# Palmprint Recognition with Three Dimensional Features

**Thesis Defense**
**M.Sc. in Software Technology**

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# Acknowledgement

- David Zhang
- Lei Zhang
- Wei Li



Firstly, I would like to thank my advisor, David Zhang, for leading me into biometrics research, for insightful remarks and useful advice during my MSc. study, and for his advice on how to conduct scientific research. It has been an privilege to work under his supervision. I would also like to thank Professor Lei Zhang for what I have learned in the Multi- media Computing course. The experience not only leads to a more systematic knowledge of the area, but also urges me to practice everything with real data.
During my time working on this dissertation, Dr. Wei Li helped me a lot in the data processing part. I want to thank him for saving me a huge amount of time dealing with the dataset.

**Why?**

**What?**

**How?**

# Why?

# Motivation

**personal authentication**

# Motivation

## personal authentication

- password
  - most used
  - but most easily subverted



Passwords are by far the most used and most easily subverted method of personal authentication. If an organization institutes policies to ensure secure passwords (such as frequently changed alphanumeric upper/lower case combination of at least 10 characters) the inconvenience is so great that such a policy will be violated in an overwhelming number of cases.

# Motivation

## personal authentication

- smartcard
  - more secure
  - but will you carry dozens of smartcards with you everyday?



Every time a person uses a smartcard, the implicit assumption is that the computer has not been compromised. The possibility always exists that the computer (or any other device implanted on the Net along the way) has been infected by a hidden software routine that exploits the user's identity after authentication has been accomplished. Because users authenticate themselves to a potentially compromised computer, they can never be secure in their subsequent computer transactions.
