# Part 3b: The Classification Problems continued

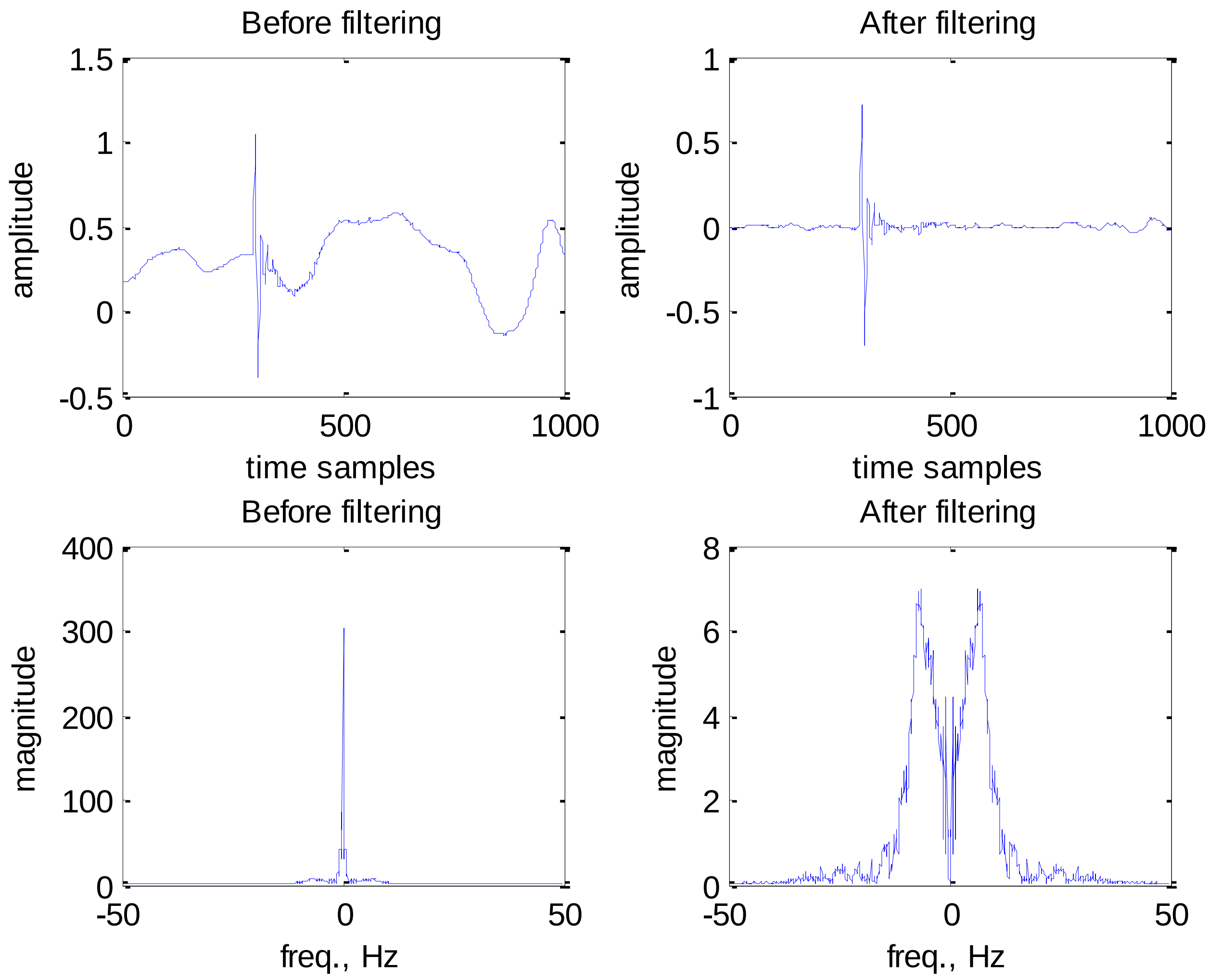
- Neural networks and support vector machines do not have the restrictions of statistical classifiers and are thus particularly suitable for classification problems with remote sensing.

  Part 3b is based on the following chapters.

