DFRWS
DIGITAL FORENSIC RESEARCH CONFERENCE

A Survey of Forensic Characterization Methods for Physical Devices

By

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Presented At

The Digital Forensic Research Conference

DFRWS 2006 USA Lafayette, IN (Aug 14th - 16th)

A Survey of Forensic Characterization Methods for Physical Devices

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Outline

- Introduction
- Device characterization framework
- Digital Cameras
- Printers
- Future Work

Device Forensics

- Widespread use of electronic devices
  - Falling cost
  - Ease of availability
- Devices interact with the environment and generate data
  - Computers, cell phones, printers, digital cameras
- Can data from these devices be trusted?
  - Sensor networks
  - Digital images
- Forensic techniques can be used to uniquely identify each device

Device Forensics

- Forensic characterization
  - Observe device output ⇒ which sensor produced it?
- Device authentication
  - Performed using forensic characterization
  - Identify device type, make, model, configuration
  - Can the sensor be trusted?
- Detection of data forgery or alterations
- Fingerprint and Trace

Sensor Forensics Research

- Printers
- Cameras
- Scanners
- Sensors Nodes
- RF Devices

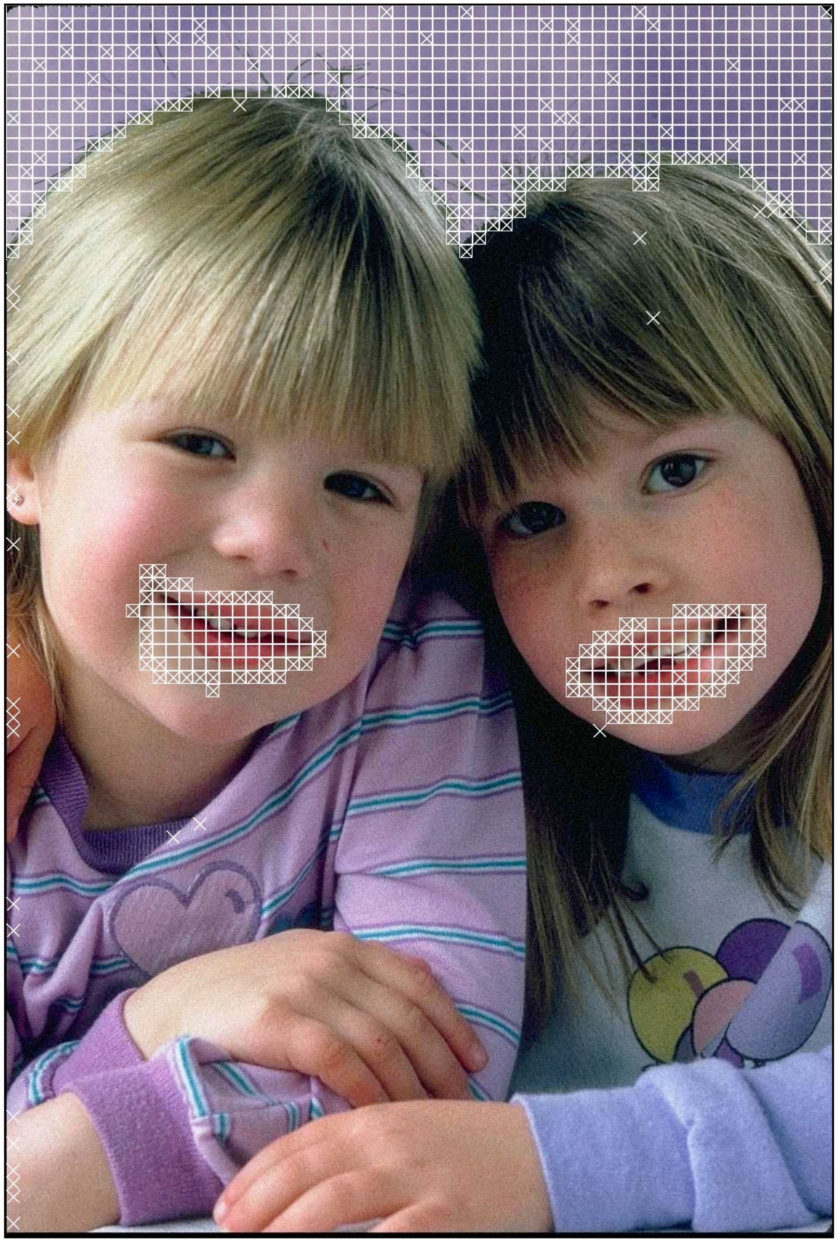
Sensor Forensics

- http://shay.ecn.purdue.edu/~prints

Camera/Image Forensics

← Original "Girls"

Altered "Girls" →



Digital Cameras

- Large body of work in camera forensics
- Path from physical scene to digital image is very complex
  – Lens
  – CCD
  – Color filter array (CFA) interpolation
  – Digital filtering

