Artificial Neural Networks for Biometric Applications

PRESENTED BY:

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SEPT. 2003

ANN for Biometric Applications

- Problem Statement: Speaker Verification
- Review of Speaker Verification
- Review of Radial Basis Function Networks
- Minimal Resource Allocation Networks (MRAN)
- Application of MRAN to Speaker Verification
- Experimental Results
- Conclusions and Future Work

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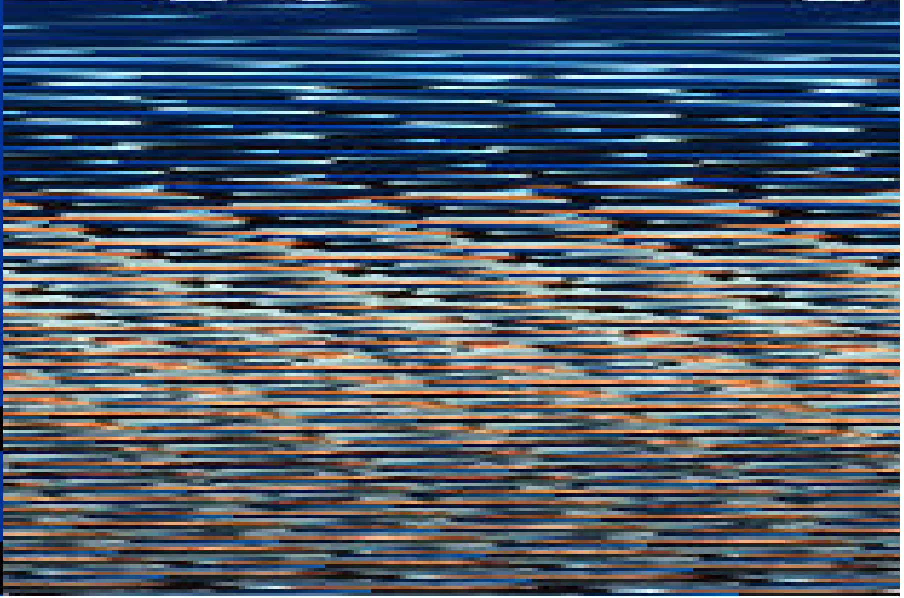
How to Tell the Real Saddam from His Doubles?

1. Saddam has at least three doubles – Reuters, Sept. 27, 2002.
2. Hard to know if Saddam tape is genuine – CNN, July 30, 2003.

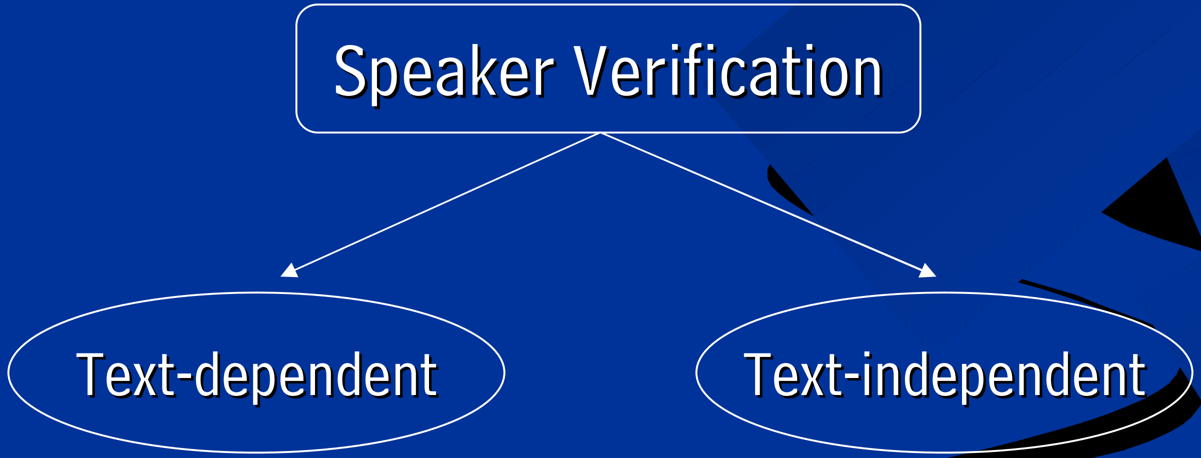
- How to tell whether a 'Saddam' is the real one or not?
- Possible approaches