1) A Universal Neural Network-Based Infrasound Event Classifier (Chapter 3)
2) Multi-sensor Approach to Automated Classification of Sea Ice Image Data (Chapter 25)
3) SAR Image Classification by Support Vector Machine (Chapter27)

# A Neural Network-Based Infrasound Event Classifier

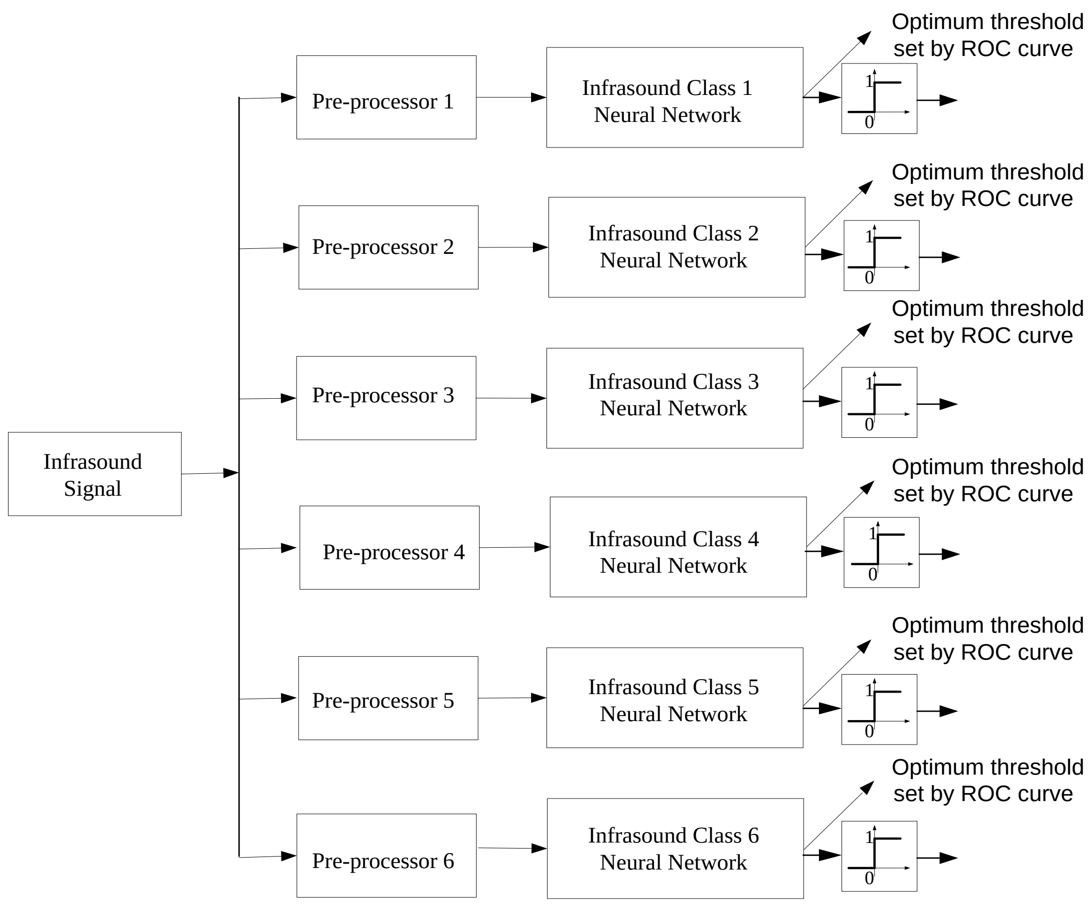
## (Acoustic wave of 0.01 Hz to 10 Hz)



# Overview

- Infrasound can come from nature such as volcano eruptions, earthquakes, severe weather, tsunamis, etc. Infrasound can also result from man-made events such as mining blasts, the space shuttle, high-speed aircraft, artillery fire, rockets, vehicles and nuclear events. Because of relatively low atmospheric absorption at low frequencies, infrasound waves can travel long distances in the earth's atmosphere and can be detected with sensitive ground-based sensors.
- For classification study, the six infrasound classes considered in the chapter are: vehicle, artillery fire, jet, missile,rocket and shuttle. A parallel set of six neural networks is used. Customized feature vectors are computed optimally for each classifier and are based on cepstral coefficients and a subset of their associated derivatives (differences).