Perhaps the greatest inhibition to the use of smartcards in electronic commerce is their variety. The chances of adoption of smartcards as the universal means for authentication of individuals in electronic commerce are nil. Access security requirements vary depending on the severity of risks and local circumstances. Therefore, a wide range of smartcard solutions is almost certain to persist. Technology obsolescence and proliferation will continue to inhibit the adoption of smartcards and reduce the applicability of this means for solving personal privacy issues.

# Motivation

**personal authentication**

- biometrics
  - fingerprint, palmprint, iris, face, voice
  - code complex enough
  - high availability

# Motivation

**personal authentication**

- palmprint
  - texture
  - geometry

# Motivation

**personal authentication**

- palmprint
  - texture - almost fully explored
  - geometry - **<u>not yet</u>**

# What?

# Verification & Recognition

**based on palmprint captures**

# Research Questions

- How much information lies the palmprint geometry?
- How to take advantage of the additional information?

# Literature Review

- 2D techniques achieved high accuracy

Adams Kong, David Zhang, and Mohamed Kamel. A survey of palmprint recognition. Pattern Recognition, 42(7):1408–1418, July 2009.

# Literature Review

- 3D devices are available

D Zhang, Guangming Lu, Wei Li, Lei Zhang, and Nan Luo. Three Dimensional Palmprint Recognition using Structured Light Imaging. In Biometrics: Theory, Applications and Systems, 2008. BTAS 2008. 2nd IEEE International Conference on, pages 1–6, 2008.

# Literature Review

- Texture-based methods on 3D data
  - Mean Curvature Image
  - Gaussian Curvature Image

D Zhang, Guangming Lu, Wei Li, Lei Zhang, and Nan Luo. Palmprint Recognition Using 3-D Information. Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on, 39(5):505–519, 2009.

# Literature Review

- Geometry-based methods on 3D data
  - Surface Type

D Zhang, Guangming Lu, Wei Li, Lei Zhang, and Nan Luo. Palmprint Recognition Using 3-D Information. Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on, 39(5):505–519, 2009.

# Literature Review

- Fusion of texture and geometry features

W. Li, D Zhang, L. Zhang, G. Lu, and J. Yan. 3-D palmprint recognition with joint line and orientation features. Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on, (99):1–6, 2011.

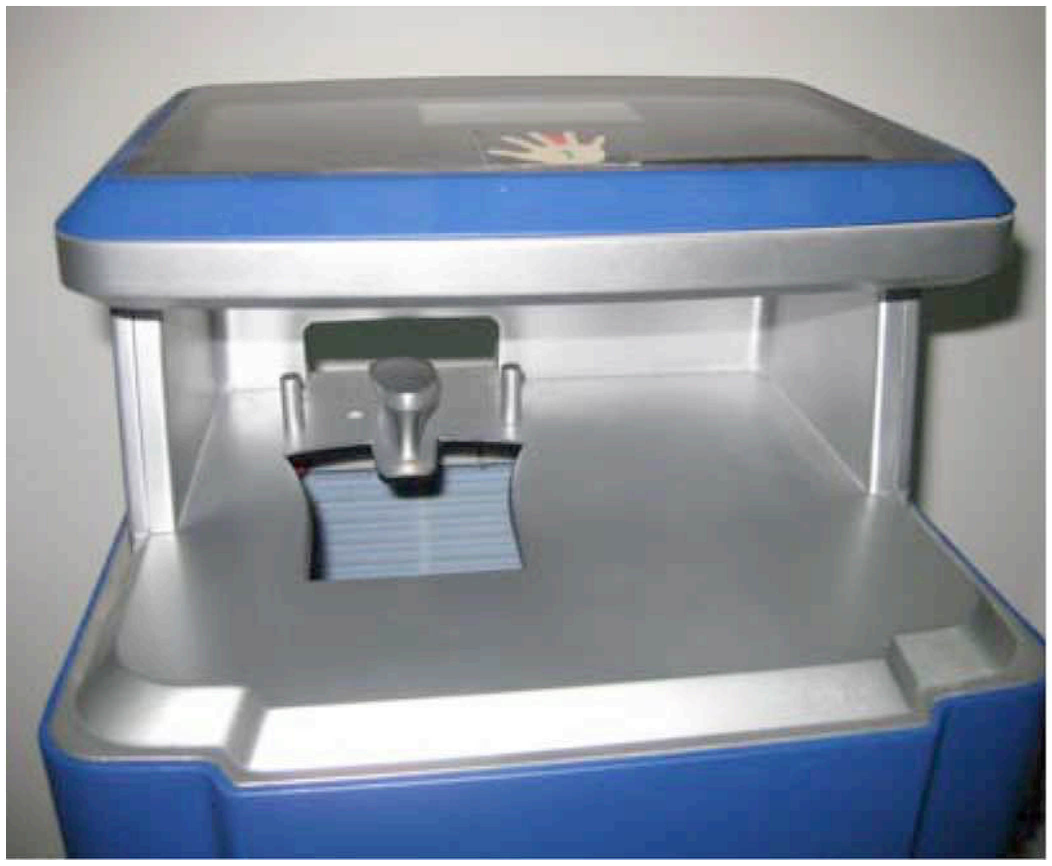
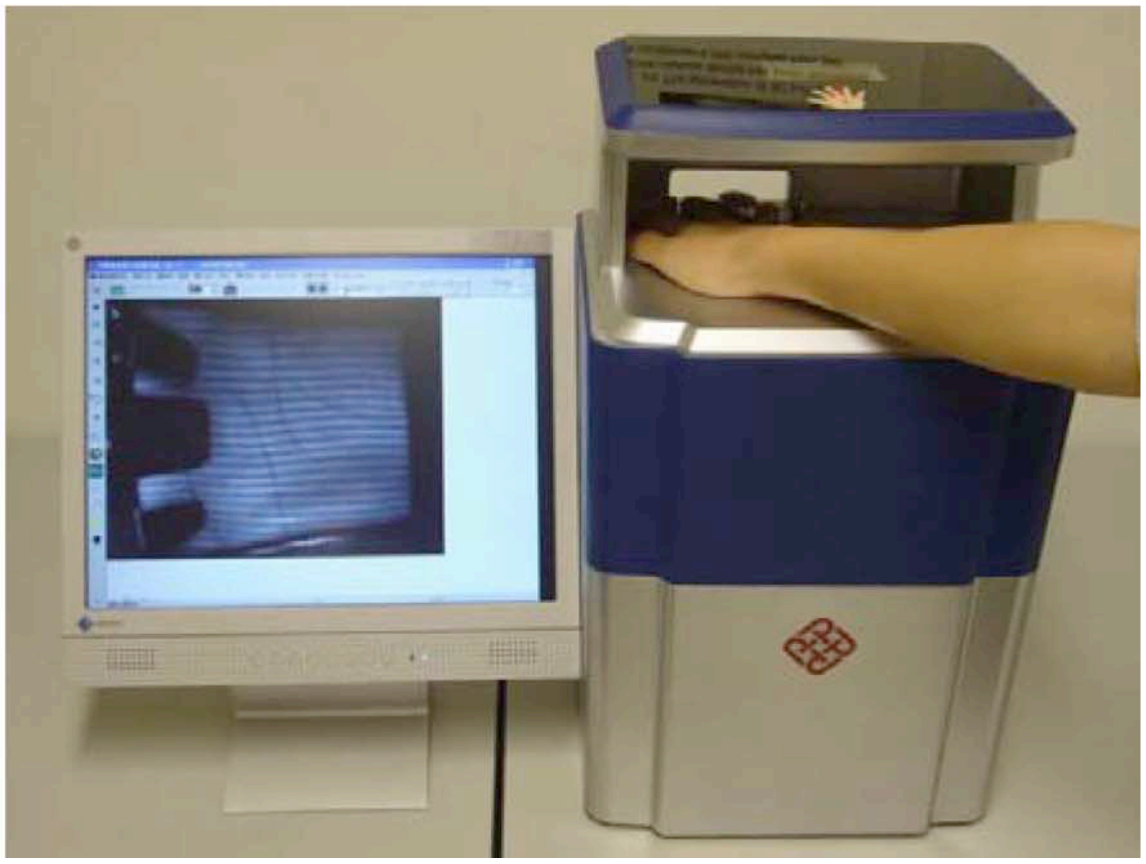
# How?