  - DNA Test
  - Face Recognition
  - Speaker Verification



Introduction to Speaker Verification

- Speaker Verification is aimed to decide, given a sample of speech, whether a specified candidate speaker said it.
- Speaker Verification can be categorized into:



Speaker Verification

Text-dependent

Text-independent

The speaker is supposed to say predefined words and he must cooperate

No restriction. The speaker can say anything.

Applications of Speaker Verification

- Access control, eg. computer access control
- Telephone voice authentication
- Automatic speaker labeling of recorded meetings for audio indexing
- Many other applications …

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Review of Speaker Verification

- Statistical method
  - Using long-term statistics calculated on a very long acoustic sequence
  - Problem: Sensitive to the variability of the transfer function of the channel
  - C. Montacie improved it using a multi-dim autoregressive model in 1992
- Vector quantization
  - Proposed by F. K. Soong
  - Vector quantization of spectral or cepstral vectors
- Hidden Markov Models (HMM)
  - 'Linear predictive HMM and the speech signal' – A. B. Poritz, 1982.
- Artificial neural networks
  - Multilayer perceptrons
  - RBF and EBF - M. Man-Wai & K. Sun Yuan
  - EBF performs better than vector quantization method and large RBF networks

Review of Speaker Verification

- Can other kinds of RBF networks outperform EBF networks?
- MRAN, a sequential learning RBF, performs better than conventional RBF networks and some of EBF networks

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RBF Networks: Fundamentals

- Exact interpolation problem:

$$\{X_i\} \xrightarrow[y_i = f(X_i)]{f(.)} y_i$$

- The RBF approach to exact interpolation problem:
  - Form a set of basis functions, one for each data set.
  - RBF function is of the form: $\mathbf{F}\,(\,\|\,\mathbf{x} - \boldsymbol{\mu}\,\|\,)$
  - f(x) can be taken to be a linear combination of the outputs of all RBFs:

$$f(x) = \sum_k \underset{\text{Weight factor}}{\underset{\uparrow}{w_k}} \Phi\left(\left\| x - \underset{\text{Center of the function}}{\underset{\uparrow}{m_k}} \right\|\right)$$

RBF Networks: Fundamentals

- RBF Function:
  - Non-linear
  - Choices: thin plate spline, multi-quadratic, Gaussian kernel
  - Gaussian function is the most common one:

$$\Phi(x) = \exp\left(-\frac{x^2}{2s^2}\right)$$

Factor controlling radius of influence of the function

- Generalization to multi-variable output can be done by mapping input vectors X_i onto corresponding output vectors Y_i

