Radial Basis Function (RBF) Networks

Lecture 14

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Radial Basis Function Networks

- Overview
- Regularization Network
- Generalized RBFNs
- Applications

Overview

- A Feed-Forward Neural Network
- Designed to a Curve-Fitting problem in a high dimensional space
- Strict Interpolation
- Three Layers: Input , Hidden, and Output

Comparison of RBF Networks and MLP-Similarities

- RBF Networks and MLP are examples of nonlinear layered feed-forward networks.
- Universal Approximators
- RBF networks capable of mimicking MLP or Vice versa.

Comparison of RBF Networks and MLP- Differences

- **Network Architecture-**

  MLP – One or more hidden layers

  RBF network - Single hidden layer

- **Computation nodes**

  MLP – Hidden or Output layer – Share a common neuronal model.

  RBF Network – Hidden and Output layer serve different purpose

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Comparison of RBF Networks and MLP- Differences

- **Hidden and Output Layer -**

  MLP – Usually hidden and output layer nonlinear

  RBF network - Hidden – Nonlinear, Output – Linear

Activation Function

  MLP – Hidden - Inner product of input vector and synaptic weight vector

  RBF Network – Hidden Euclidean Norm (distance) between the input vector and the center of the unit

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Comparison of RBF Networks and MLP- Differences

- **Approximations to Nonlinear input-output mapping**

  MLP – Constructs **GLOBAL approximations**

  RBF network – Using exponentially decaying localized nonlinearities (e.g. Gaussian Functions) constructs **LOCAL approximations**.

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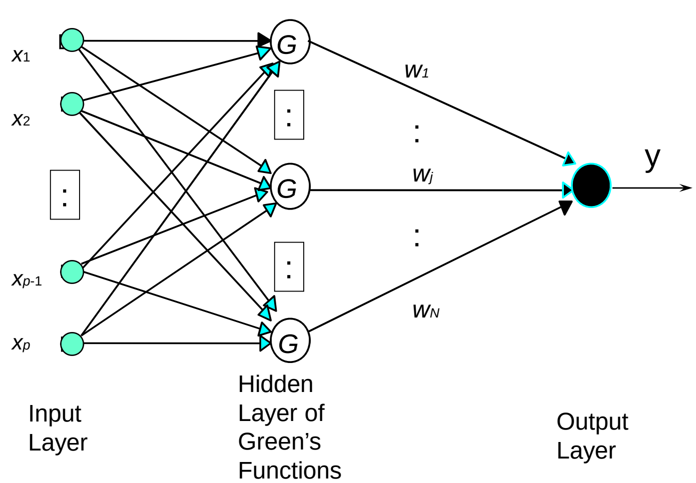
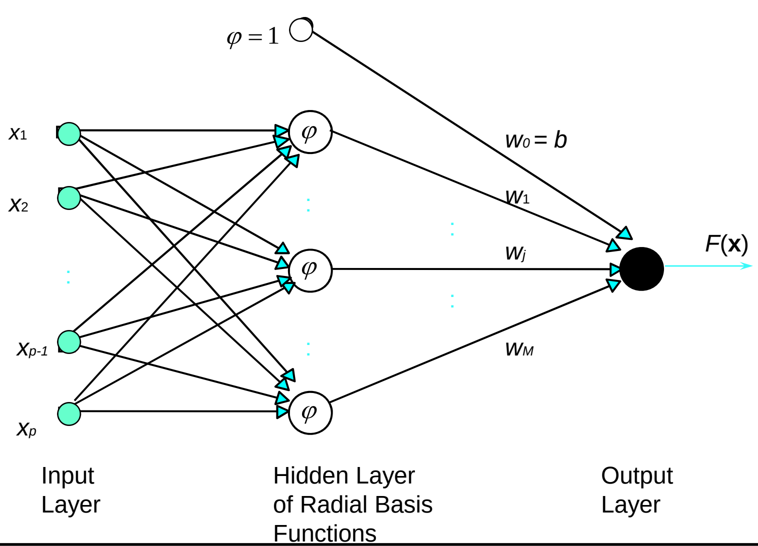
The Regularization Network