# Method

- Data collection (regards to Wei Li)
- Data processing
- Recognition system

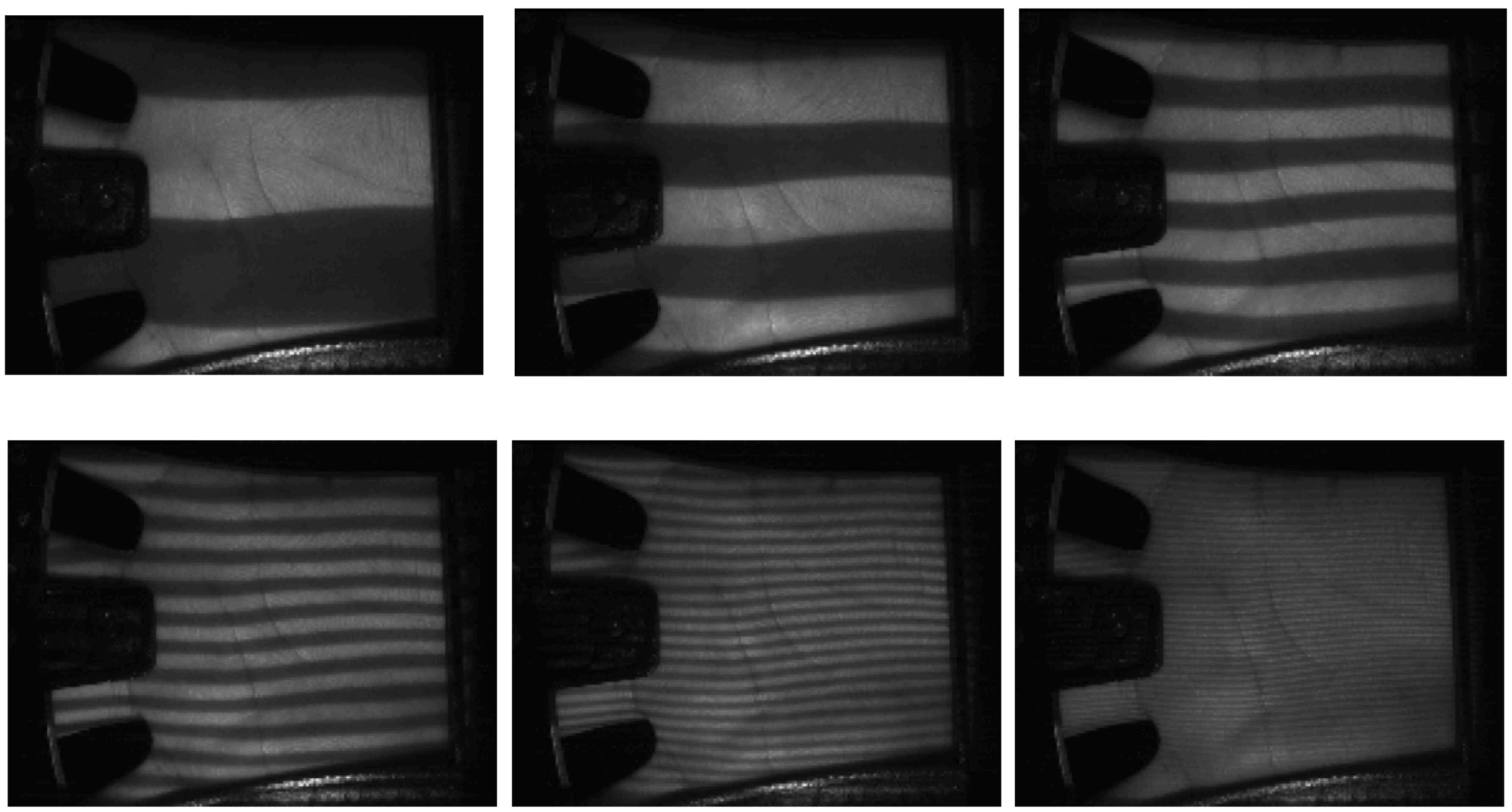
# Data Collection

- Structural Light Imaging

# Data Collection

- Structural Light Imaging



# A Sample

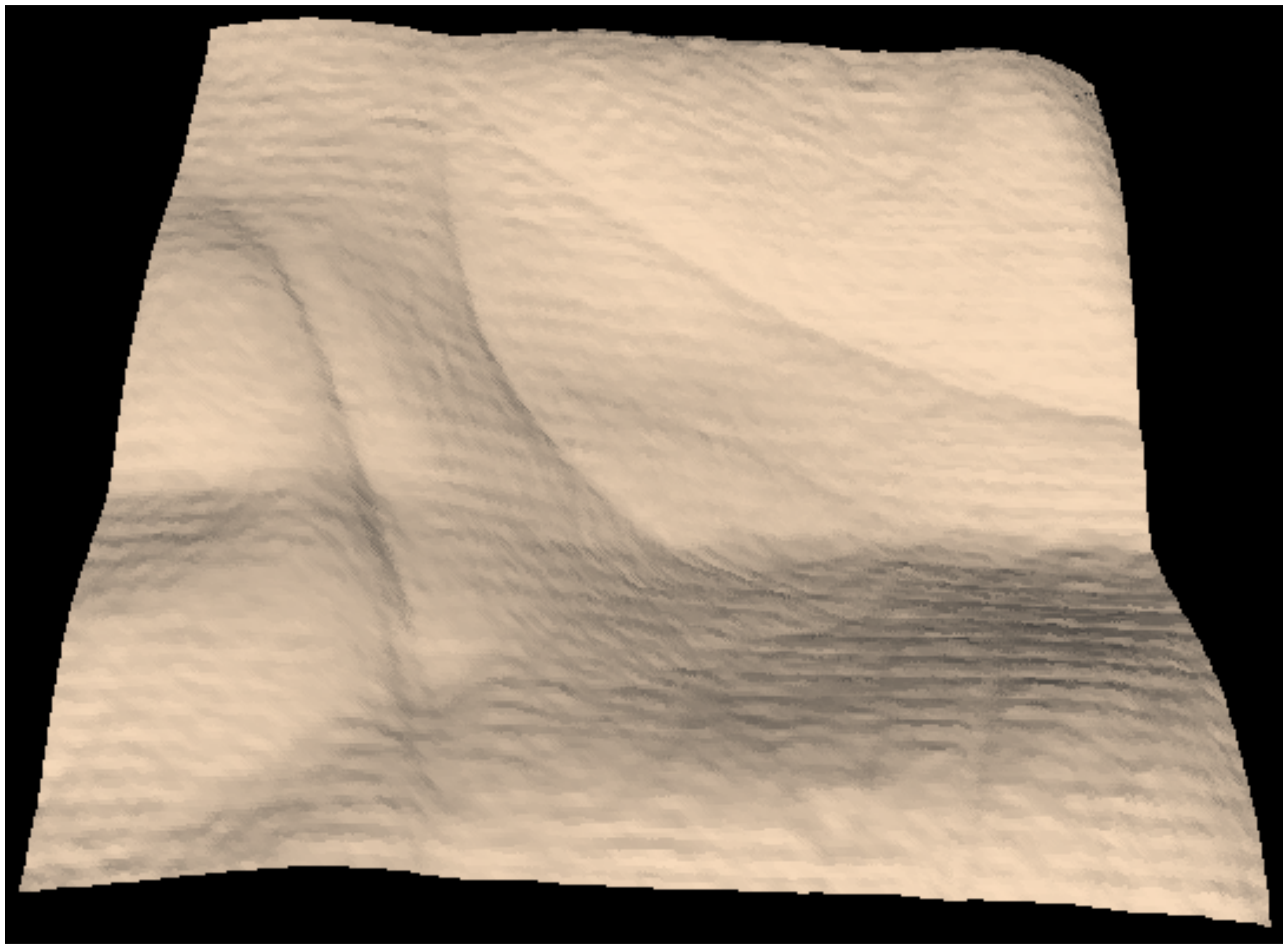
- 768x576
  single precision float depth matrix

# Data Processing

- ROI extraction
- Feature extraction
- Dimension reduction
- Feature matching

# Region of Interest

- 400x400, down-sample to 200x200





A rectangle mask, from (234,68) to (634,468) is used to crop the ROI.

# Noise Cancellation

- Gradient Threshold

$$|\nabla D| = \sqrt{\left(\frac{\partial D}{\partial x}\right)^2 + \left(\frac{\partial D}{\partial y}\right)^2}$$



pp.54

```
[fx, fy] = gradient(Z);
fxy = fx.^2 + fy.^2;

noiseP = find(fxy >0.1);
% 0.1 used for corrected and smoothed Sub3D,
% 1 used for original Sub3D
```

# Feature Extraction

- Maximum Depth
- Horizontal Cross-section Area
- Radial Line Length

# Maximum Depth

- Depth from a **reference plane** to the **deepest point**

# Maximum Depth

- Reference plane

$$d_r = \frac{1}{\sum_{i=R_s}^{R_e} \sum_{j=C_s}^{C_e} m_{ij}} \sum_{i=R_s}^{R_e} \sum_{j=C_s}^{C_e} (d_{ij})$$



Rectangle (65,6) to (136,35).
Rs = 65, Re = 136, Cs = 6 and Ce = 35
By examine a random 20 samples, gradient of this area is relatively small, i.e. this area is flat.

