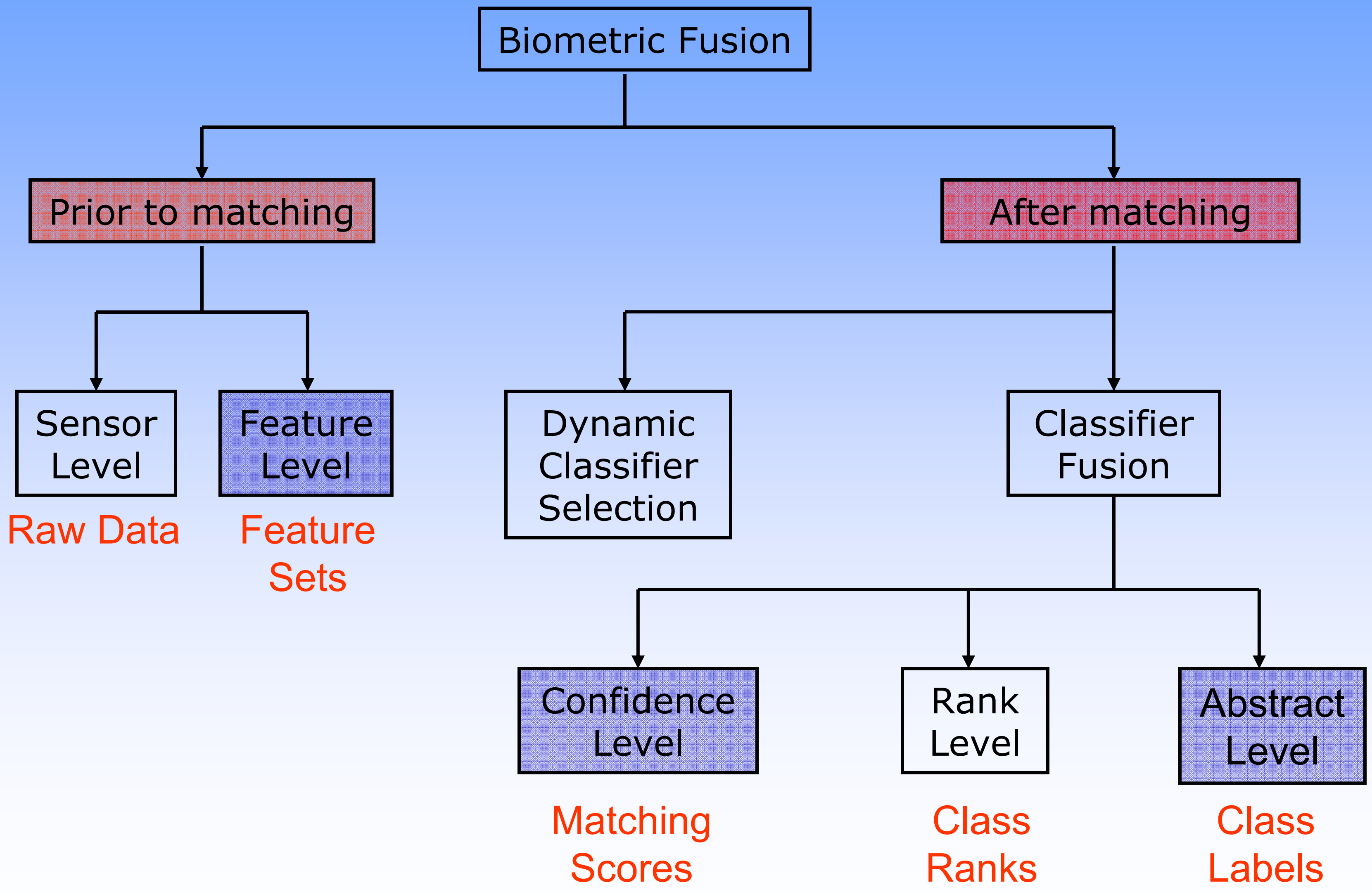
Match Score Level Fusion
Score normalization
User-specific parameters