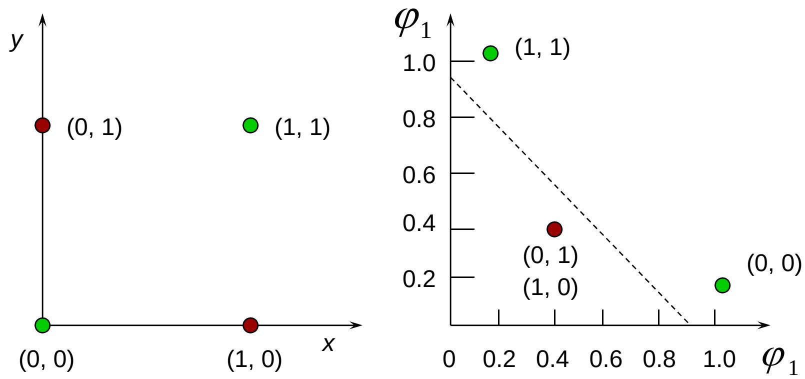
The Regularization Network

- A *universal approximator*
- Has the *best-approximation* property
- Computes the optimal solution
- One-to-one correspondence
- Computationally complex for large *N*

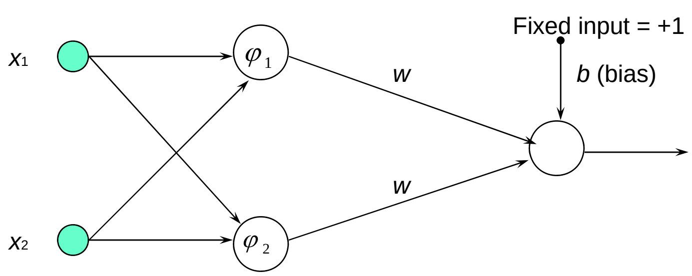
The Generalized RBFNs



The XOR Problem



The RBFN for the XOR Problem

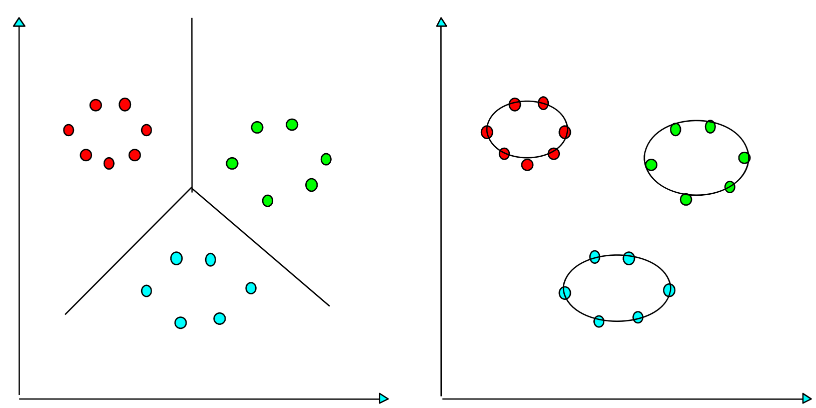


Data Point, j	Input Pattern, $\mathbf{x}_j$	Desired Output, d_j	Actual Output, y_i
1	(1, 1)	1	+0.901
2	(0, 1)	0	-0.01
3	(0, 0)	1	+0.901
4	(1, 0)	0	-0.01

Applications

- Image Processing
- Speech Recognition
- Pattern Recognition
- Time-Series Analysis
- Radar Point Source Location
- Medical Diagnosis
- Process Faults Detection

Decision Surfaces in Two Dimensions



Multi-layer Perceptron   Radial Basis Function Network

Color Image Classification Problem in an Industrial Application

FERAT SAHIN
Bradley Department of Electrical Engineering
Virginia Polytechnic Institute and State University
July 8, 1998

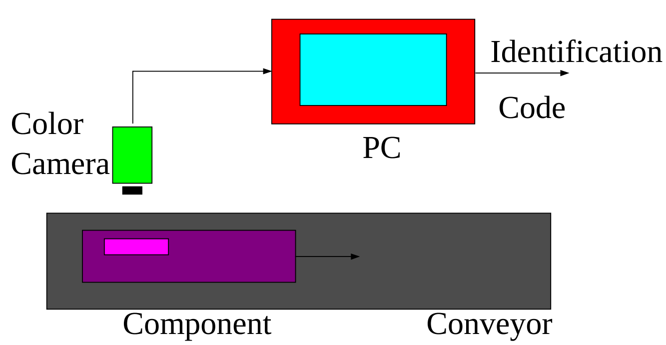
Overview of Presentation

- The Color Classification System
- Definitions
- RBFN Solution to the Color Image Classification Problem
- Comparisons and Discussion
- Conclusions and Future Directions

The Color Classification System

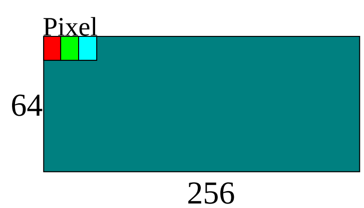
- Background
  - Automatic Vision-based Classification System
  - American Woodmark Corporation
- System Overview