# Maximum Depth

- Deepest point

$$d_{max} = \max_{i=R_s}^{R_e}(\max_{j=C_s}^{C_e}(d_{ij}))$$



Rs = 41,Re = 160,Cs = 65 and Ce = 190

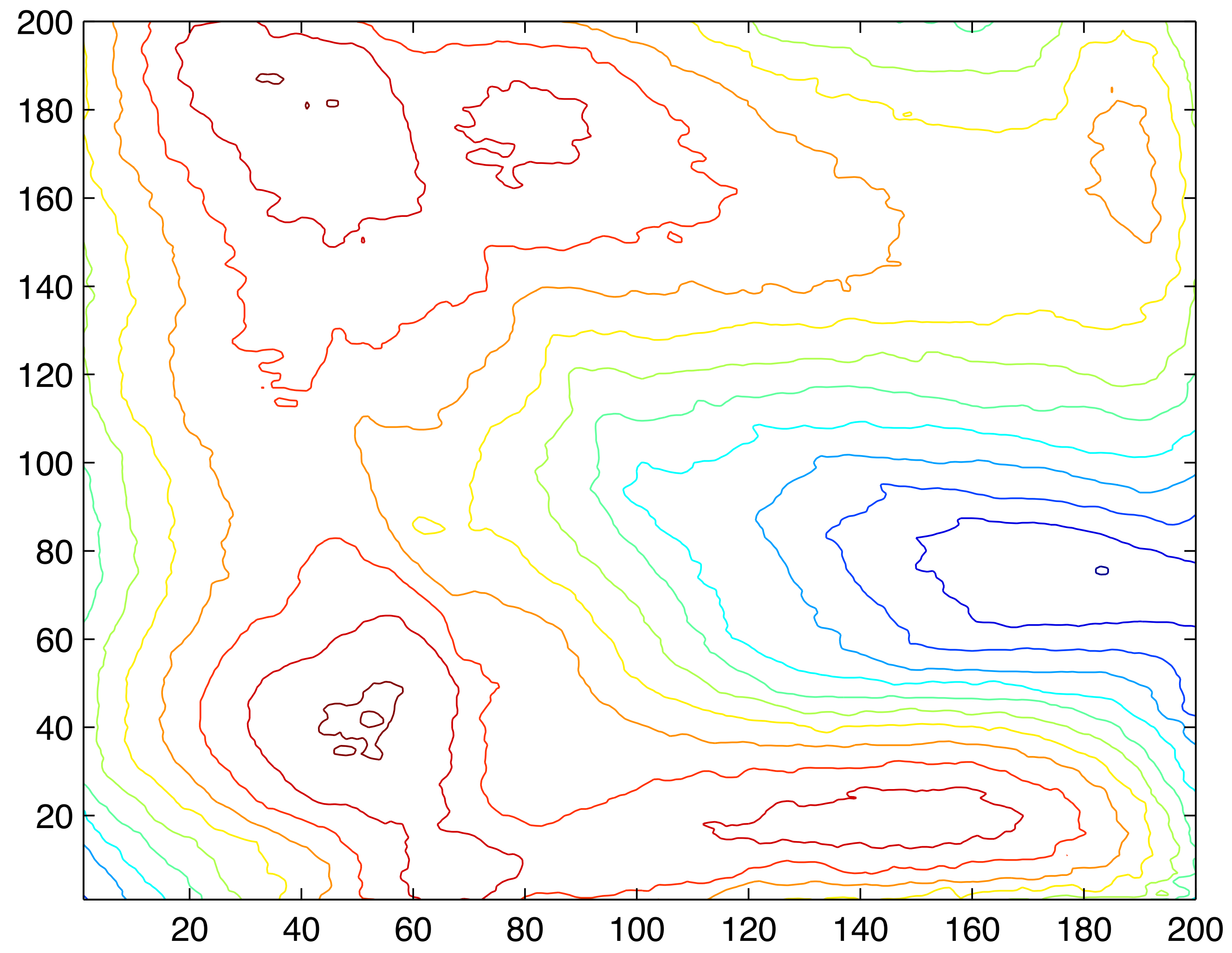
# Maximum Depth

- Maximum Depth (MD)

$$MD = d_{max} - d_r$$

# Horizontal Cross-section Area

- Contour view

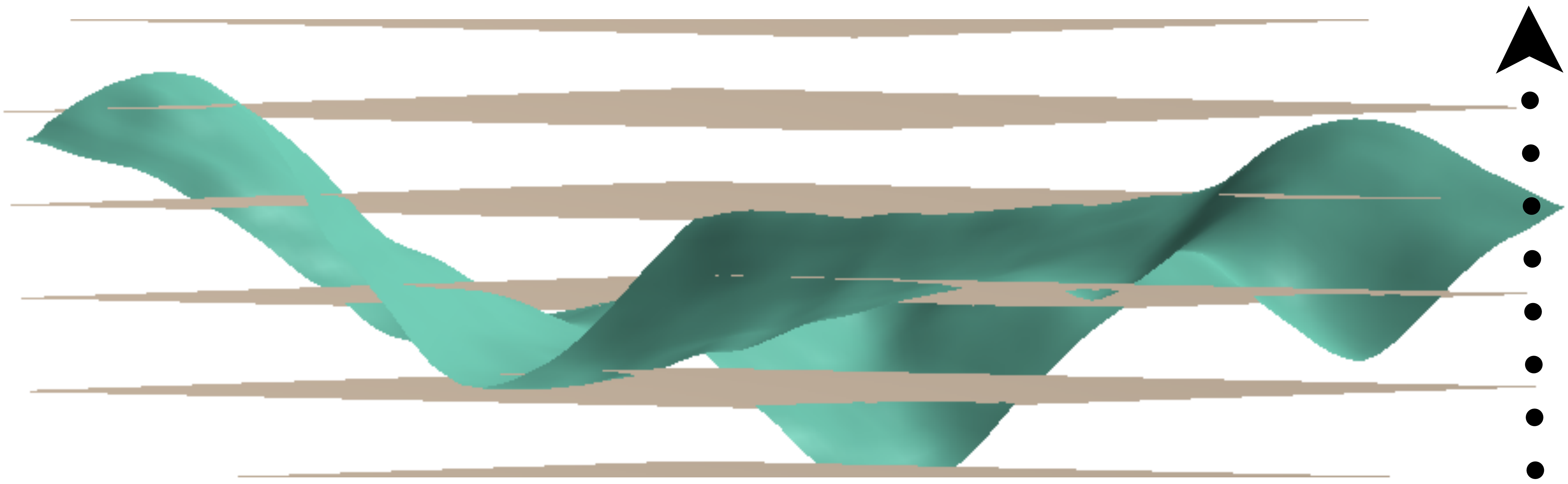





The regions of different given depth ranges can be used to describe a sample.

# Horizontal Cross-section Area

- Cut the ROI



# Horizontal Cross-section Area

- Group pixels to N levels

$$G_{ij}^{k} = \begin{cases} 1 & \text{if } d_{ij} > h \cdot (N - k + 1)/N, \\ 0 & \text{otherwise} \end{cases}$$

$$k = 1, 2, \ldots, N; i = 1, 2, \ldots, 200; j = 1, 2, \ldots, 200;$$



dij is the depth value of the ith row and jth column pixel of the ROI defined in 3.1 and h is the palmprint depth defined by Equation 3.6