# Architecture of a parallel bank of 6 radial basis function neural networks



# RBF NN architecture

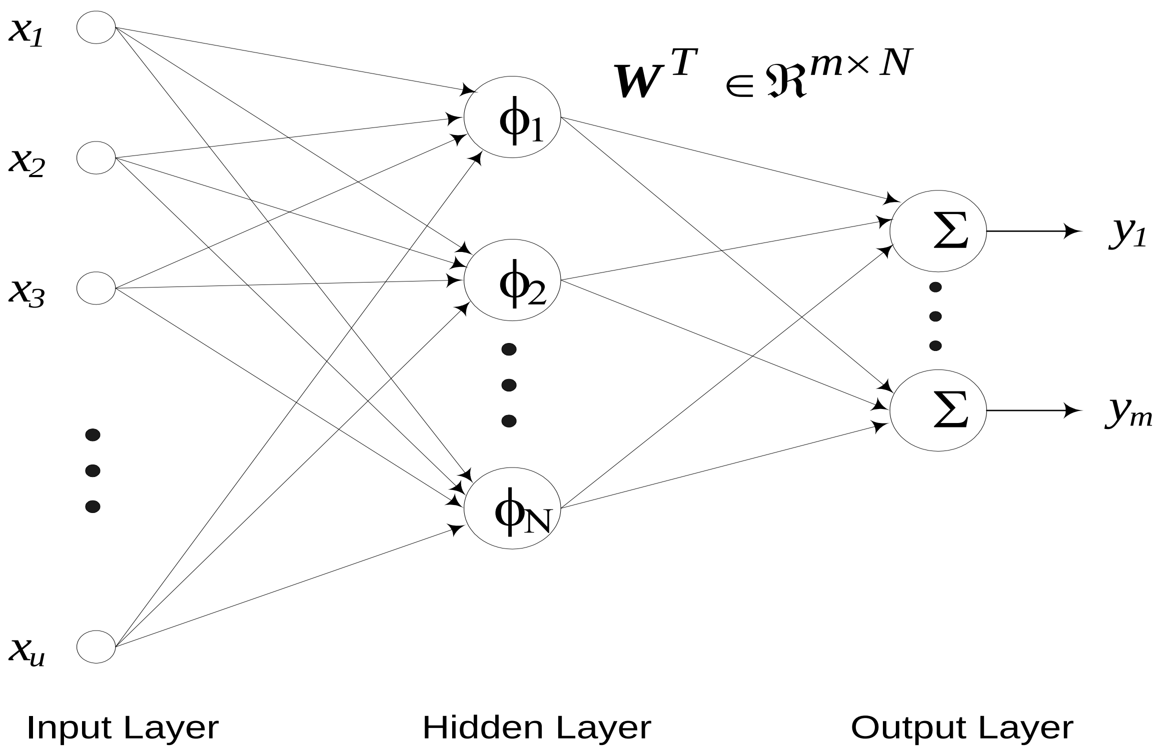


Table 1: Infrasound Classes Used for Training and Testing

| **Class Numb er** | **Event** | **No. of SOI (Total of 574)** | **No. of SOI used for Training (Total of 351)** | **No. of SOI used for Testing (Total of 223)** |
|---|---|---|---|---|
| 1 | Vehicle | 8 | 4 | 4 |
| 2 | Artillery Fire (ARTY) | 264 | 132 | 132 |
| 3 | Jet | 12 | 8 | 4 |
| 4 | Missile | 24 | 16 | 8 |
| 5 | Rocket | 70 | 45 | 25 |
| 6 | Shuttle | 196 | 146 | 50 |

- The data preprocessing and feature extraction processes are fairly similar to speech processing

* Because of multiple detections, the average correct classification (ACC) is defined as

$$ACC = \frac{\text{No. of correct predictions}}{\text{No. of predictions}} = \frac{p+s}{p+q+r+s}$$

*where:*

*p*: number of correct predictions (classifications) that an occurrence is positive

*q:* number of incorrect predictions that an occurrence is positive

*r:* number of incorrect of predictions that an occurrence negative

*s:* number of correct predictions that an occurrence is negative

- An ACC of 94.6% is reported by the authors.
- Comments: The total number of samples available is small and the numbers of samples for all classes are highly uneven.