System Overview

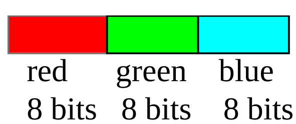


Images of Eight Different Wooden Cabinets

The Structure of the Images



The Number of Pixel an Image : 64x256 = 16384



Each pixel has 24 bits (3 bytes)
An Image is 16384x24 = 49152 bytes

The most important issues in a pattern recognition system

- Selection of a suitable color space
- Quantization of the color space(feature extraction)
- Finding an appropriate classification method
- Acquisition of a model database of images

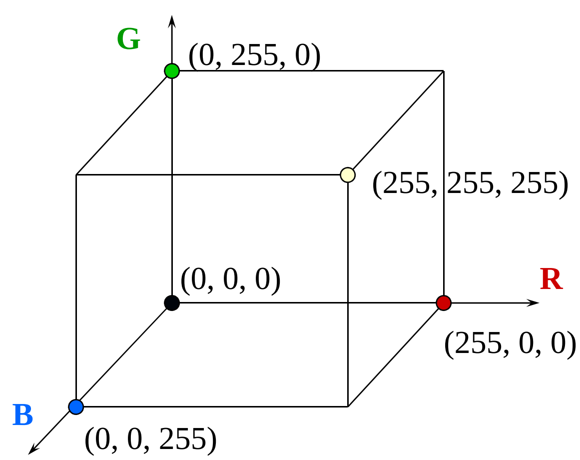
Definitions

- Color Spaces
- Color Quantization
- Color Classification Methods

Color Spaces

- RGB Space
- Normalized RGB Space

RGB Space



Normalized RGB Space

$$N_c = \frac{C}{(R+G+B)} \quad \text{for } C \in \{R,G,B\} \text{ and } R+G+B \neq 0$$

$$N_r + N_g + N_b = 1$$

$$Y = c_1R + c_2G + c_3B \quad \text{where } c_1 + c_2 + c_3 = 1$$

$$T_1 = \frac{R}{(R+G+B)}$$

$$T_2 = \frac{G}{(R+G+B)}$$

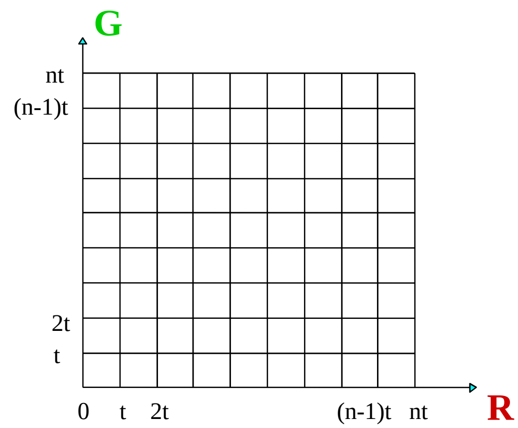
Y: Luminance

T_1, T_2: Chromatic

Color Quantization

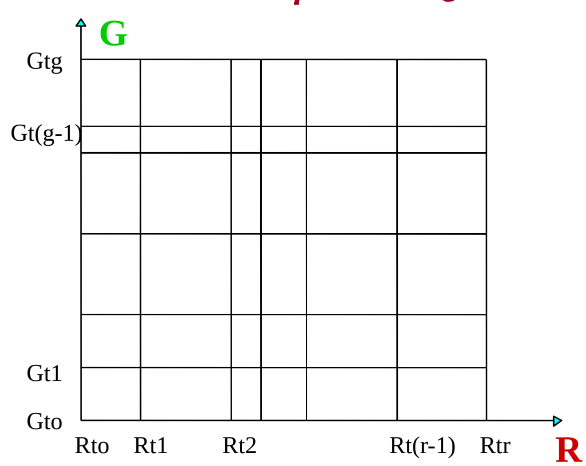
- Uniform Quantization
- Nonuniform Quantization
- Clustering and Vector Quantization