Arun Ross
Assistant Professor
West Virginia University
Morgantown, West Virginia, USA
ross@csee.wvu.edu

http://www.csee.wvu.edu/~ross

Levels of fusion



Ross, Jain 2004

Fusion at the match score level

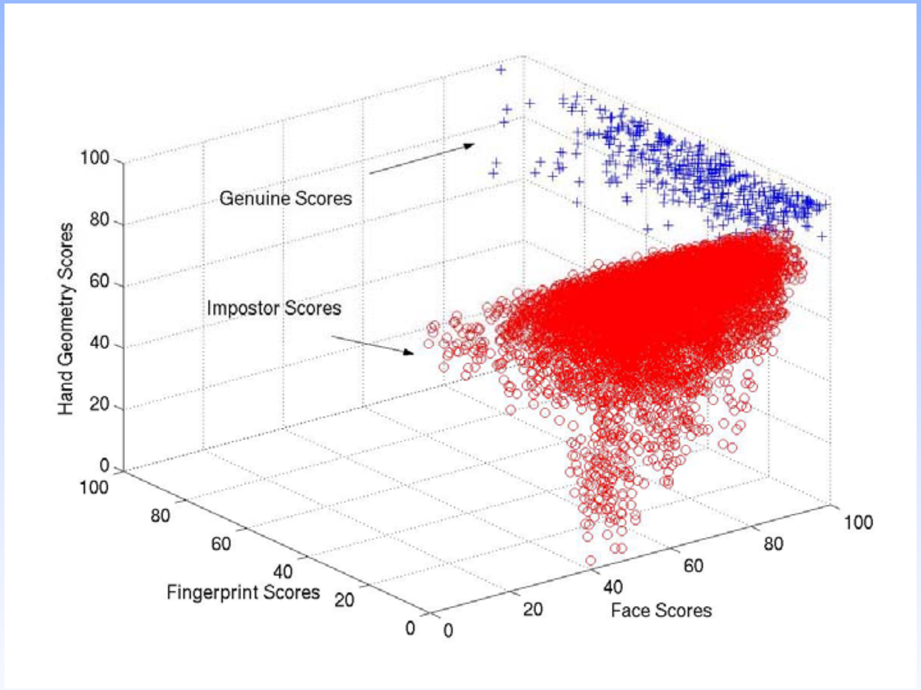
- Match scores output by multiple matchers are consolidated
- Two approaches exist in the context of verification:
  - A feature vector is constructed using the match scores; feature vector is assigned to one of two classes: "genuine" or "impostor"
    - e.g., discriminant analysis, KNN, decision trees, random forests, SVMs, etc.
  - A single scalar score is generated from multiple matching scores; a classifier operates on the new score
    - e.g., min-, max-, sum-, median rule

