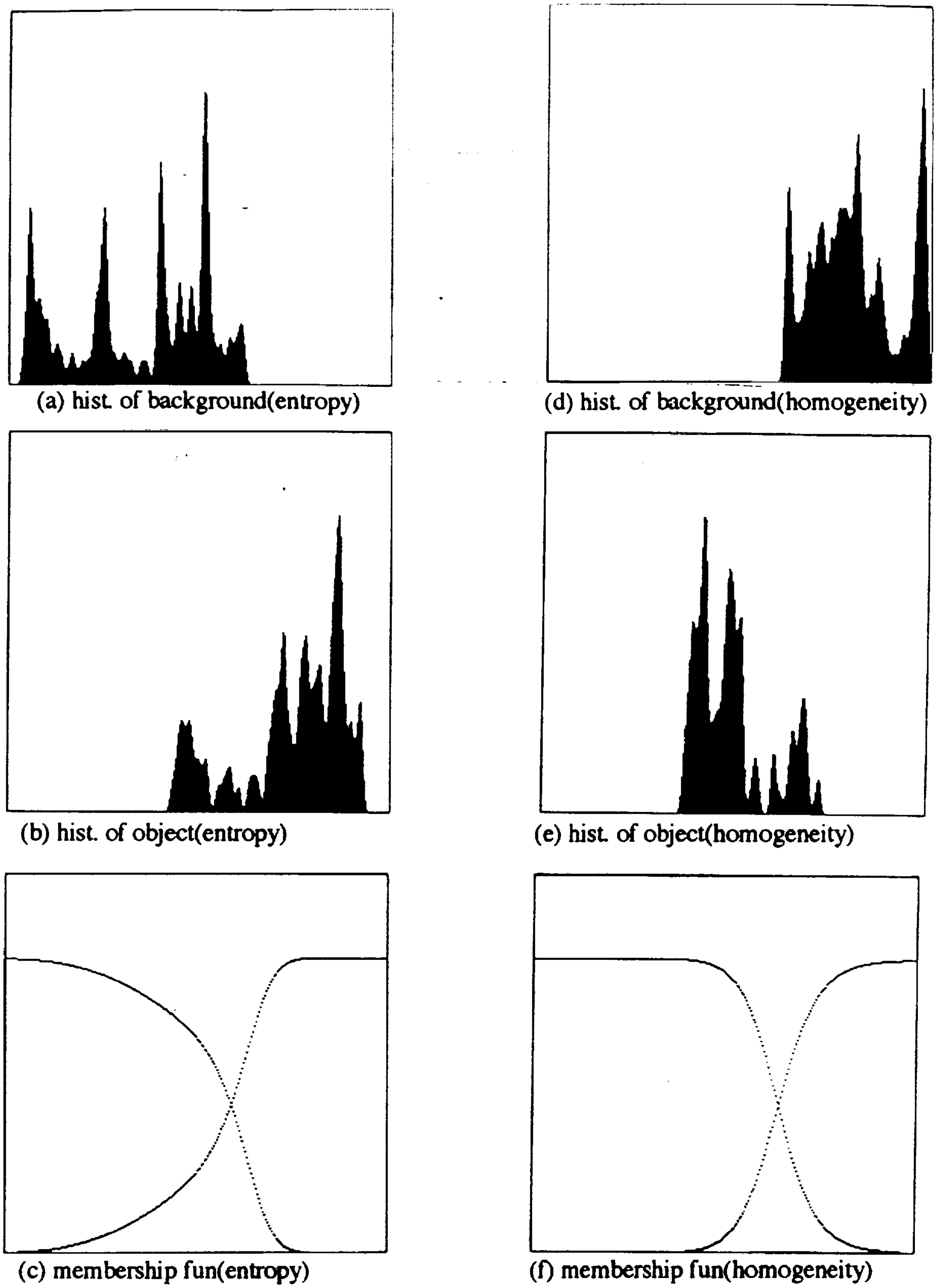
(b) hist. of object(contrast)

(e) hist. of object(diff. entropy)

(c) membership fun(contrast)

(f) membership fun(diff. entropy)

Fig 3.1 Histogram of background and object, and corresponding membership function.