# Neural Network sea ice classification of remote sensing data

- Comments: The classification errors can be grouped into two categories: (1) labelling inconsistencies and (2) classification induced errors. The errors in the first group are due to mixed pixels, transition zones between different ice regimes, temporal change of physical properties, sea ice drift, within-class variability, and limited training and test data sets. The errors in the second group are traditional errors induced by the classifier. They can be due to the selection of an improper classifier for the given problem, its parameters, learning algorithms, input features, etc.

| Sensor | Date/Time (GMT) | No. of images | No. of *in-situ observations* |
|---|---|---|---|
| RADARSAT Scan SAR | 30 April 1998/11:58 | 1 | 56 |
| ERS-2 SAR | 30 April 1998/06:39 | 3 | 25 |
| Meteor-3 TV camera | 30 April 1998/03:16 | 1 | >56 |

# Description of pattern classes and training/testing sample sizes

| Sea ice class | Description | # training vectors | # test vectors |
| --- | --- | --- | --- |
| 1. Smooth first-year ice | very smooth first-year ice of medium thickness (70-120 cm) | 150 | 130 |
| 2. Medium deformation first-year ice | deformed medium and thick (>120 cm) first-year ice, deformation is 2-3 using the 5 grade scale | 1400 | 1400 |
| 3. Deformed first-year ice | the same as above, but with deformation 3-5 | 1400 | 1400 |
| 4. Young ice | grey (10-15 cm) and grey-white (15-30 cm) ice, small floes (20-100 m) and ice cake, contains new ice in between floes space | 1400 | 1400 |
| 5. Nilas | nilas (5-10 cm), grease ice, areas of open water | 1400 | 1400 |
| 6. Open water | mostly open water, at some places formation of new ice on water surface | 30 | 26 |

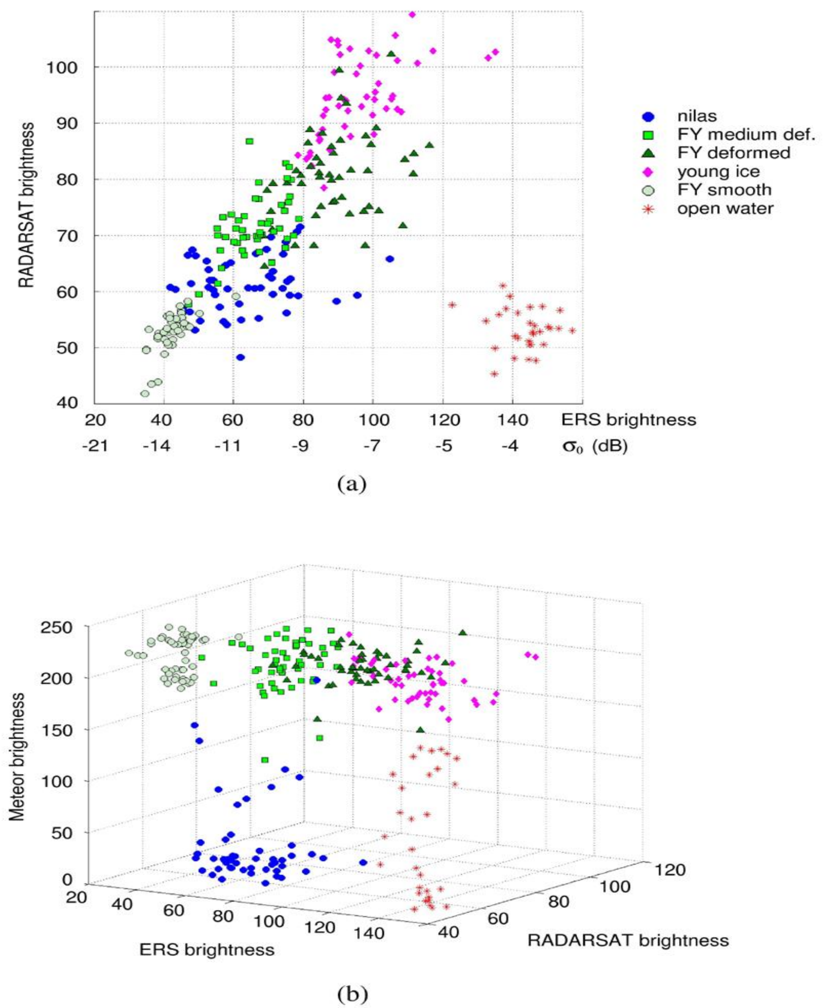
# LDA percentage of correct classification on test data set

| Image features | FY smooth | FY medium | FY def. | Young ice | Nilas | OW | Total |
|---|---|---|---|---|---|---|---|
| ERS mean and texture | 93.1 | 50.6 | 67.9 | 81.4 | 55.2 | 92.3 | 64.6 |
| RADARSAT mean and texture | 43.1 | 60.6 | 65.9 | 89.1 | 60.9 | 46.2 | 68.5 |
| ERS and RADARSAT mean and texture | 91.5 | 74.4 | 80.6 | 93.2 | 81.3 | 100.0 | 82.6 |
| ERS, RADARSAT mean and texture, Meteor mean | 99.2 | 86.6 | 81.7 | 93.4 | 97.4 | 100.0 | 90.1 |

