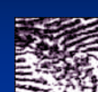
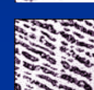
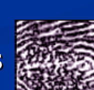
Level 3 Features

- In the broadest sense, level 3 features are any not classifiable as Level 1 and Level 2.
- There is no generally agreed upon definition of Level 3 features.
- A NIST working group is in the process of defining Level 3 features.
  - No conclusions as this is written

Some Level 3 Feature Candidates

- Pores 
- Ridge Shapes 
- Incipient Ridges 
- Scars 
- Warts 
- Creases 
- Deformations 

From: BIOMETRICS
Dr. Andrzej Drygajlo

Sweat Pore Chosen As Feature

- The sweat pore feature was selected for this first portion of the study by two criteria:
  - Usefulness to examiners
  - Detectability by Support Vector Machines
- Disadvantage: Sweat pores may not be visible
  - Ink and powder tends to fill pores
- Advantages
  - Numerous
    - 2700 per square inch (approx.)
  - Distinctive
    - Highly variable in:
      - Size: 88 to 220 microns
      - Spacing along ridge is random (9-18 pores/cm or ridge approx.)
      - In any position across ridge
      - Shape: round, oblong, tri

Examples of Sweat Pores at 500 dpi

Image Enhancement

- Conservative enhancement used to preserve information
  - Contrast and brightness enhancement by level adjustments
  - Sharpening (un-sharp mask)
- 500 dpi original image
  - Captured with solid-state fingerprint sensor

Image Enhancement Example

Original

Enhanced

Support Vector Machines

- Support Vector Machines (SVM)
  - Learning machines based on statistical learning theory
  - Trained by examples
  - Classifies previously unseen inputs
- Solid mathematical foundation in Vapnik Chervonenkis theory [Vapnik, 1995a][Smola, 2000]
- Maps training vectors into higher (possibly infinite) dimensional space
  - Using "kernel trick" all computation is done with dot products in low dimensional training vector space.
- All the following were once considered to be different classes of Artificial Neural Networks.
  - Radial Basis Function
  - Sigmoidal Multi layer Perceptron
  - Polynomial
  - Linear
  - Many others
- All the above have been shown to be special cases of an SVM

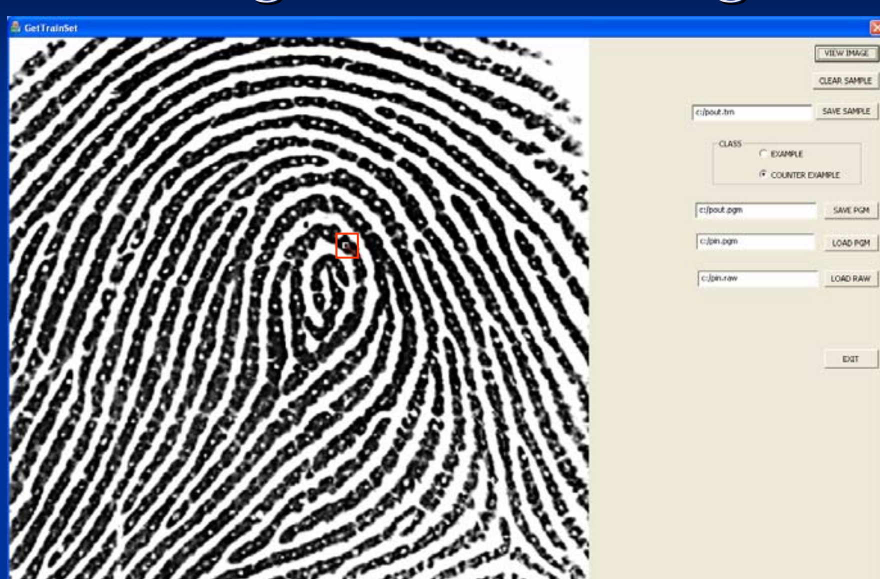
Training and Evaluation Methods

- Trained using SVM-light software
  - Courtesy of Thorsten Joachims [Joachims, 2002a] [Joachims, 2002c] [Klinkenberg, Joachims, 2000a] [Joachims, 2000b] Joachims, 1999a]
    - Available without charge at http://svmlight.joachims.org
  - Another version [CHANG 2001], LIBSVM, also available without charge
- Radial Basis Function Kernel was used
  - $K(x_i, x_j) = \exp(-\gamma \mid\mid x_i^T - xj \mid\mid^2)$
- Accuracy evaluated by leave-one-out method

Characteristics of SVMs

- Generalizes from training examples
- Constructs arbitrarily complicated, optimal, non-linear decision surfaces
- Every solution is global; no local minima
- Training is a conventional quadratic programming problem
  - Many different optimizers can be used
  - Specialized optimizers improve performance
- Training complexity is calculable
  - Cubic in number of support vectors
  - Support vectors are typically much fewer than training vectors
- Provides confidence level on decisions
- Accuracy estimate is produced with little additional computation
  - Leave-one-out cross validation

Training Set Selection Program



Training Set Example Selection

- Select correct classification
- Click on an image point
  - Computer program determines training vector components
- Save as training vector
- Components currently based on:
  - Central intensity pattern
  - Radial intensity pattern
- Ridge slope is estimated
  - Will be used for other level 3 features

Estimating Accuracy

- **Cross-validation**, the basic procedure
  - Separate data set into two sub-sets
    - Training set
    - Test set
  - Train classifier on Training Set
  - Measure accuracy on Test Set
- **n-set Cross-validation** improves accuracy
  1. Separate data into n sub-sets
  2. Train on n - 1 subsets, reserving one subset
  3. Measure accuracy on reserved sub-set
  4. Repeat 2 through 3 for all sub-sets
- **Leave-One-Out method**, limit of n-set method, still more accurate
  1. Train on all but 1 example
  2. Classify that example
  3. Repeat steps 1 and 2 for all examples
  4. Calculate error rate as: number of errors / number of training examples
  - Impractical for many types of classifiers: requires re-training for each example
- SVM performs Leave-One-Out accuracy estimation with little extra computation

Training Process

- Training set size: 483 samples
- CPU time for training: < .01 seconds
- CPU time for classification: < .01 seconds
- CPU time for leave-one-out cross-validation: .03 seconds.

Estimated Accuracy by Leave-One-Out Method

- **No errors found by cross-validation**
- Recall: 100% (TAR x 100)
  - Percentage of pores correctly classified (221 pores; 221 correctly classified)
- Precision: 100%
  - Percentage of samples classified as a pores that actually are pores
- Overall accuracy: 100%
  - 483 samples; 483 correctly classified, 0 misclassified
  - 262 pores; 262 correctly classified. 0 misclassified
  - 221 non-pores, all correctly classified

Estimated Accuracy

- TAR (True Accept Rate) = 1.0
- FAR (False Accept Rate) = 0.0

Discussion

- Results are suggestive, but not conclusive
- Sample size is too small to make useful accuracy estimates
  - Because there were no errors, with 95% confidence, the error rate is known to be less than 0.621% (3/sample size) (Rule of 3) [Gamassi, 2004] [Louis 1981] [Jovanovic 1997] [Wayman 2000]
- Errors are too few in number
  - "To be 90% confident that the true error rate is within ± 30% of the observed error rate, there must be at least 30 errors." [Gamassi, 2004] [Doddington, 2000] (Rule of 30)

Future Research

- Expand and evaluate pore training set
- Scan image for pores and display detection regions
- Calculate ROC using confidence levels
- Evaluate performance on other level 3 features
- Expand study to include 1000 dpi fingerprints
- Scan latent fingerprint images and display detection regions

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