(a) hist. of background(entropy)

(d) hist. of background(homogeneity)

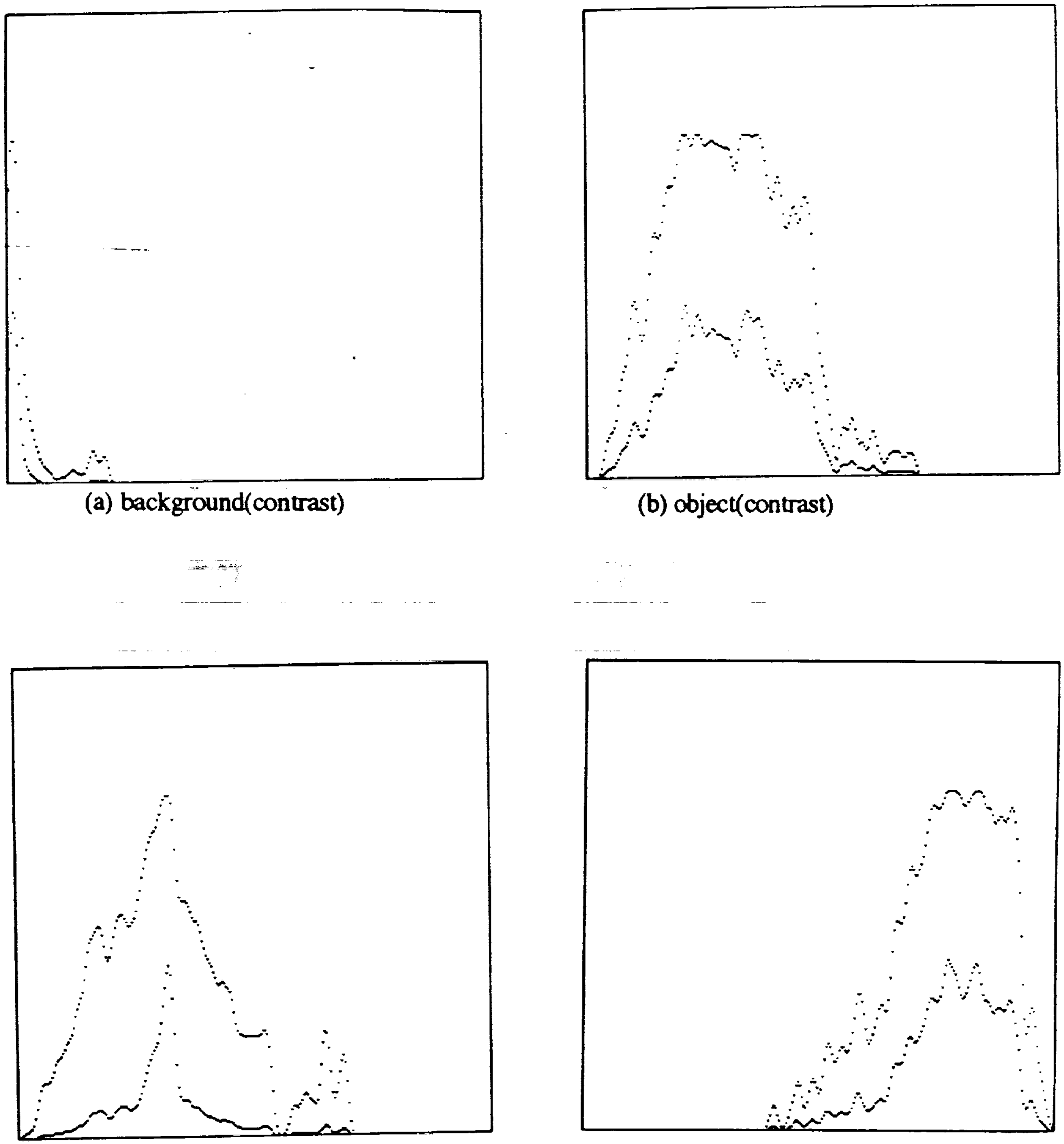
(b) hist. of object(entropy)

(e) hist. of object(homogeneity)

(c) membership fun(entropy)

(f) membership fun(homogeneity)

Fig 3.2 Histogram of background and object, and corresponding membership function.