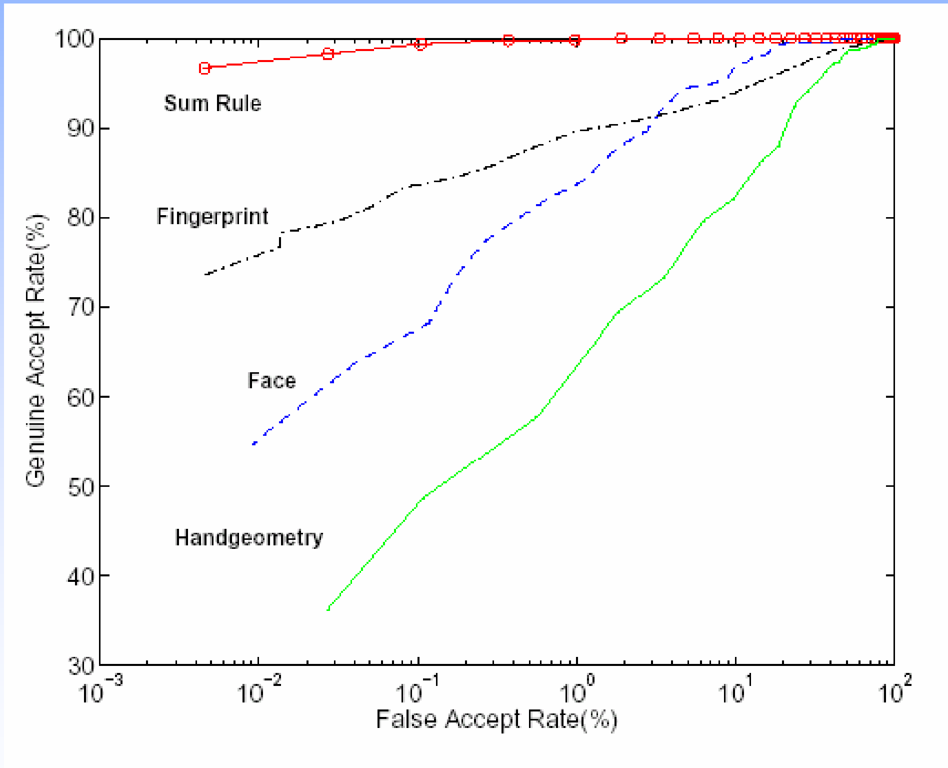
Ross, Jain 2004

Fusion methodology

- Sum rule (weighted average of individual scores) has been shown to improve the system performance:

$$S = w_1 s_1 + w_2 s_2 + w_3 s_3$$





Ross, Jain 2004

Score normalization

- Scores output by individual matchers:
  - Non-homogeneous: distance or similarity
  - Ranges may be different; e.g., [0,100] or [0,1000]
  - Distributions may be different

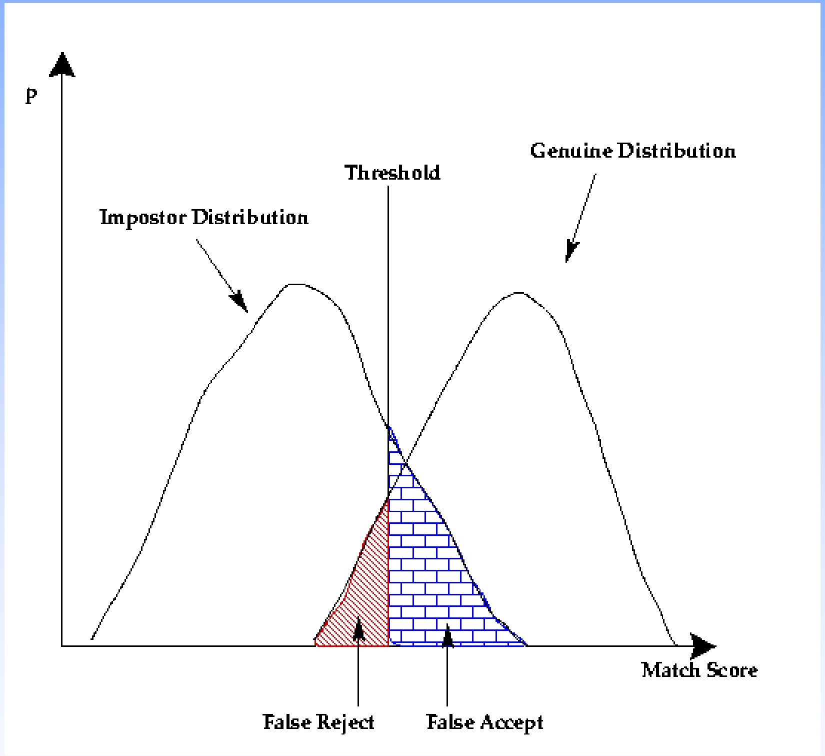
- To facilitate fusion:
  - Modify the location and scale parameters of score distributions of individual matchers
  - Apply transformation to scores present in the genuine-impostor overlap region