# Horizontal Cross-section Area

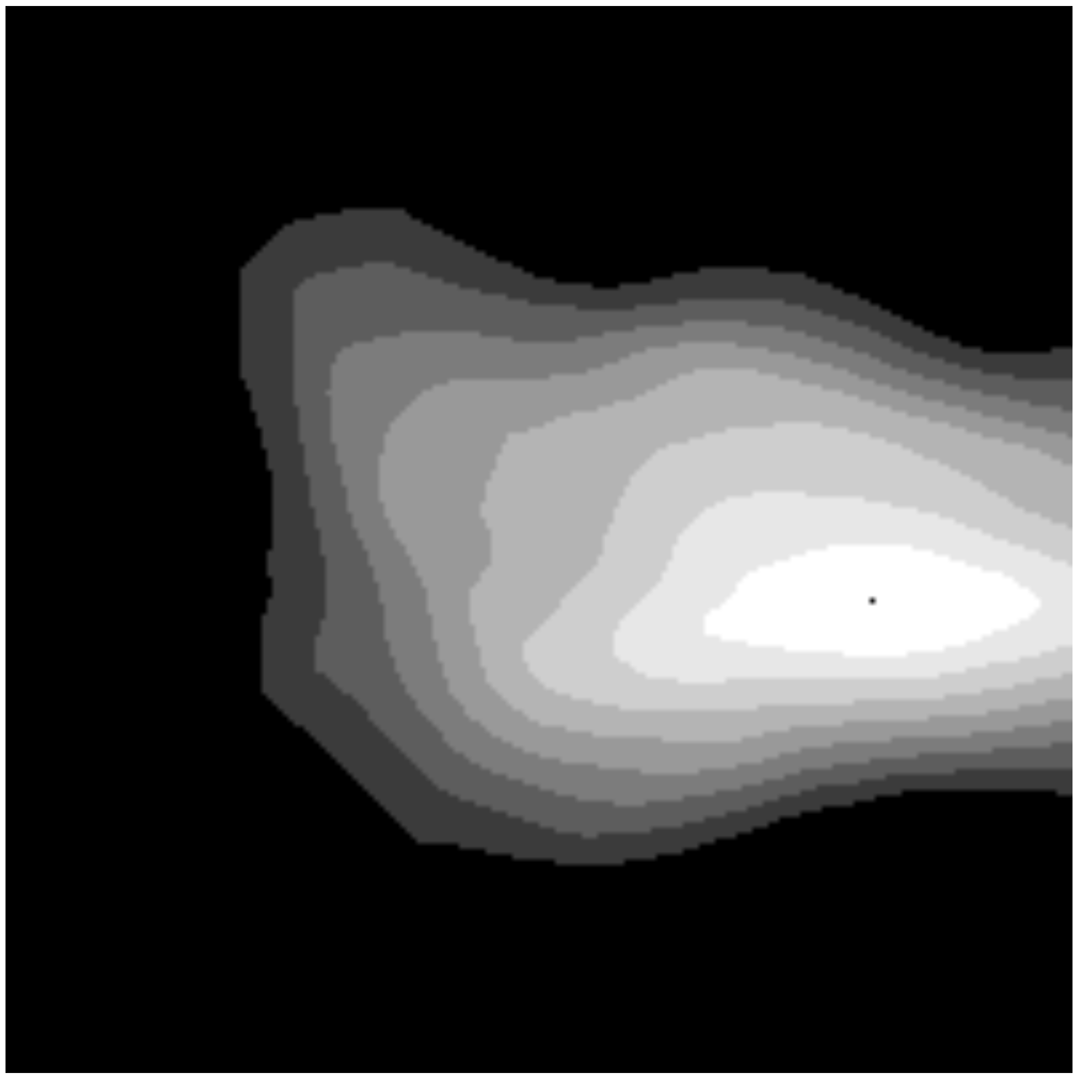
- Stabilization: grow while connected

$$L^k = \begin{cases} G^1 & k = 1 \\ G^k \cap (L^{k-1} \oplus \Theta^{k-1}) & k = 2, 3, \ldots, N \end{cases}$$



∩ denotes logical AND, ⊕ denotes a morphological dilation operation and Θk is a disk morphological structuring element whose size can be calculated by 35 − 3 × k (which is suitable for N = 8 by experience).

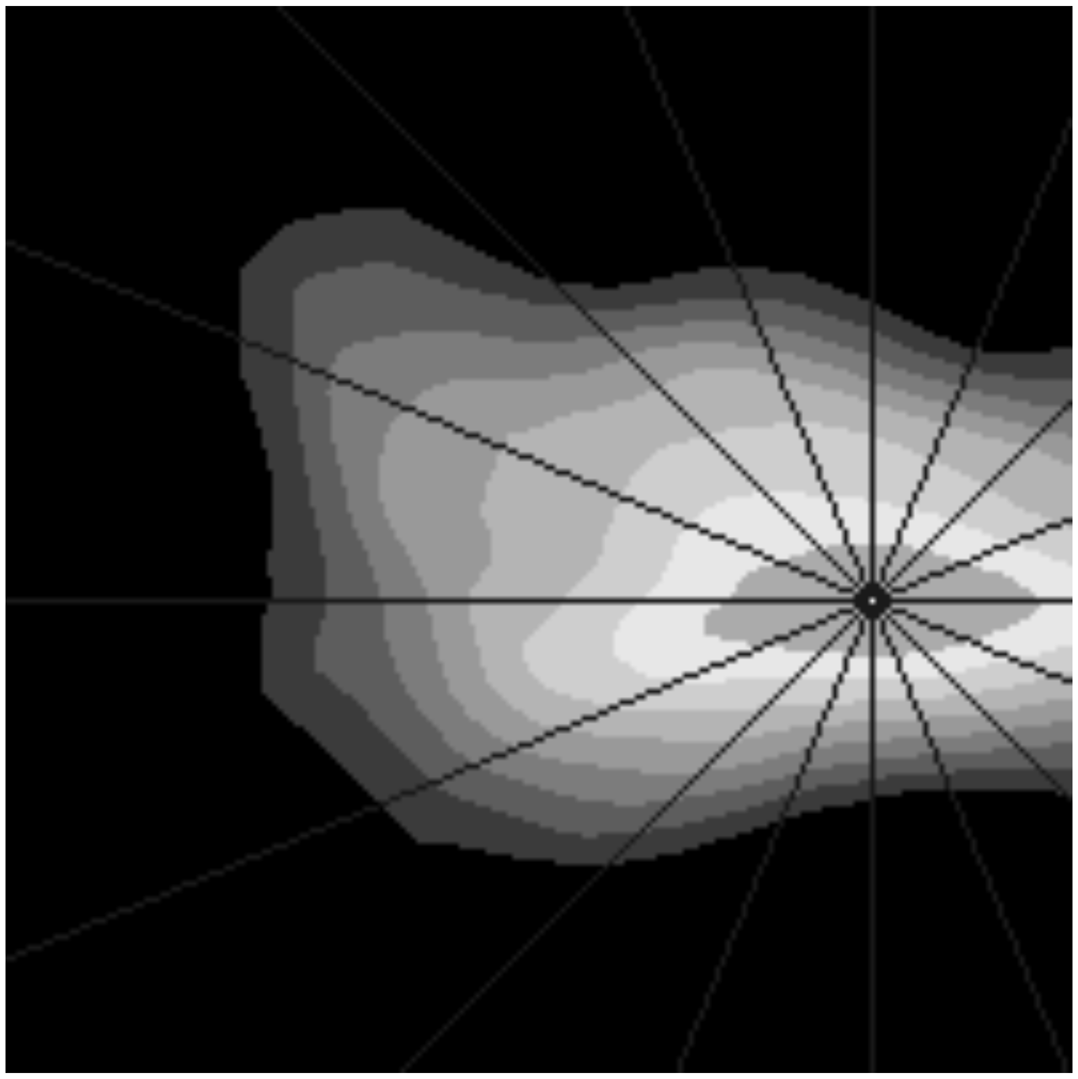
# Horizontal Cross-section Area



# Radial Line Length

- Finer description of the shape of HCA at each level
- Using the length of M line segments

# Radial Line Length



# Combined Feature Vector

- F consists of MD+HCA+RLL
  - F has 1+N+NxM dimensions

# Dimension Reduction

- Project F to a lower dimensional space
- Preserve as much information as possible

$$\tilde{F} = W^T F$$

# Dimension Reduction

- Orthogonal Linear Discriminant Analysis

JP Ye. Characterization of a family of algorithms for generalized discriminant analysis on undersampled problems. Journal of Machine Learning Research, 6:483–502, 2005.



Linear discriminant analysis (LDA) has been known to be one of the most optimal dimensionality reduction methods for classification. However, a main disadvantage of LDA is that the so-called total scatter matrix must be nonsingular. But, in many applications, the scatter matrices can be singular since the data points are from a very high-dimensional space, and thus usually the number of the data samples is smaller than the data dimension. This is known as the undersampled problem.

Code by Zhizheng Liang at
http://www.mathworks.com/matlabcentral/fileexchange/20174-2dlda-pk-lda-for-feature-extraction

# Feature Matching

- Coarse-level matching

$$Similarity = \|\tilde{F}_1 - \tilde{F}_2\| = \sum_{i=1}^{\Gamma}(f_i^1 - f_i^2)^2$$

# Improved Matching

- Ranking Support Vector Machine

Thorsten Joachims. Optimizing search engines using clickthrough data. In KDD '02: Proceedings of the eighth ACM SIGKDD international conference on Knowledge discovery and data mining. ACM Request Permissions, July 2002.