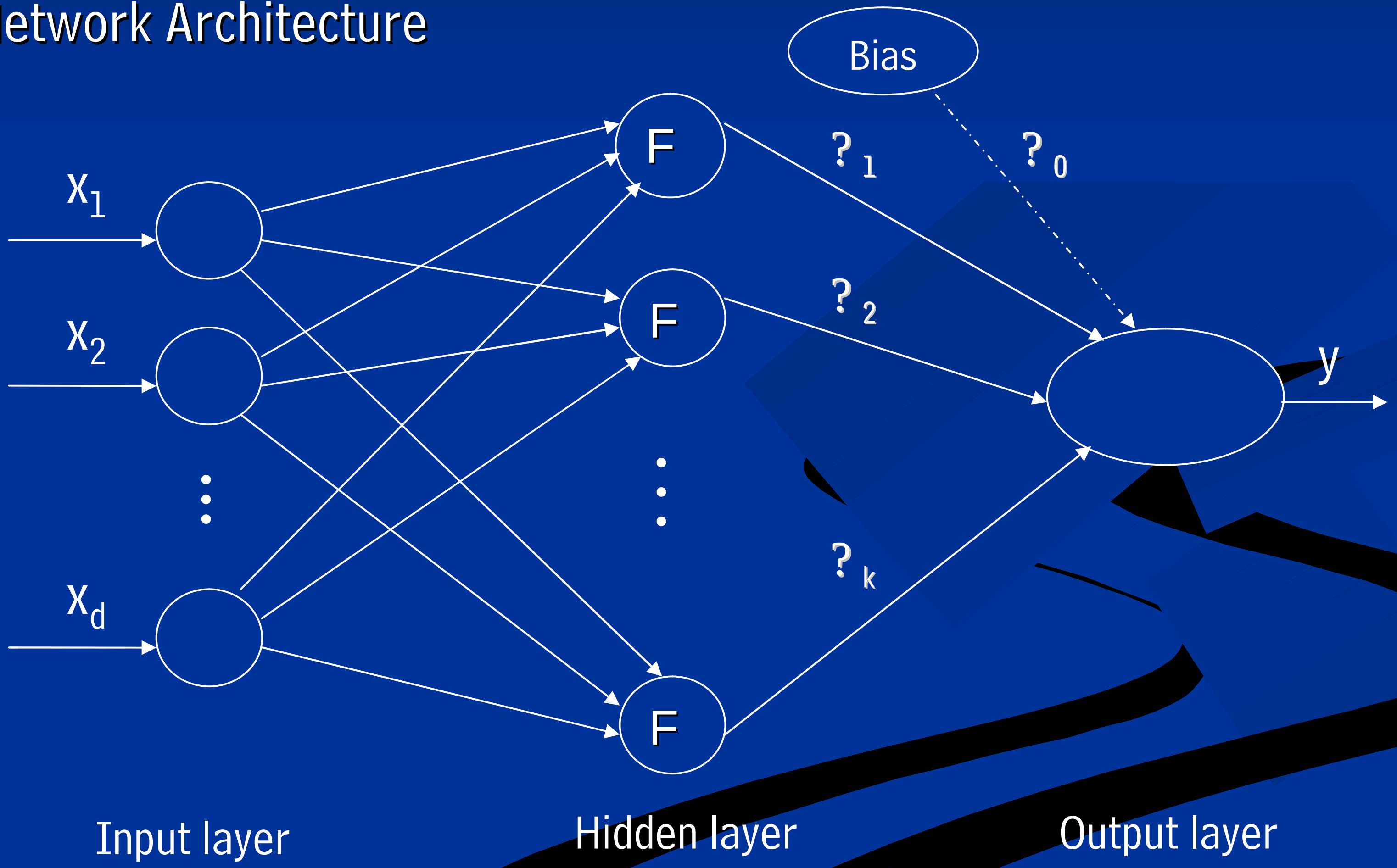
Radial Basis Function Networks

- RBF Network model is built on the base of the exact interpolation
- Improvements:
  - Restriction for strict function interpolation removed – Broomhead & Lowe
  - Centers of basis functions are not constrained to the values of input data set
  - Bias parameters can be included
- RBF Network model after improvements made:

$$\underbrace{y}_{\text{Output}} = \sum_{k}^{K} \underbrace{w_k}_{\text{Weight factor}} \underbrace{\Phi_k}_{\text{Radial basis function}}(x) + \underbrace{w_0}_{\text{Bias}}$$

Architecture of RBF Networks

- Network Architecture



Radial Basis Functions

- RBF Network model

$$y = \sum_{k}^{K} w_k \Phi_k(x) + w_0$$

Number of hidden neurons

Bias

Connection weight for each hidden unit

- Gaussian function as the radial basis function

$$\Phi(x) = \exp\left(- \frac{\left\| x - m_k \right\|^2}{2s^2} \right)$$

Center position of the hidden neuron

Width value for the Gaussian function

Radial Basis Function Networks

- Problem: Difficult to choose the right number of hidden neurons
- S. Lee & R. Kil developed a Hierarchically Self-Organizing Learning algorithm to determine the number of hidden units