- Robustness: insensitivity to the presence of outliers
- Efficiency: proximity of the obtained estimate to the optimal estimate when the distribution of the data is known

Ross, Jain 2004

Normalization schemes

- Min-max normalization
- Decimal scaling
- Z-score normalization
- MAD
- Tanh estimators
- Double sigmoid function
- Biweight estimators

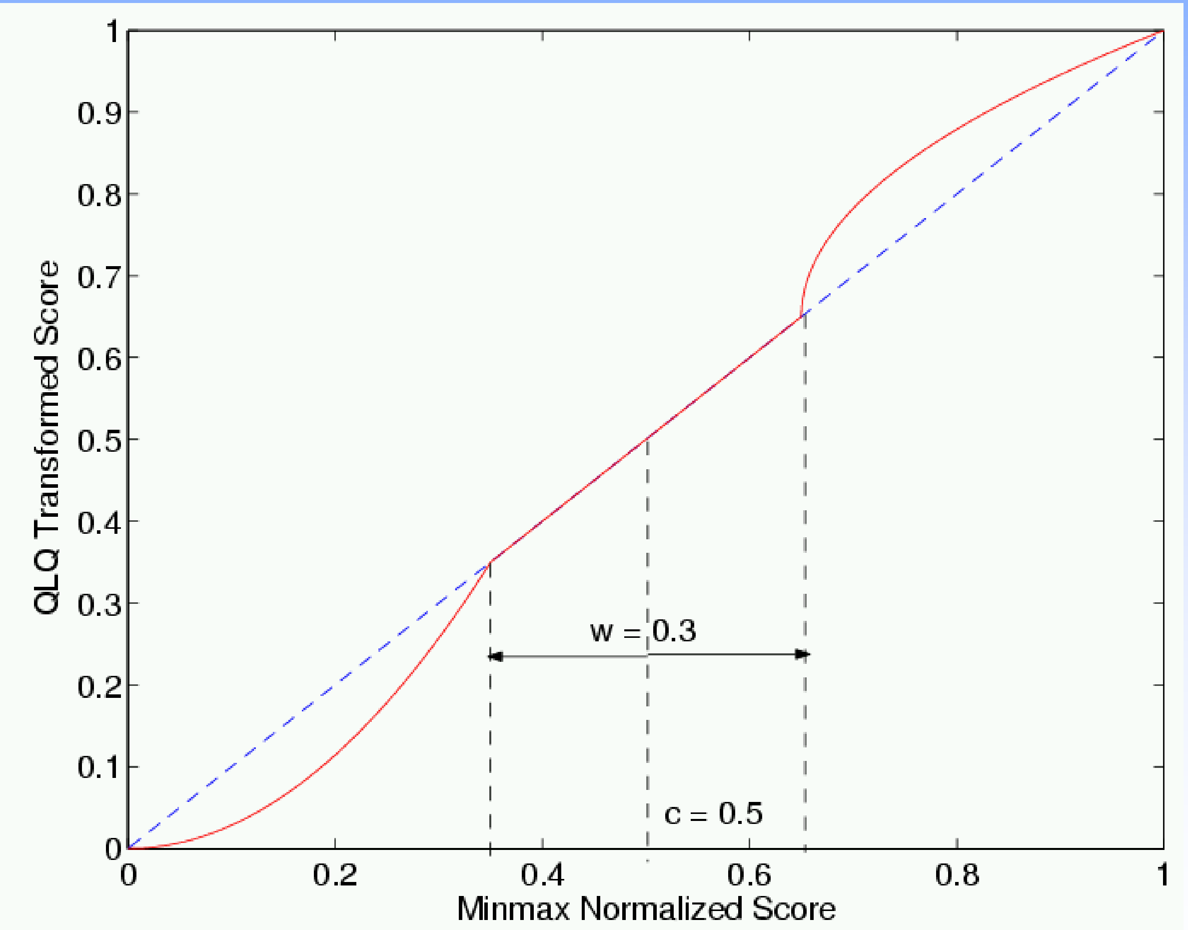


Scores in the region of overlap (false accept and false reject errors) are transformed