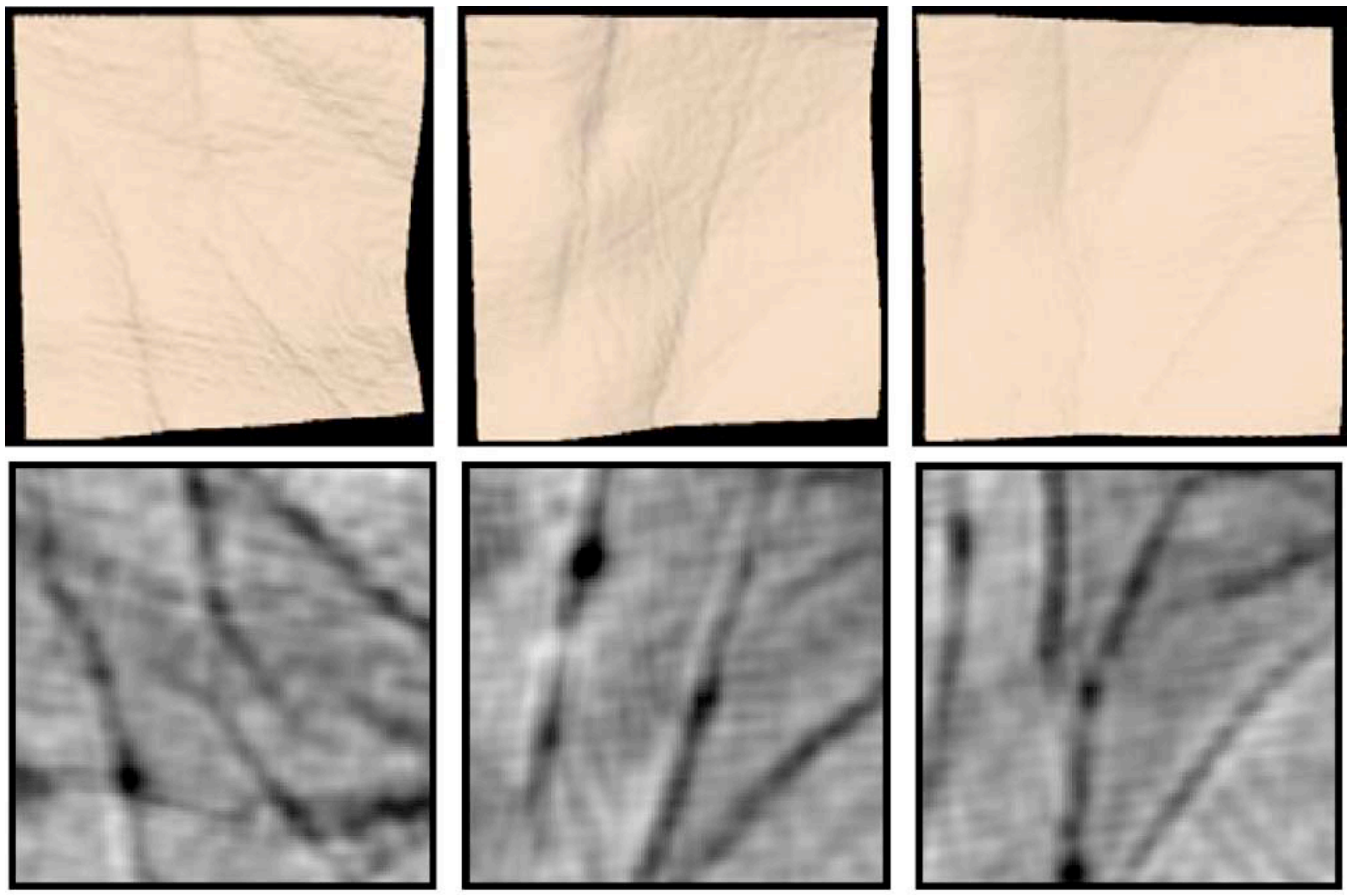


Internet search strategy.
Rank the candidate samples in the database.

Code by Joachims at
http://www.cs.cornell.edu/people/tj/svm_light/svm_rank.html

# Fine-matching Feature

- Mean Curvature Image





Why? High error rate.

# Experiment

- 8000 samples
  - 4000 for training
  - 4000 for testing
- Matlab

# Optimizing Parameters

- Recall that we have a feature vector of 1+N+NxM dimensions
- And we want to reduce the dimension to $\mathbf{\Gamma}$

# Optimizing Parameters

- Choosing N and M (by EER)

| | M=8 | M=16 | M=32 | M=64 |
|---|---|---|---|---|
| N=4 | 14.3 | 19.15 | 14.35 | 14.07 |
| N=8 | 14.2 | 16.3 | **12.32** | 12.54 |
| N=16 | 18.11 | 18.35 | 15.21 | 14.11 |



Table 4.1
The best result, as adopted in Chapter 3, is N = 8 and M = 32.