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Resource Allocation Networks

- Batch learning vs. sequential/incremental learning
- Platt proposed a sequential learning method for Resource Allocation Networks (RAN)
  - Hidden neurons are added based on the novelty of the training pattern inputs. If not novel, LMS is used to update network params.
- Kadirkamanathan & Niranjan improved RAN by replacing the LMS with the Extended Kalman Filter (EKF) – RANEKF
- Drawback of RAN – noise data points may trap the network to create redundant hidden neurons

Minimal Resource Allocation Networks

- L. Yingwei, N. Sundararajan and P. Saratchandran improved RAN by adding a pruning strategy. The resulting network is known as Minimal Resource Allocation Networks (MRAN).
- Growth strategy of MRAN: same as that of RAN, comprised of allocation of new hidden units and adjustment of network params.
- Criteria to add a new hidden unit:

$$\|x_n - u_{nr}\| > e_n \qquad\qquad e_n = |y_n - f(x_n)| > e_{\min}$$

$$e_{rmsn} = \sqrt{\frac{\sum_{i=n-(M-1)}^{n} e_i^2}{M}} > e_{\min 1}$$

Minimal Resource Allocation Networks

- If one or more criteria can not be satisfied, no hidden neurons will be added and network parameters will be updated using an Extended Kalman Filter.
- Pruning strategy of MRAN: a hidden unit should be pruned if its output contribution is less than a threshold over a certain number of consecutive iterations.

$$y_n = \sum_{k=1}^{K} w_k \Phi_k(x_n) + w_0$$

Total network output

$$o_k = w_k \Phi_k$$

A hidden unit’s contribution to the total output

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Application of MRAN to Speaker Verification – The Speech Database

- TIMIT – a phonetically balanced continuous speech corpus, containing speech from 630 speakers representing 8 major dialect divisions of American English.
- 258 speakers from the first four regions of the corpus are involved in the experiments:

SET	REGION	MALE	FEMALE	TOTAL
Speaker set	2	46	30	76
Anti-speaker set	1	20	18	38
Pseudo-imposter set	4	38	30	68
Imposter set	3	53	23	76

Application of MRAN to Speaker Verification – The Speech Database

- Speaker set: contains all the target speakers;
- Data of anti-speakers in the anti-speaker set is used to train the neural network for each target speakers during speaker enrollment;
- Data of pseudo-imposters in pseudo-imposter set is used to determine the decision threshold for each network;
- Data of imposters in imposter set is used in verification phase to calculate the false acceptance rate.