Ross, Jain 2004

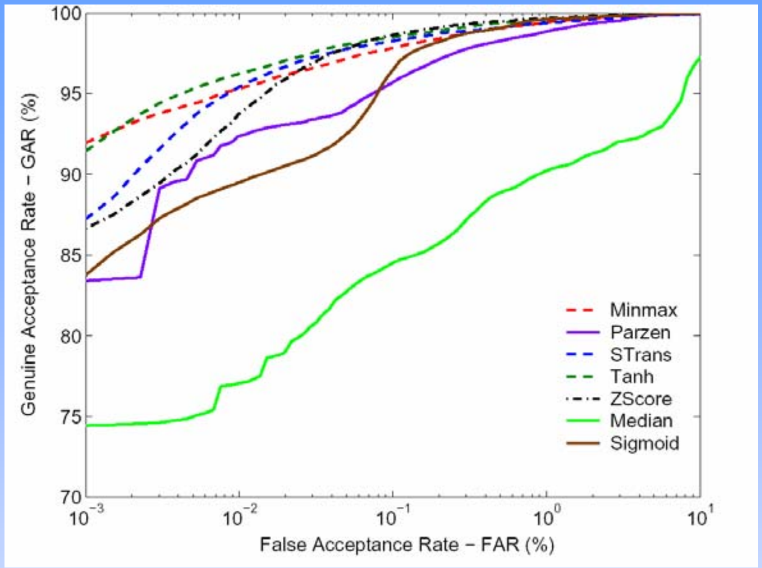
Transforming scores in overlap region

- QLQ transformation:

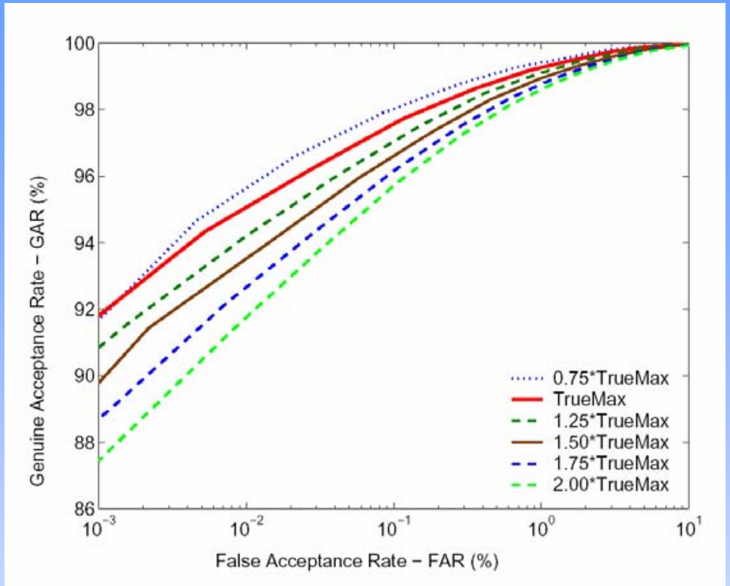


Ross, Jain 2004

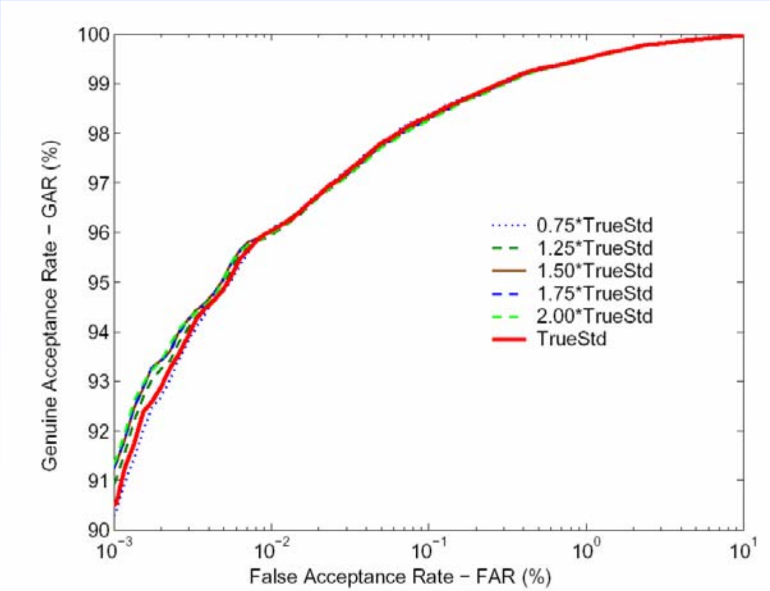
Effect of normalization



(a) Results of various schemes



(b) Sensitivity to outliers - minmax



(c) Sensitivity to outliers - tanh

Jain et al, "Score Normalization in Multimodal Biometric Systems", Pattern Recognition, 2005

Ross, Jain 2004

Summary of normalization techniques

Normalization Technique	Robustness	Efficiency
Min-max	No	N/A
Decimal scaling	No	N/A
z-score	No	High (optimal for Gaussian data)
Median and MAD	Yes	Moderate
Double sigmoid	Yes	High
tanh-estimators	Yes	High
Biweight estimators	Yes	High

Jain et al, "Score Normalization in Multimodal Biometric Systems", Pattern Recognition, 2005

Ross, Jain 2004

User-specific parameters

- There are two design parameters in a multimodal biometric system:
  - Matching thresholds for each biometric
  - Weights assigned to individual biometrics
- The above parameters can either be the same across users or customized for each user
- We have shown that user-specific parameters improve system performance

Jain, Ross, "Learning user-specific parameters in a multibiometric system", Proc. International Conference on Image Processing (ICIP), Rochester, New York, September 22-25, 2002