Uniform Quantization

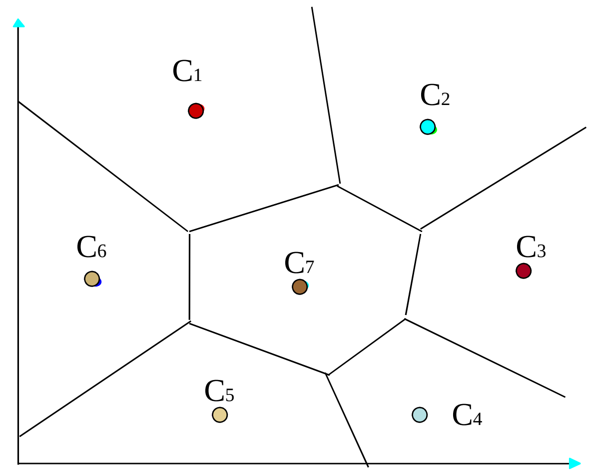


nt = 256

Non-uniform Quantization



Clustering or Vector Quantization



• Color Classification Methods

- Minimum Distance Classifiers
- Radial Basis Function Networks

Minimum Distance Classifiers

- Euclidean Distance

$$d_1^2(x, y) = \sum_{i=1}^{k} (x_i - y_i)^2$$

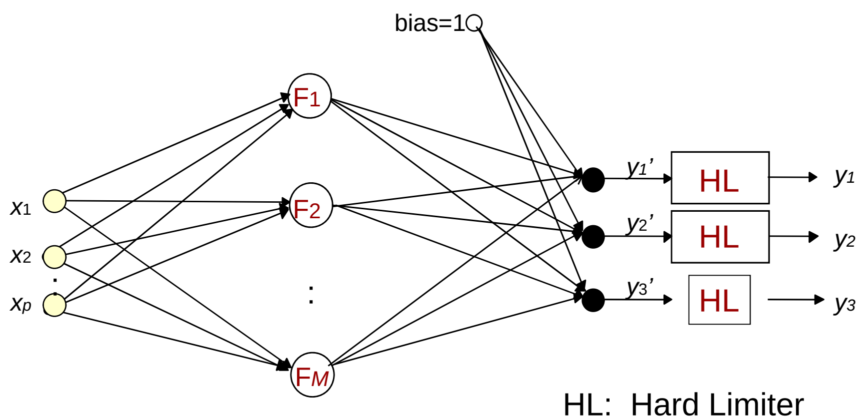
- City-block Metric Distance

$$d_2(x, y) = \sum_{i=1}^{k} |x_i - y_i|$$

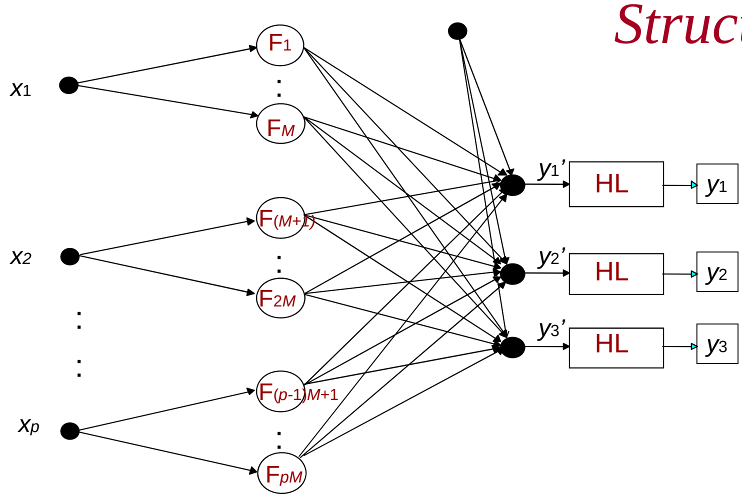
RBFN Solution to the Color Image Classification Problem

- Network Structures
  - The Generalized RBFNs
  - Proposed One-dimensional RBFNs
- Input Features
- Methods

The Generalized RBFN Structure



Proposed One-dimensional RBFN Structure



Input Features

- The Average Values of Colors
- Covariance Matrix

$$\Sigma = \begin{bmatrix} \sigma_{rr} & \sigma_{rg} & \sigma_{rg} \\ \sigma_{rg} & \sigma_{gg} & \sigma_{gb} \\ \sigma_{rg} & \sigma_{gb} & \sigma_{bb} \end{bmatrix}$$