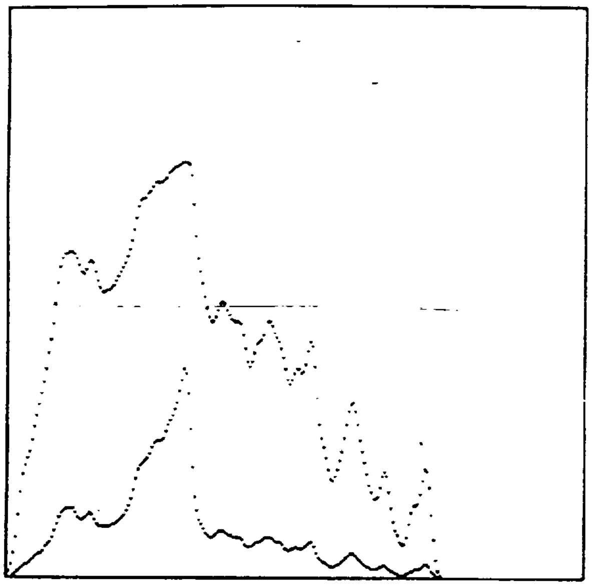
(a) background(contrast)

(b) object(contrast)

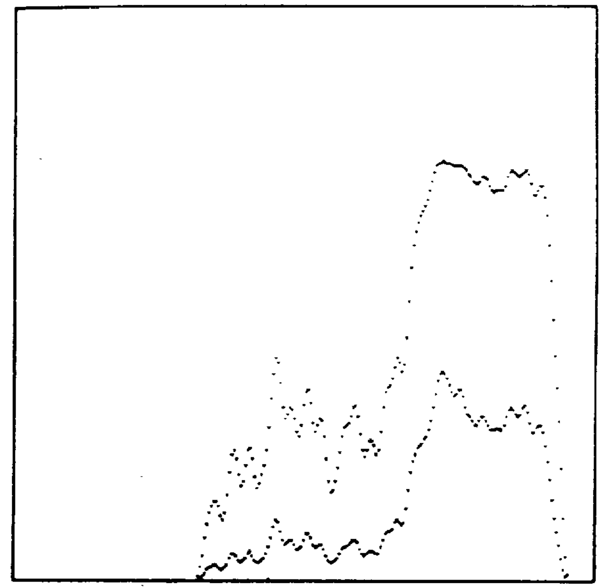
(c) background(diff. entropy)

(d) object(diff. entropy)

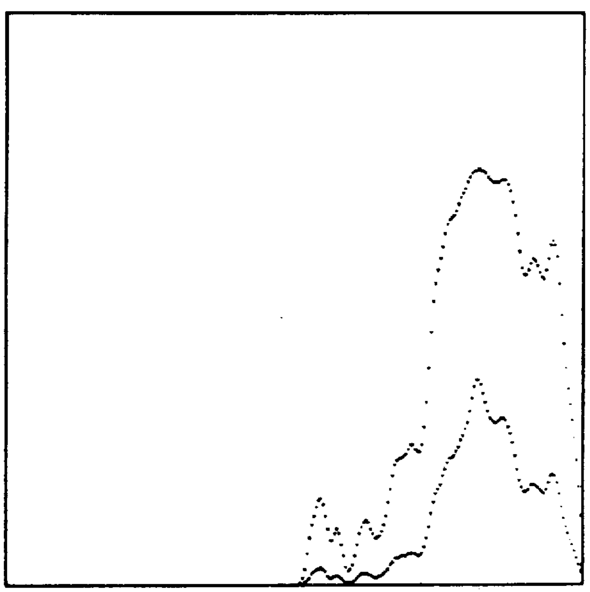
Fig 4.1 membership and p.d.f by Dubois and Prade :
small graphe is p.d.f and big one is membership.



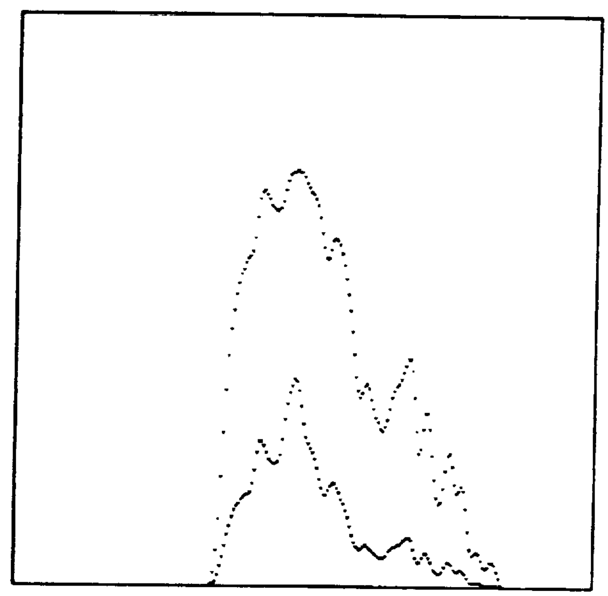
(a) background(entropy)