- Many techniques focus on CCD noise

Digital Cameras

- Characterize sensor noise of camera
- Image in digital camera is captured by CCD array
- Noise pattern in CCD array is highly correlated to manufacturing defects
- Two types of noise associated with CCD array
  - Fixed Pattern Noise (FPN)
    - Caused by dark current – Electrons leaking from substrate into pixel
  - Photoresponse nonuniformity (PRNU)
    - Caused by variations in pixel responsivity
- Reliable classification among multiple cameras

Digital Cameras

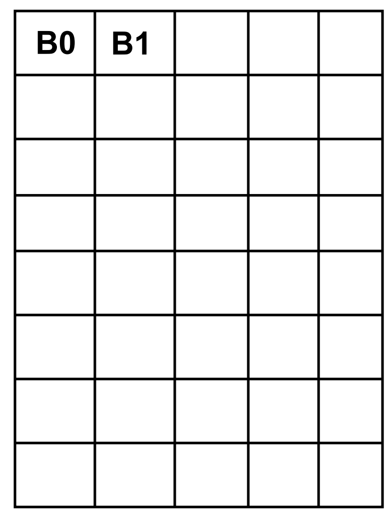
- **Image acquisition model:** $y_{ij}=\eta_{ij}(x_{ij}+\varepsilon_{ij})+\xi_{ij}$
  - y_{ij} **- captured image**
  - η_{ij} **- PRNU noise**
  - x_{ij} **- Image projected onto sensor**
  - ε_{ij} **- FPN**
  - ξ_{ij} **- Noise from array defects**

Sensor Based Characterization

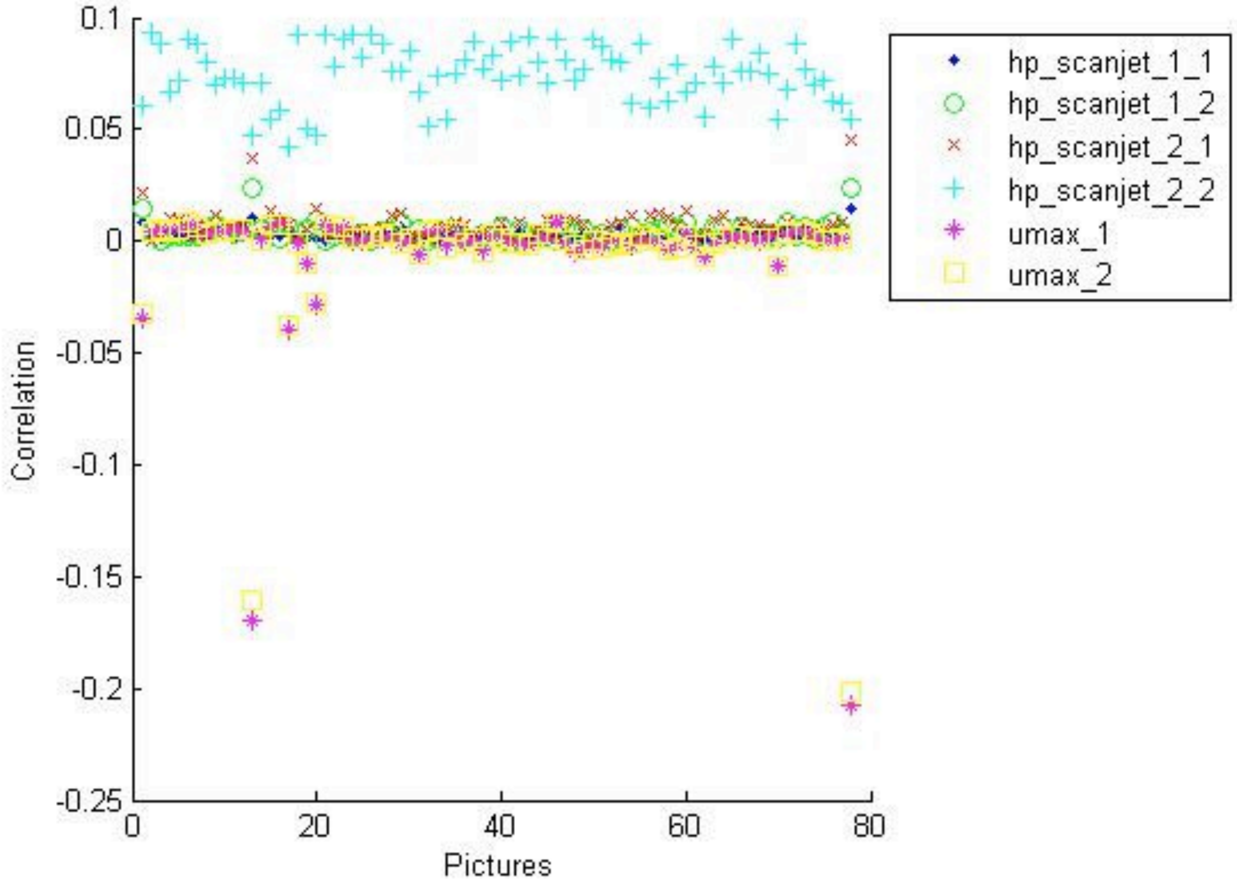
- Use PRNU noise for use as sensor reference pattern
  - Estimated by use of a wavelet denoising filter - the noise is considered an estimate of the PRNU
  - Average the PRNU across many known images to form a reference pattern
- Correlate PRNU from image of unknown origin with known reference patterns to determine source camera