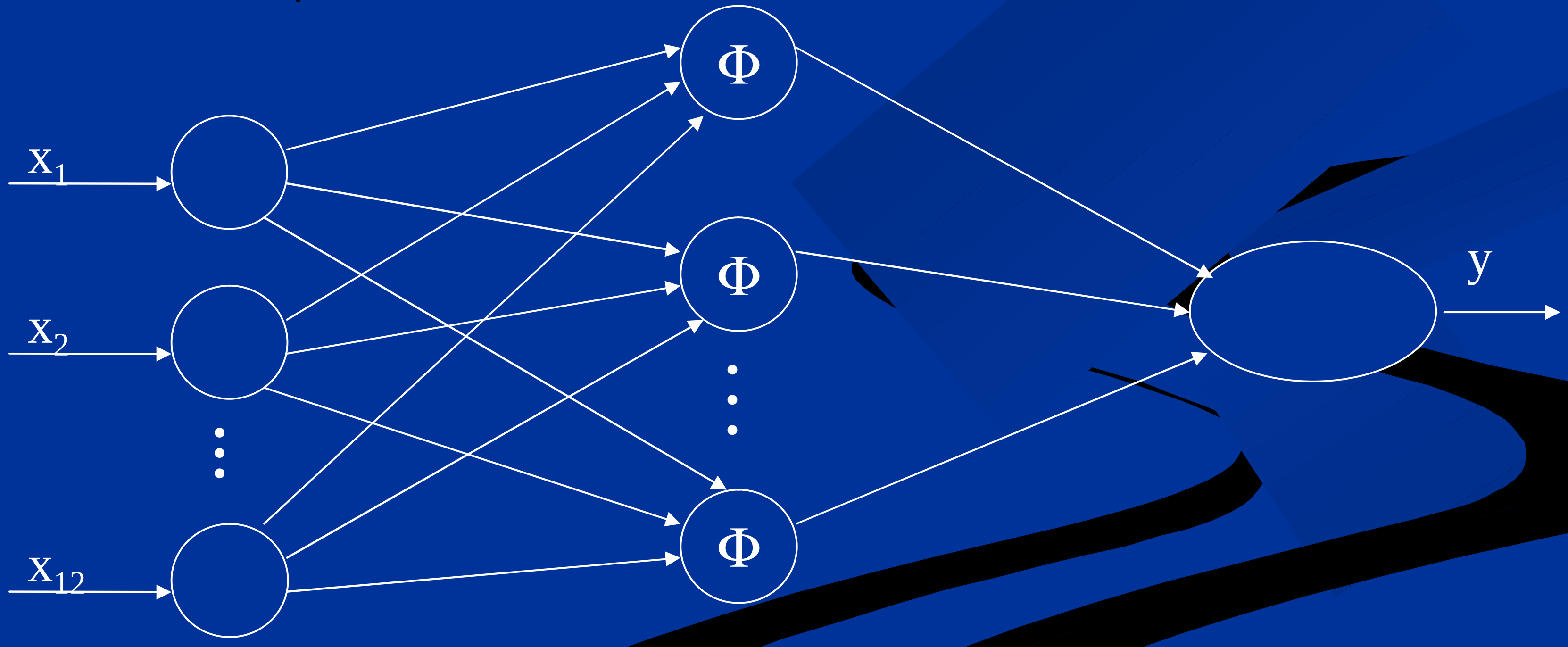
- Each speaker reads three types of sentences: 2 Dialect (SA), 5 Compact (SX) and 3 Diverse (SI) sentences.

Application of MRAN to Speaker Verification – Feature Extraction

- Cepstral coefficients are the best features for speaker verification
- 12th order LP-derived cepstral coefficients are used as feature vectors in the experiments
- Speech signals are pre-emphasized by a filter with transfer function $H(z) = 1 - 0.95z^{-1}$
- Silent regions are removed

Application of MRAN to Speaker Verification – Enrollment

- Each speaker in the speaker set is assigned a radial basis network which models the characteristics of his or her voice
- Network setup:



Input layer Hidden layer Output layer

Application of MRAN to Speaker Verification – Steps of Enrollment

1) Using the target speaker’s data and all anti-speakers’ data to train a MRAN network

   Ratio of training vectors between the target speaker class and anti-speaker set class is around 1:38 ---- Highly unbalanced!

Anti-speaker 1’s data	The speaker’s data	Anti-speaker 2’s data	The speaker’s data	…	Anti-speaker 38’s data	The speaker’s data

   Supervised training: target speaker’s output is 1; -1 otherwise.

2) Determining the decision (acceptance or rejection) threshold using pseudo-imposter set

Application of MRAN to Speaker Verification – Verification Phase

- Each network trained will be verified against the target speaker and a set of imposters
- False Rejection Rate (FRR) – probability of not detecting the target speaker when present

$$E_{FRR} = N_{MISS} / N_{TARGET}$$

- False Acceptance Rate (FAR) – probability of falsely detecting the target speaker when not present

$$E_{FAR} = N_{FA} / N_{IMPOSTER}$$

Application of MRAN to Speaker Verification – Verification Phase

- Equal Error Rate (ERR) – when the decision threshold is properly adjusted, FRR and FAR can be equal and the value of ERR equals to that of FAR or FRR
- Verification Process: an input feature vector sequence $T=[X_1, X_2, \cdots, X_t]$ extracted from an utterance spoken by an unknown speaker is fed into the network. Average output:

$$\bar{y} = \frac{1}{t}\sum_{i=1}^{t} f\left(x_i\right)$$

- Verification decisions:

Decision threshold

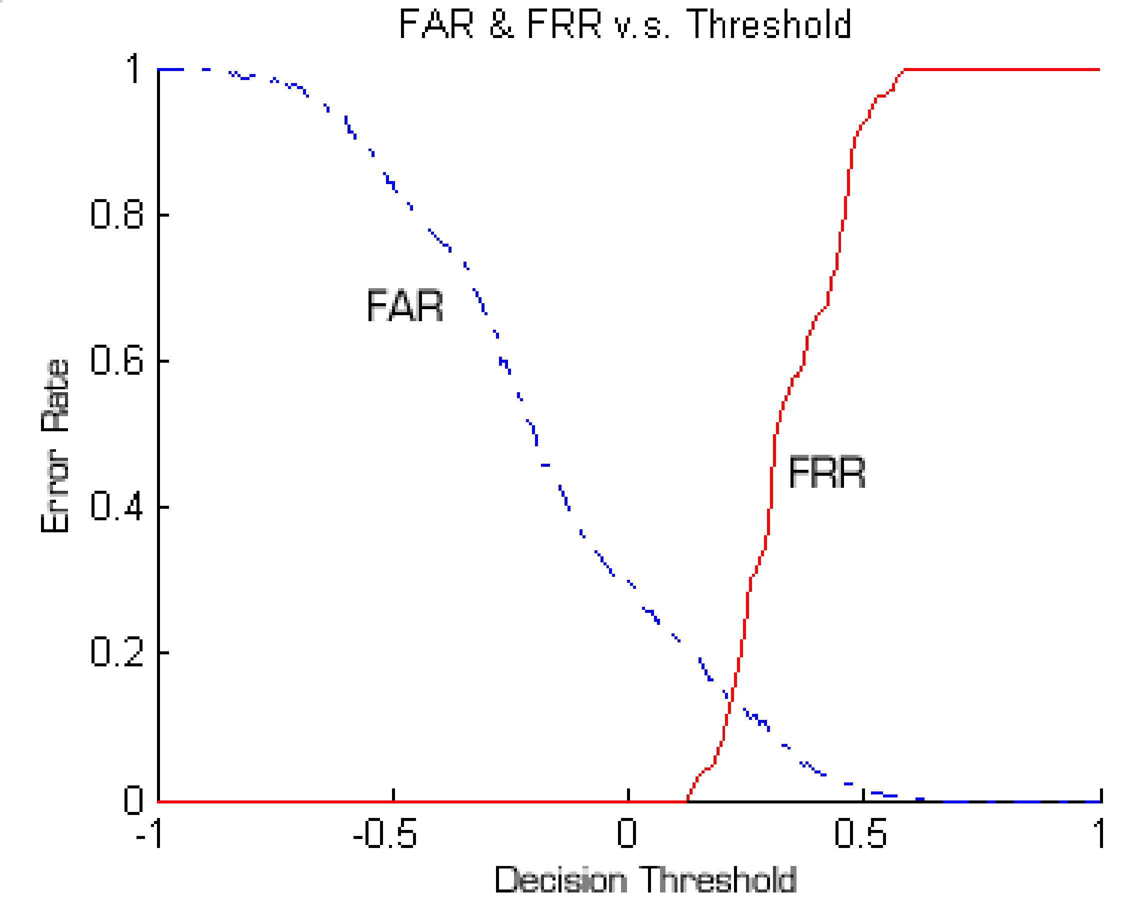
$$\begin{cases} \bar{y} > x \Rightarrow accept \\ \bar{y} \leq x \Rightarrow reject \end{cases}$$