# MLP (back-propagation trained neural network) performance

| Image features / MLP parameters | FY smooth | FY medium | FY def. | Young ice | Nilas | OW | Total |
|---|---|---|---|---|---|---|---|
| ERS and RADARSAT mean values / 2-10-6, 80 cycles | 91.5 | 68.3 | 71.1 | 82.7 | 78.1 | 100.0 | 75.5 |
| ERS, RADARSAT, and Meteor mean values / 3-10-6, 80 cycles | 99.2 | 87.0 | 69.4 | 84.0 | 97.0 | 100.0 | 84.8 |
| ERS and RADARSAT mean values, forth order central moment, cluster shade, Meteor mean value / 7-6-6, 200 cycles | 99.2 | 84.6 | 81.8 | 93.1 | 97.3 | 100.0 | 89.5 |

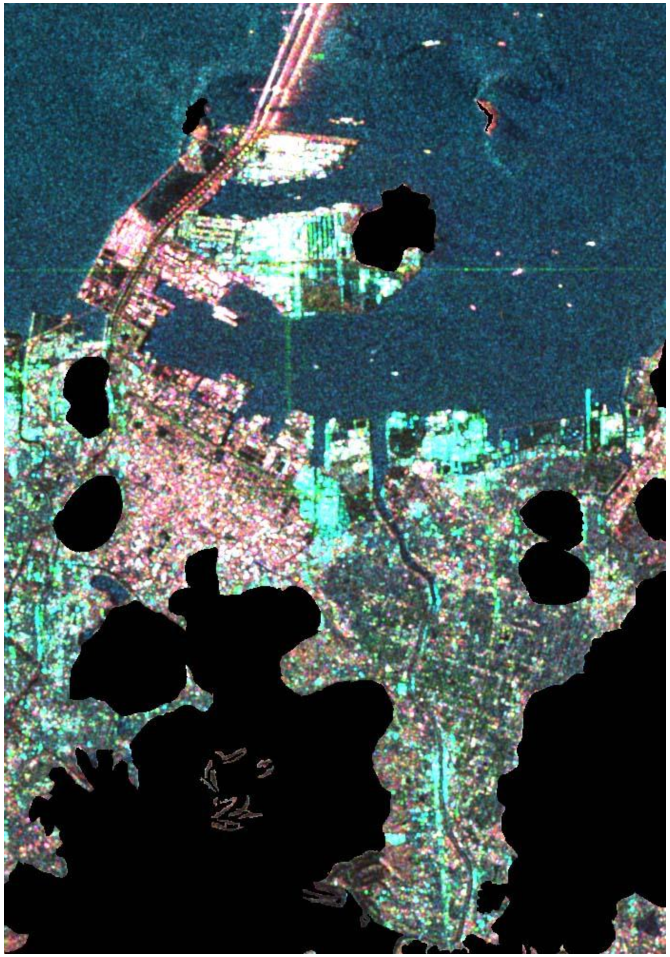
Fig. 5. Image brightness scattergrams for (a) ERS, RADARSAT and (b) ERS, RADARSAT SAR, and Meteor TV images plotted using a subset of training feature vectors.