(b) object(entropy)

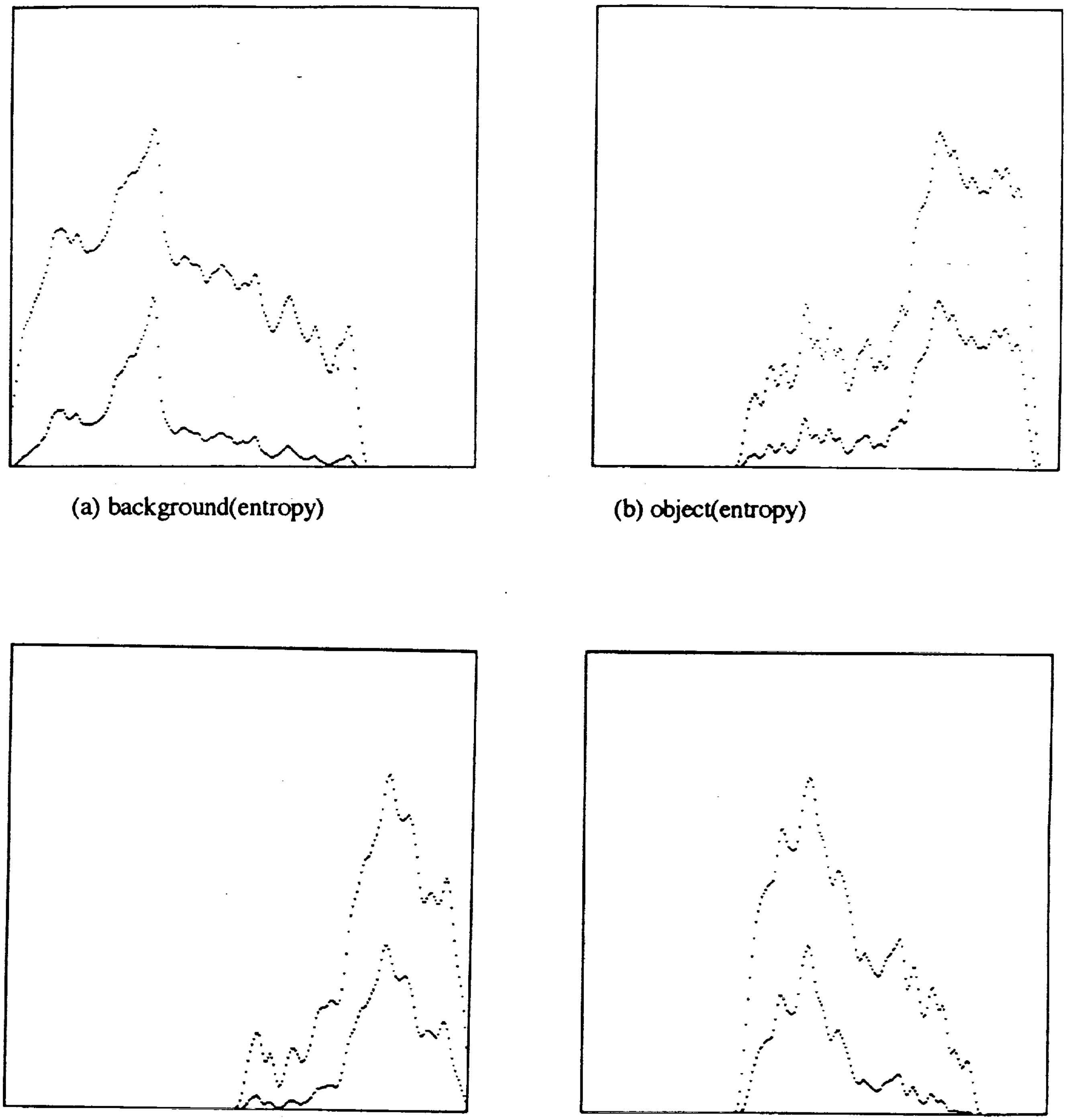


(c) background(homogeneity)



(d) object(homogeneity)

Fig 4.2 membership and p.d.f by Dubois and Prade :
small graphe is p.d.f and big one is membership.