Application of MRAN to Speaker Verification – Decision Threshold

- Decision threshold is determined in the enrollment phase
- Decision threshold is determined using feature vectors derived from utterance of pseudo-imposters
- Decision threshold is set to the threshold at which False Acceptance Rate reaches a predefined value (2 percent in our experiments) – feed data of pseudo-imposters into the network and adjust the threshold until the FAR reaches 2 percent

Application of MRAN to Speaker Verification – Decision Threshold

- Many ways to calculate the decision threshold



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Application of MRAN to Speaker Verification – Experimental Results

- 76 experiments for all the speakers in the speaker set. Experimental results are then compared with those by M. Ran-Wai and K. Sun-Yuan
- Summary of experimental results over total 76 networks corresponding to 76 speakers:

MRAN Experimental Results

Rates	Equal Error Rate	False Acceptance Rate	False Rejection Rate	No. of hidden neurons
Avg. Value	**0.948%**	**3.183%**	**5.306%**	**57.46**
STDEV	**1.399%**	**2.471%**	**15.636%**	**24.85**

Application of MRAN to Speaker Verification – Experimental Results

- Geometric Mean Error (GME) – another statistic offering the desired ability of comparing systems

$$E_{GME} = \sqrt{E_{FAR} * E_{FRR}}$$

- GME is not perfect – it tends to decrease as the FRR is increased

Application of MRAN to Speaker Verification – Results Comparison

- Results compared with those by M. Ran-Wai and K. Sun-Yuan

NETWORKS	NUMBER OF HIDDEN UNITS	COMPLEXITY	EER	FAR	FRR	GME
RBF	61	917	7.46%	20.72%	53.93%	33.43%
MRAN	57	804	0.95%	3.18%	5.30%	4.10%
EC	10	922	0.44%	0.46%	14.99%	2.62%
EED	35	912	0.47%	1.78%	15.07%	5.18%
EEF	10	922	0.37%	3.52%	6.74%	4.87%

Application of MRAN to Speaker Verification – Results Comparison

- MRAN outperforms the conventional RBF and some of the EBF networks in terms of geometric mean error (GME) with the minimum complexity, i.e., number of parameters of the network

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Conclusions

- With the minimum complexity, MRAN outperforms conventional RBF networks and
- its performance is comparable or even better than EBF networks

Future Works

- Extend MRAN to elliptical basis function
- Compare the extended EBF MRAN with RBF MRAN and other kinds of neural networks in terms of error measures and complexity

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Thank You

Q & A

Supplemental Slides

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Elliptical Basis Function Networks

- RBF units are hyperspherical. High recognition accuracy can be achieved when the components of the training vectors are independent. If this is not the case, more basis functions are required.
- It would be beneficial if full covariance matrices could be incorporated into the RBF structure so that complex distribution could be represented without the need for using a large number of basis functions → EBF.

Elliptical Basis Function Networks

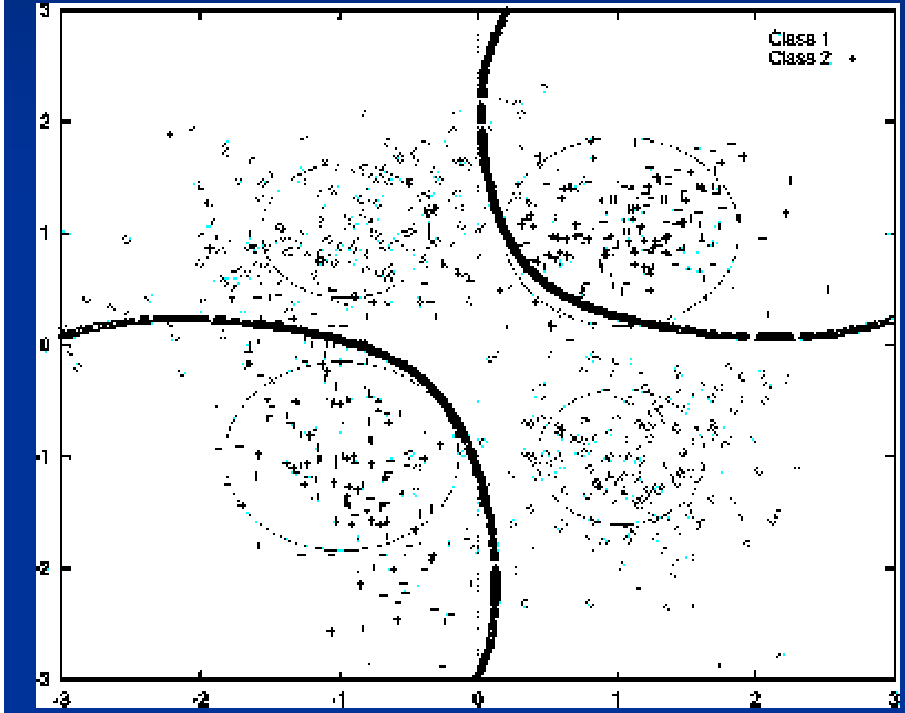
- EBF networks can be considered as an extension of the RBF networks
- The kth output of an EBF network with I inputs and K function centers has the form: (N inputs, M outputs, K hidden units)