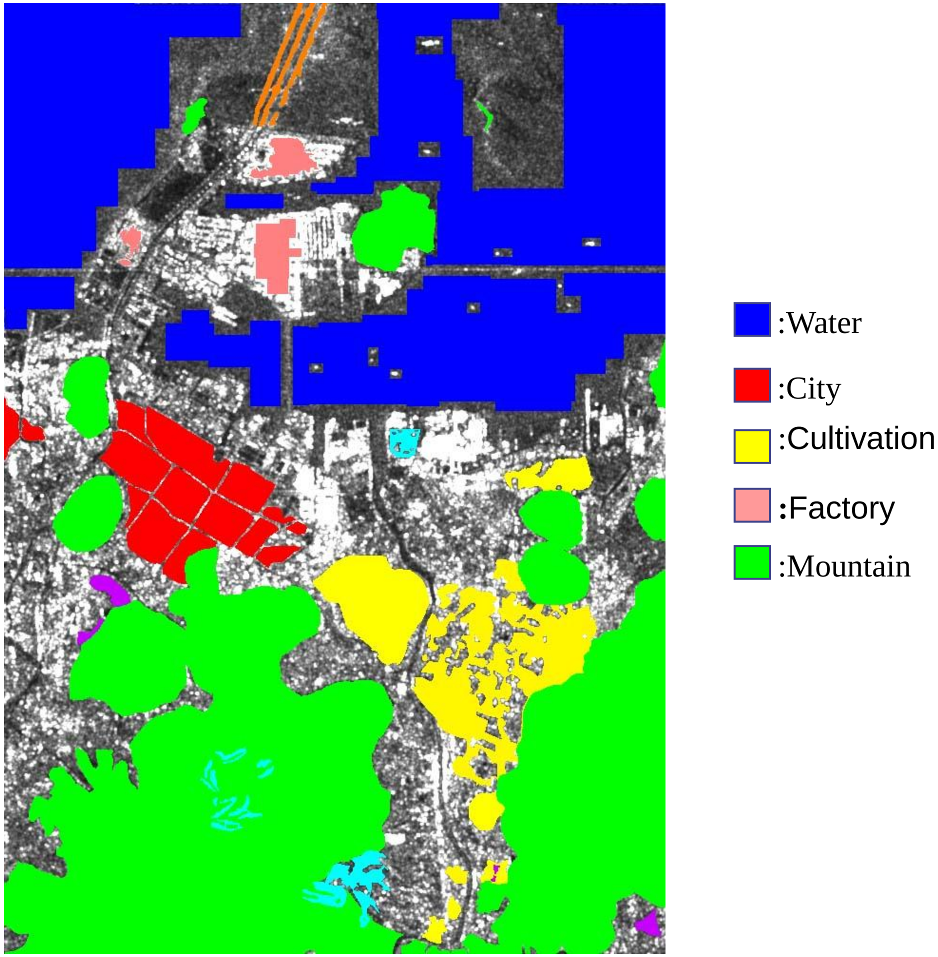
## SAR Image Classification by Support Vector Machine

- The target images from SAR are divided into the area of $8 \times 8$ pixels for calculation of texture features. There are a total of 88 features, calculated using GLCM (Gray Level Co-occurrence Matrix) Cij and GLDM (Gray Level Difference Matrix). K-L distances are used for feature selection. Selected features are input to SVM.
- Four pattern classes considered for land classification are: water, cultivation, city and factory with 133201, 16413,11376,2685 data points respectively.
- Binary SVM classification is performed in stages. Input data are classified into two sets, or a set of water and cultivation areas, and a set of city and factory areas at the first stage. At the second stage, those two sets are classified into two categories, respectively. In this step, it is important to reduce the learning costs of SVM and a method is proposed to reduce the SVM learning cost.
- Gaussian kernel is used for SVM.

# Target data (region of Kagawa Prefecture, Sakaide City, Japan in Oct. 1994)



# The ground truth data for training.
(The mountain region is not classified because of backscatter)



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Selected features (based on area of 8x8)

| Category | Texture features |
| --- | --- |
| Water, Cultivation / City, Factory | Correlation(1,2), Sum average(1) |
| Water / Factory | Variance(1) |
| City / Factory | Energy(1), Entropy(6), Local homogeneity(2) |

(No. in parentheses indicates SAR band.)

Note: Selected means 6 features described in previous slide, while All means all 88 texture features.

Table 3. Classification accuracy(%).

| | Water | Cultivation | City | Factory | Average |
|---|---|---|---|---|---|
| Selected | 99.82 | 94.37 | 93.18 | 89.77 | 94.29 |
| All | 99.49 | 94.35 | 92.18 | 87.55 | 93.39 |

The mountain region is not classified because of the backscatter.

# Concluding Remarks for Part 3b

- The remote sensing data has a lot of within class and inter-class variations such that statistical distributions cannot capture adequately the data characteristics. The problem is compounded by noise and disparity of data available for all classes.
- For the above reasons, neural networks and support vector machines are better suited for remote sensing classification.
- Future fully automated classification systems are likely to employ neural networks and support vector machines.