# Optimizing Parameters

- Choosing $\Gamma$

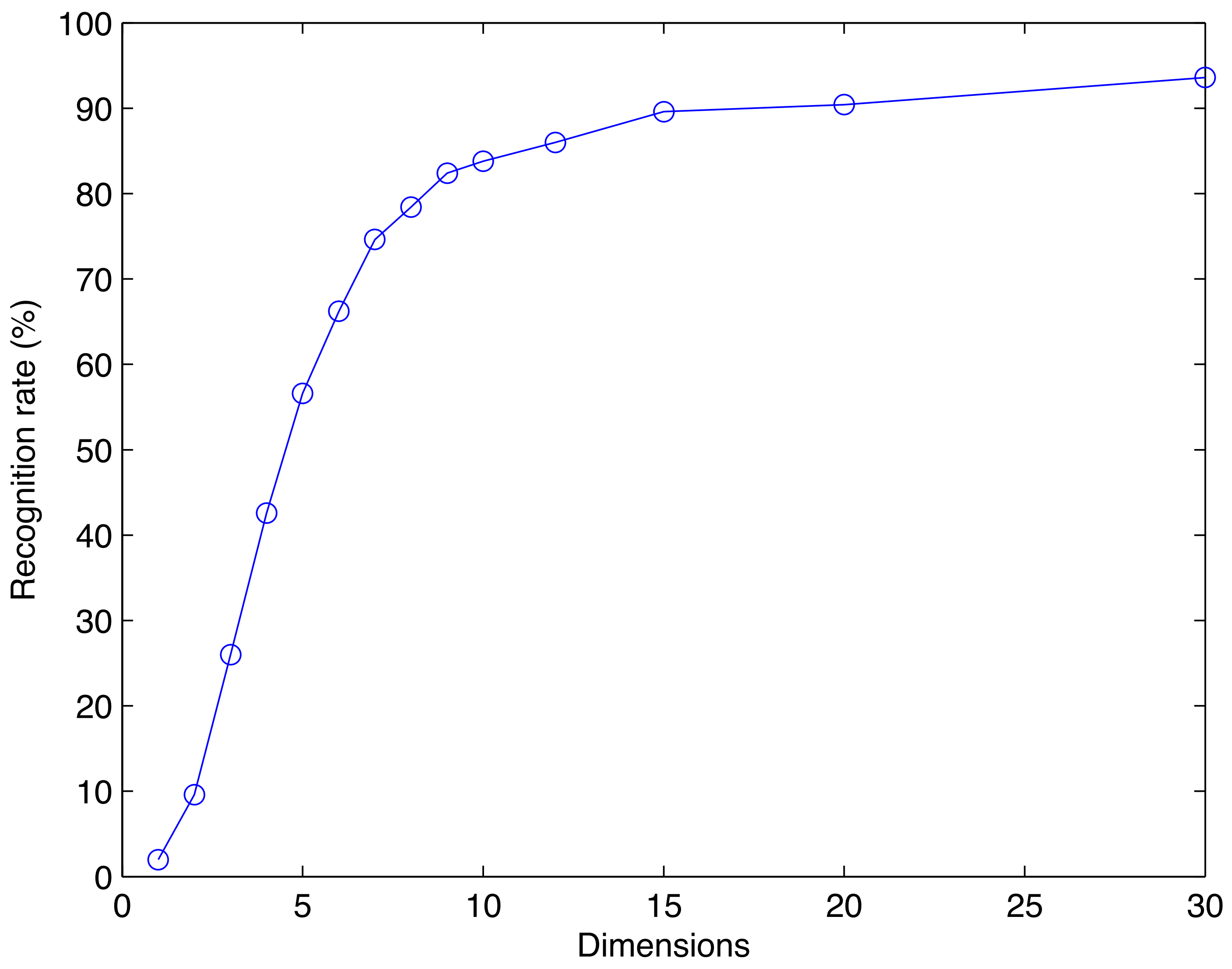





Table 4.3
$\Gamma = 15$ is a good choice for the following experiments with balanced recognition rate and computation.

# Performance Metrics

- Error rate

$$\text{error rate} = \frac{\text{number of false match}}{\text{total number of probe}} \times 100\%$$

- Penetration rate

$$\text{penetration rate} = \frac{\text{number of accessed template}}{\text{total number of template in the database}} \times 100\%$$



Obviously there is a trade-off between error rates and penetration rates.
Generally speaking, if there is no classification, there are two retrieval strategies:
1 all of the templates in the database are visited and the template that gives the best matching score is regarded as the matched template, if the matching score is less than a given threshold Ψ
2 given a threshold Ψ, the search continues until a match is found that is below that threshold

# Performance Results

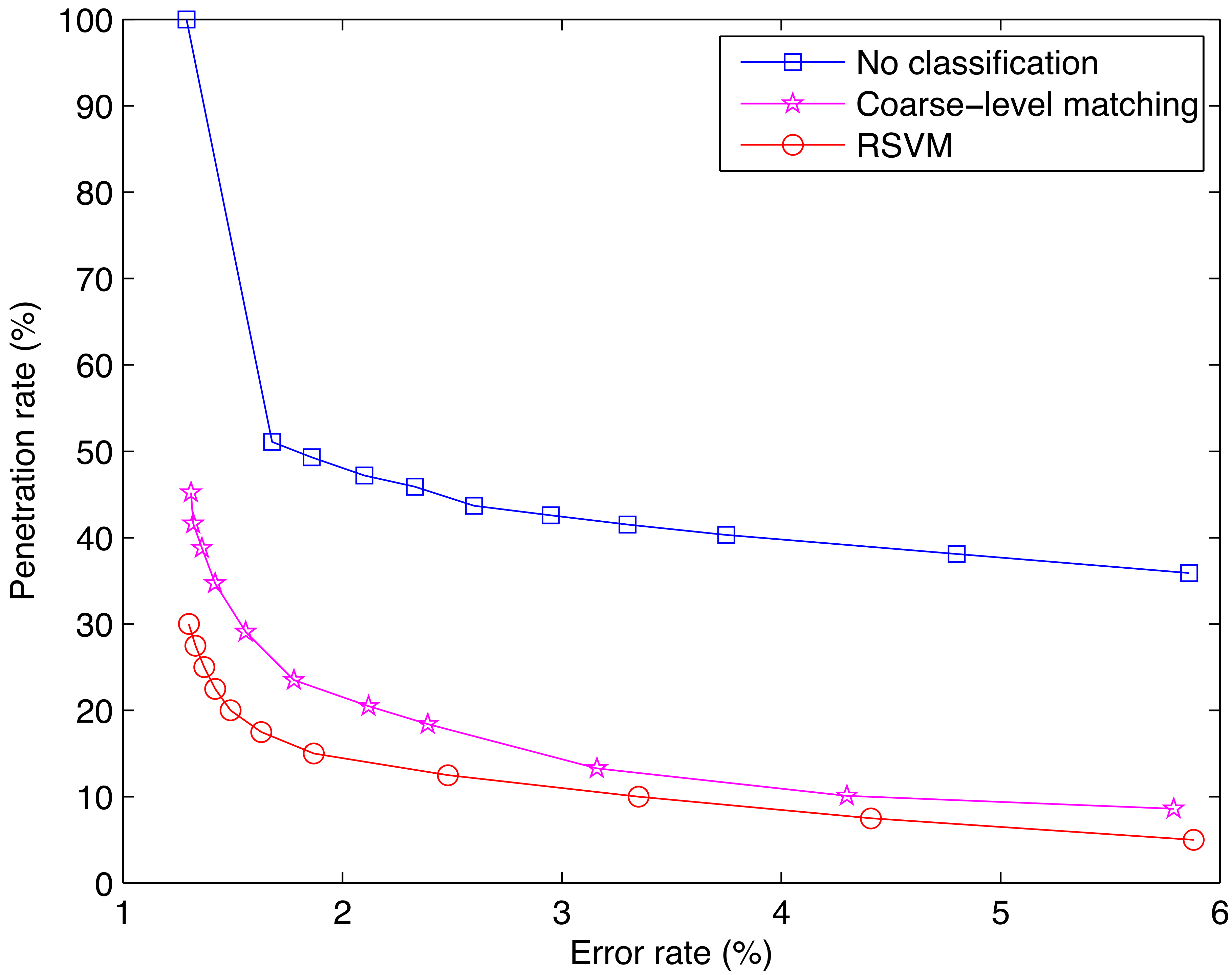





Figure 4.3
Table 4.4 through 4.6

# Speed

MCI only

| Process | Time (ms) |
| --- | --- |
| Feature extraction | 112 |
| Dimension reduction | 0 |
| Preprocess | 0 |
| MCI matching | 0.86 |
| Total (for one probe) | 456 |



Table 4.7

# Speed

with Coarse-level matching

| Process | Time (ms) |
|---|---|
| Feature extraction | 136 |
| Dimension reduction | 0.1 |
| Preprocess | 0.5 |
| MCI matching | 0.86 |
| Total (for one probe) | **292.09** |

**1.56X**



Table 4.7
Due to the lower penetration rate, the running times are greatly reduced.

# Speed

with RSVM

| Process | Time (ms) |
|---|---|
| Feature extraction | 136 |
| Dimension reduction | 0.1 |
| Preprocess | 1.56 |
| MCI matching | 0.86 |
| Total (for one probe) | **240.86** |

**1.9X**



Table 4.7
Due to even lower penetration rate, the running times are reduced further.