- The Image Partitioning
- Histogram

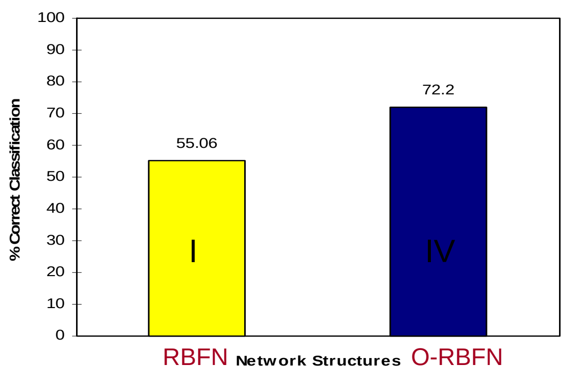
Methods

Method Name	Input Feature Type	# of Centers and RBFs	Network Structure	% Correct Classification
Method I	Average Colors (r, g, b)	8 8	Traditional RBFN	55.06
Method II	Image Partitioning (r_1, g_1, b_1.. .r_4, g_4, b_4)	8 8	Traditional RBFN	66.75
Method III	Average Colors (r, g, b)	23 23	Traditional RBFN	67.79
Method IV	Average Colors (r, g, b)	8 24	O-RBFN	72.20
Method V	Av. Colors and STDs (r, g, b, σ_r, σ_g, σ_b)	8 48	O-RBFN	77.66
Method VI	Covariance Matrix (Nine input features)	8 72	O-RBFN	78.12
Method VII	Histogram (24 elements)	8 8	Traditional RBFN	77.14
Method VIII	Histogram with white noise (24 elements)	8 8	Traditional RBFN	78.15
Method IX	Histogram (24 elements)	30 30	RBFN (Fixed Dilation)	77.34
Method X	Histogram (8 elements for each color)	21, 21 19, 19 16, 16	RBFN (Fixed Dilation)	79.74 (red) 80.25 (green) 81.81 (blue)
Method XI	Histogram (Only blue 64 elements.)	80 80	RBFN (Fixed Dilation)	84.41 (blue)

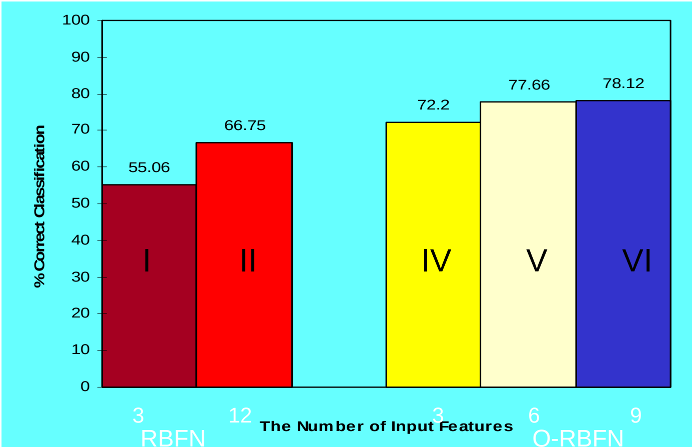
Comparisons and Discussion

- Network structure
- The number of input feature
- The number of RBFs in the Network

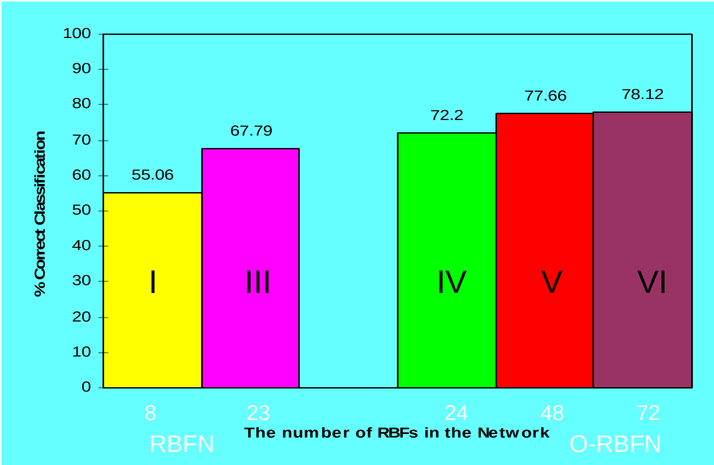
Network Structure



The Number of Input Features



The Number of RBFs in the Network



Conclusions

- RBFNs are fast and generalize the solution well.
- RBFNs are the best for the nonlinear classification
- One-dimensional RBFNs are successful
- Only one color’s histogram is enough
- RBFNs gave more accurate results

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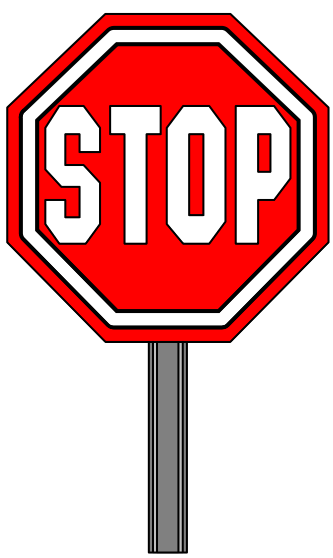

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