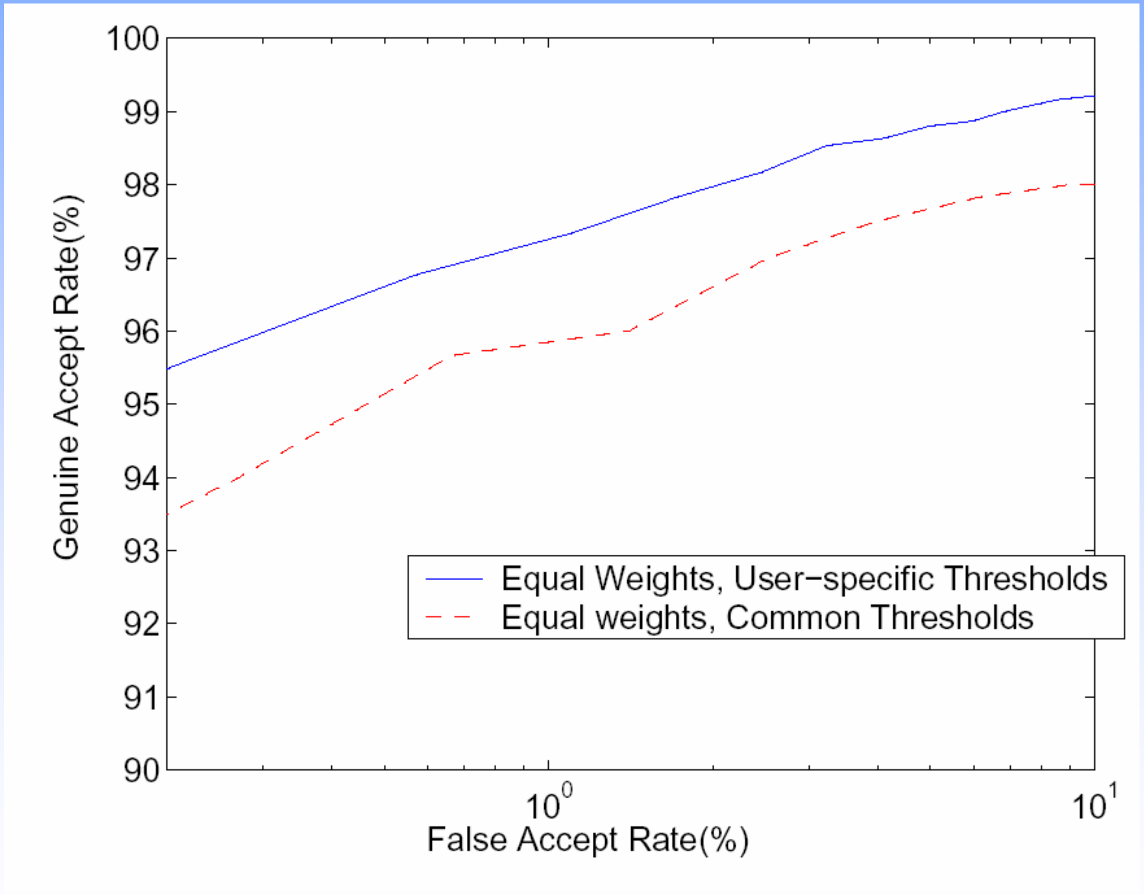
User-specific matching thresholds

User Number	Fingerprint	Face	Hand Geometry
1	14	91	94
2	17	91	95
3	15	92	95
4	12	94	95
5	11	91	90
6	11	90	92
7	16	95	94
8	19	92	97
9	11	90	96
10	19	94	93

- Results shown for 10 users who used the system on a regular basis over a period of two months
- Common threshold for
  - fingerprint: 14
  - face: 91
  - hand geometry: 94
- These thresholds correspond to a FAR of 1%

Ross, Jain 2004

Performance gain: user-specific matching thresholds



Fingerprint+Face+Hand Geometry

Ross, Jain 2004

Weighting individual traits

- Scores of different biometric could be weighted differently
  - For example, error rate of fingerprint is lower than face and hand geometry, so fingerprint score could be assigned greater weight than that of face and hand geometry
  - Weights could vary across users
- Weights are learnt from biometric data acquired during the verification phase