# Discussion

# Conclusions

- Geometric features extracted
- Matching process improved



MD, HCA and RLL

Due to lower penetration rate from either coarse matching or ranking

# Limitations

- 3D devices are *lower* in resolution (compared to 2D ones)
  - possible, but not as cost effective

# Limitations

- 3D depth values are more susceptible to movement than 2D textures
  - less stable
  - or less user-friendly

# Limitations

- General biometrics authentication limitations



Capture iris image from behind the mirror.
Get fingerprints from glass bottles.
One an individual's biometrics have been compromised, they are compromised for life and can never be trusted again.
Moreover, biometrics authentication relies on a central database. If such database is compromised, the biometrics of ALL uses in the database are compromised for life.
We cannot change any of these biometrics like changing our passwords.

http://www.strassmann.com/pubs/searchsecurity/2002-4.php

# Future work

- Try different ROI
- Find geometric features with lower error rate
- Anti-counterfeiting considerations



Thorough analysis of possible geometric features.

# Thank you.

# Q&A

# Singular Value Decomposition

$$M = U\Sigma V^*$$

- M: m×n
- U: m×m unitary matrix
- Σ: m×n rectangular diagonal matrix
- V*: n×n unitary matrix
- Low-rank matrix approximation

M: m×n (real or complex)
U: m×m unitary matrix (real or complex)
Σ: m×n rectangular diagonal matrix with nonnegative real numbers on the diagonal
V*: n×n unitary matrix (the conjugate transpose of V, real or complex)

The diagonal entries Σi,i of Σ are known as the singular values of M.

http://en.wikipedia.org/wiki/Singular_value_decomposition

# Linear Discriminant Analysis

- linear combination of features
- dimensionality reduction before classification

To find a linear combination of features which characterizes or separates two or more classes of objects or events.
The resulting combination may be used as a linear classifier, or, more commonly, for dimensionality reduction before later classification.

http://en.wikipedia.org/wiki/Linear_discriminant_analysis

# SVM Classifier

$$
\begin{aligned}
&minimize : V(\vec{w}, \vec{\xi}) = \tfrac{1}{2}\vec{w} \cdot \vec{w} + CF\sum \xi_i^{\sigma} \\
&s.t. \\
&\ \sigma \geqq 0; \\
&\ \forall y_i(\vec{w}\vec{x}_i + b) \geqq 1 - xi_i^{\sigma}; \\
&where \\
&\ b\ is\ a\ scalar; \\
&\ \forall y_i \in \{-1, 1\}; \\
&\ \forall \xi_i \geqq 0;
\end{aligned}
$$

$$\vec{w}^* = \sum_i \alpha_i y_i x_i$$

Get a strong classifier from a linear combination of weak classifiers.

Suppose $(x_i, y_i)$ is the element of a training data set, where $x_i$ is the feature vector (with information about features) and $y_i$ is the label(which classifies the category of $x_i$). An typical SVM classifier for such data set can be defined as the solution of the following optimization problem.

The solution of the above optimization problem can be represented as a linear combination of the feature vectors $x_i$.

$alpha_i$ is the coefficients to be determined

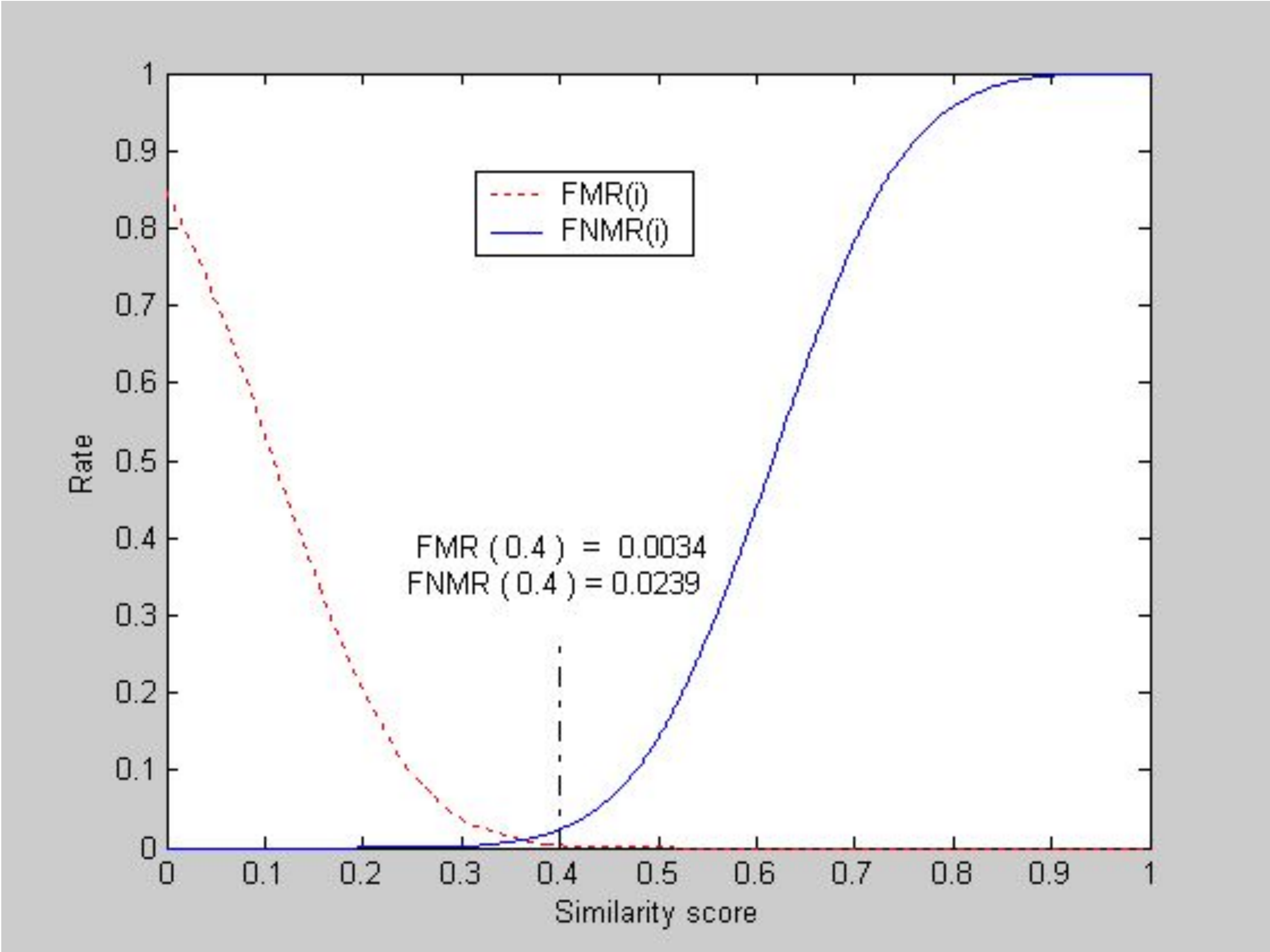
# Ranking SVM

- Training
  - Map to feature space
  - Find optimal $\omega^*$ of SVM classification
- For new query
  - Map database to feature space
  - Order feature points by their inner product with $\omega^*$

http://en.wikipedia.org/wiki/Ranking_SVM

# Equal Error Rate

- False match rate (FMR)
- False non-match rate (FNMR)




Receiver operating characteristic (ROC)

# Genuine and Impostor

✓ genuine individual accepted

× genuine individual rejected

✓ impostor rejected

× impostor accepted

No metric is sufficiently adequate to give a reliable and convincing indication of the identification accuracy of a biometric system.
A decision made by a biometric system is either a genuine individual type of decision or an impostor type of decision.

Genuine distribution: matching input measurements from the same identities
Impostor distribution: from different identities