$$y_m\left(\vec{x}_n\right) = w_{m0} + \sum_{k=1}^{K} w_{mk}\Phi_k\left(\vec{x}_n\right)$$

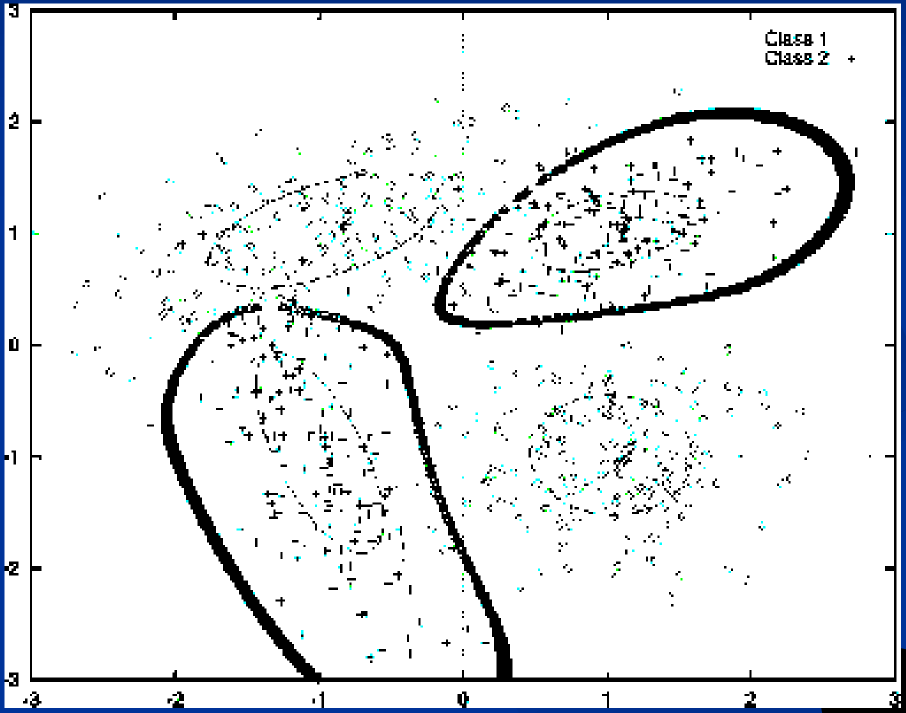
where $$\Phi_k\left(\vec{x}_n\right) = \exp\left\{-\frac{1}{2g_k}\left(\vec{x}_n - m_k\right)^T \Sigma_k^{-1}\left(\vec{x}_n - m_k\right)\right\}$$

and heuristically, $$g_k = \frac{3}{5}\sum_{j=1}^{5}\left\|\vec{m}_j - \vec{m}_k\right\|$$

EBF vs. RBF



RBF with 4 hidden units



EBF with 4 hidden units