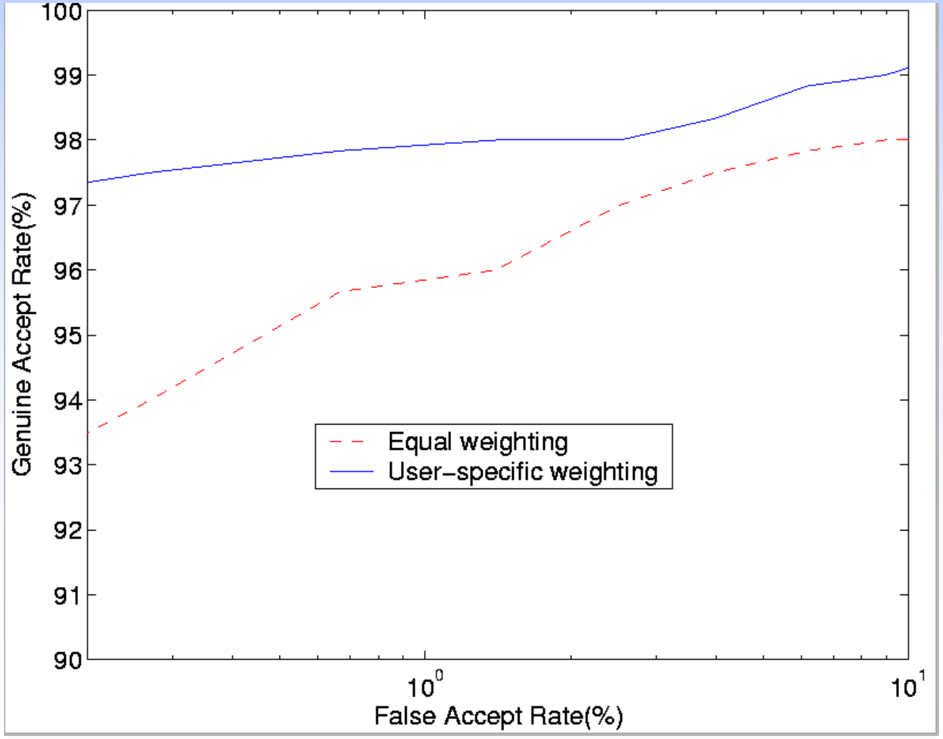
Ross, Jain 2004

User-specific weighting

User Number	Fingerprint (W_1)	Face (W_2)	Hand Geometry (W_3)
1	0.5	0.3	0.2
2	0.6	0.2	0.2
3	0.4	0.1	0.5
4	0.0	0.5	0.5
5	0.5	0.2	0.3
6	0.6	0.1	0.3
7	0.6	0.1	0.3
8	0.4	0.2	0.4
9	0.5	0.1	0.4
10	0.6	0.2	0.2

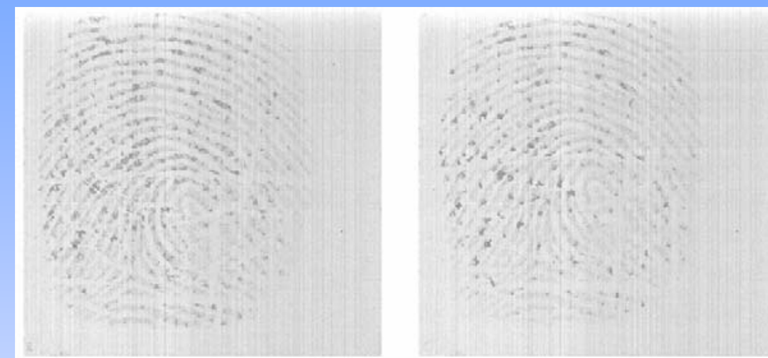
- Weights for individual biometrics vary significantly across users

- ROC curve shows performance improvement due to user-specific weighting



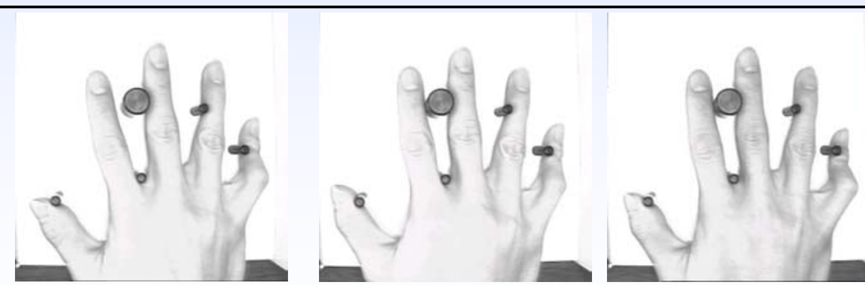
Users with low weights

- User number 4: $W_1 = 0.0$
- Ridge details in fingerprints are not very prominent



- User number 3: $W_2 = 0.1$
- Lighting and pose vary between images

- User number 2: $W_3 = 0.2$
- Incorrect placement of hand;little finger is curved



Jain, Ross, "Learning user-specific parameters in a multibiometric system", Proc. International Conference on Image Processing (ICIP), Rochester, New York, September 22-25, 2002