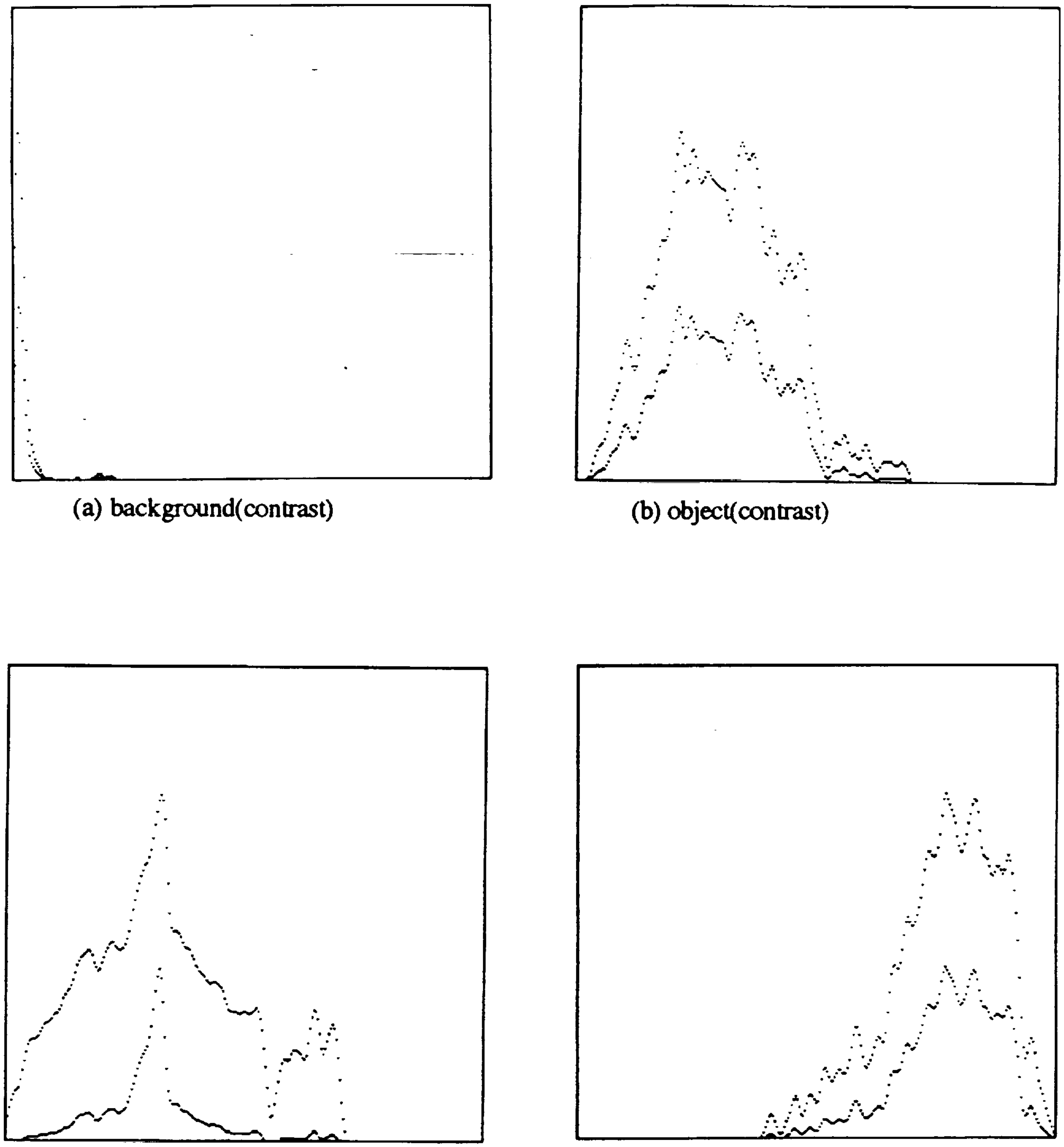
(a) background(entropy)

(b) object(entropy)

(c) background(homogeneity)

(d) object(homogeneity)

Fig 5.1 membership and p.d.f by Klir :
small graphe is p.d.f and big one is membership.



(a) background(contrast)

(b) object(contrast)

(c) background(diff. entropy)

(d) object(diff. entropy)

Fig 5.2 membership and p.d.f by Klir :
small graphe is p.d.f and big one is membership.

Clustering Methods

At the Third International Workshop on Neural Networks and Fuzzy Logic, we presented our new approach of possibilistic clustering applied to the recognition of Plano - Quadric clusters. In what follows, we present the paper which will appear in the proceedings of that Workshop, followed by other examples of the results of the algorithms. Several examples are of images of the shuttle.