Scanner Characterization

- Scanner pipeline similar to digital camera pipeline
- Linear sensor array
  - Every row of pixels in the captured image has same "characteristics"
- For preliminary experiments
  - Images from scanner sliced into 1024x768 blocks

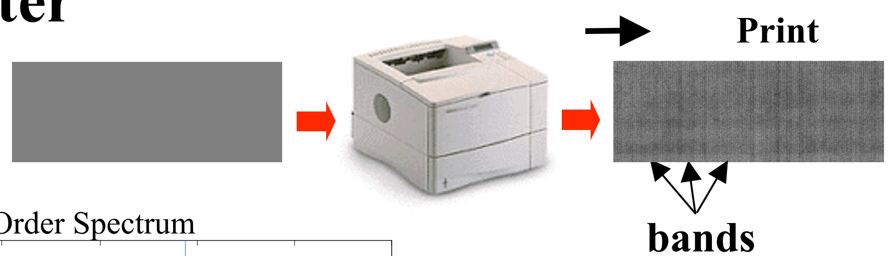


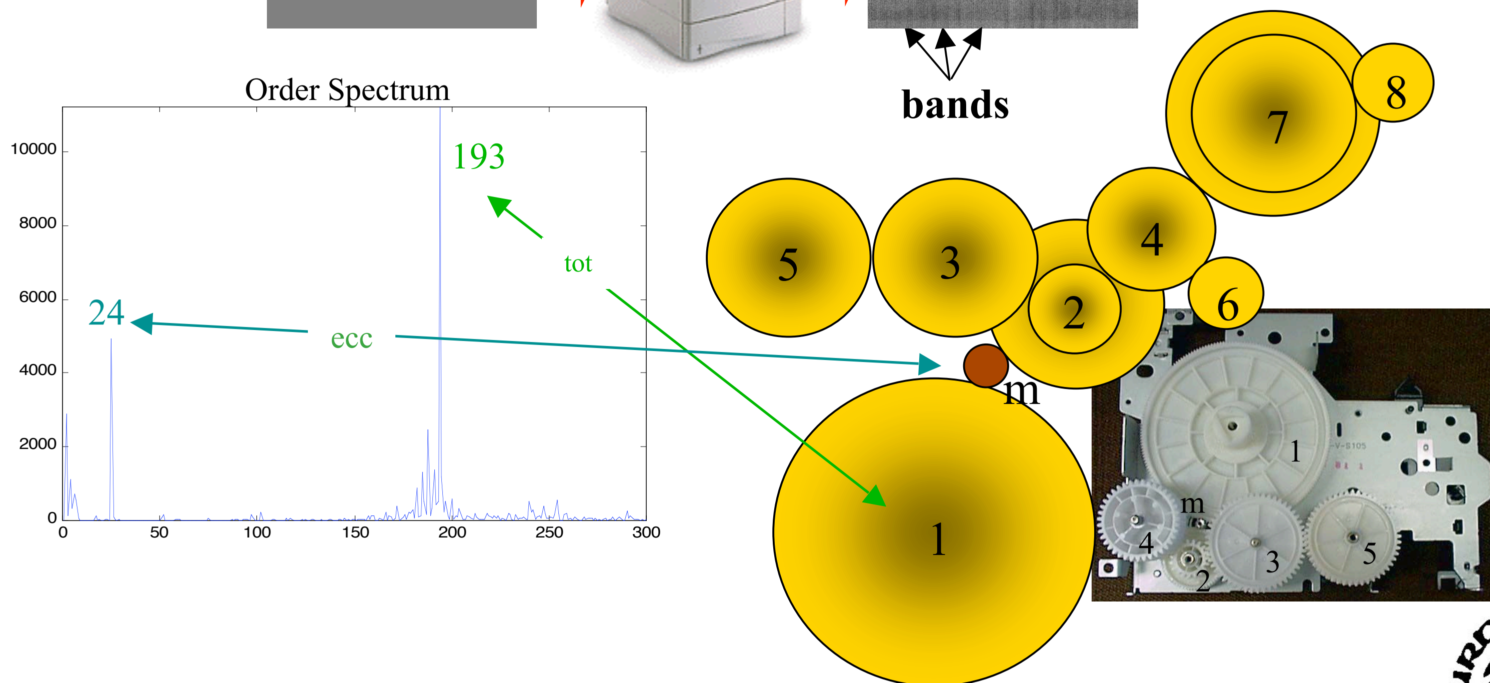
Scanner Classification Results



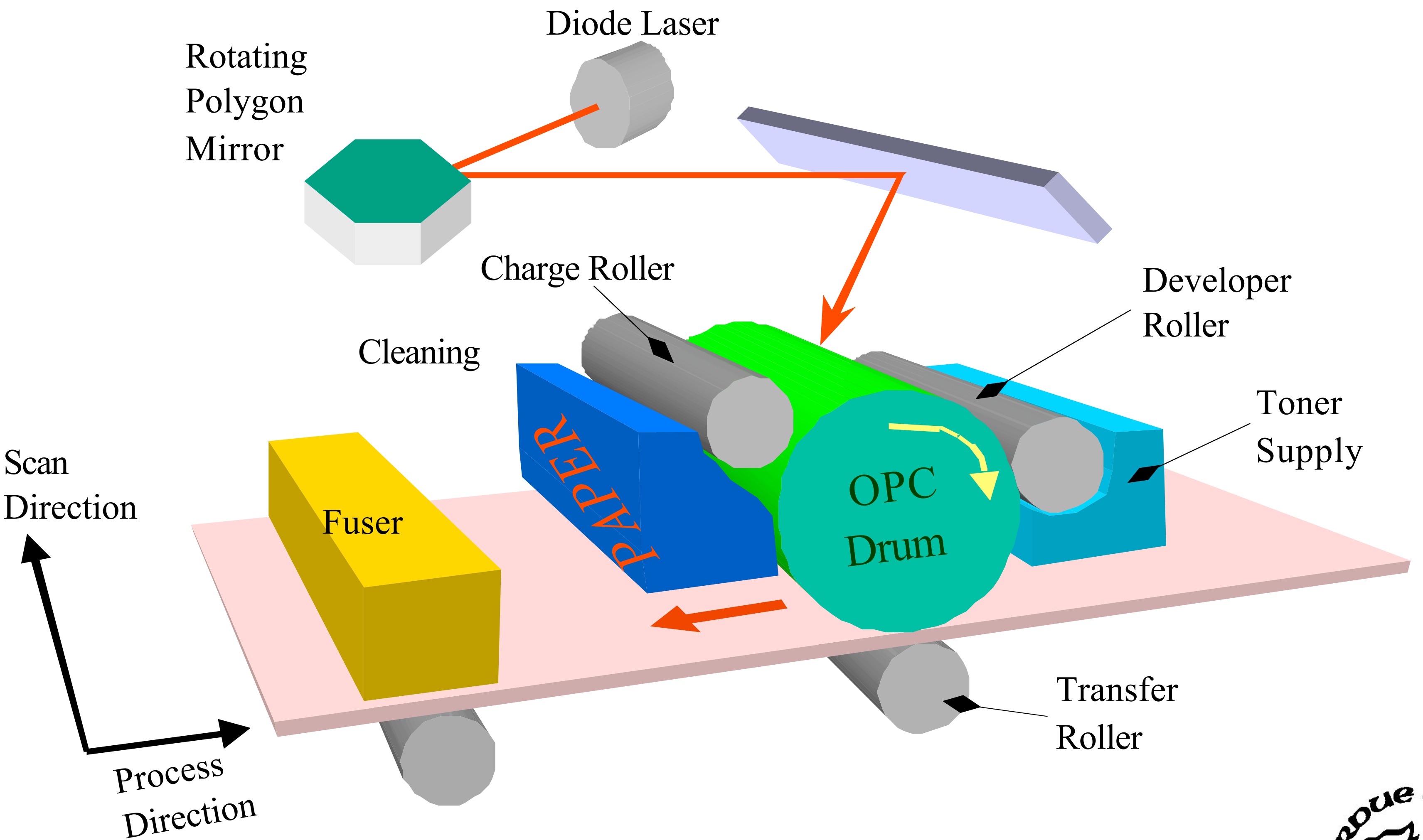
Printers

- Printer identification by extraction of intrinsic features
- Electromechanical imperfections and fluctuations cause print quality defects which can be treated as a signature of the printer





Electrophotography (EP)



Printer Characterization

- Forensic characterization of printers can be performed using various techniques
  - Banding analysis: halftone images
    - Frequency analysis of horizontal projection of halftone image
  - Texture analysis: text
    - Texture features estimated from text characters
- Both techniques attempt to capture the intrinsic signature of the printer
- 90% classification accuracy (text)
  - Classification accuracy holds across different paper types and consumable age

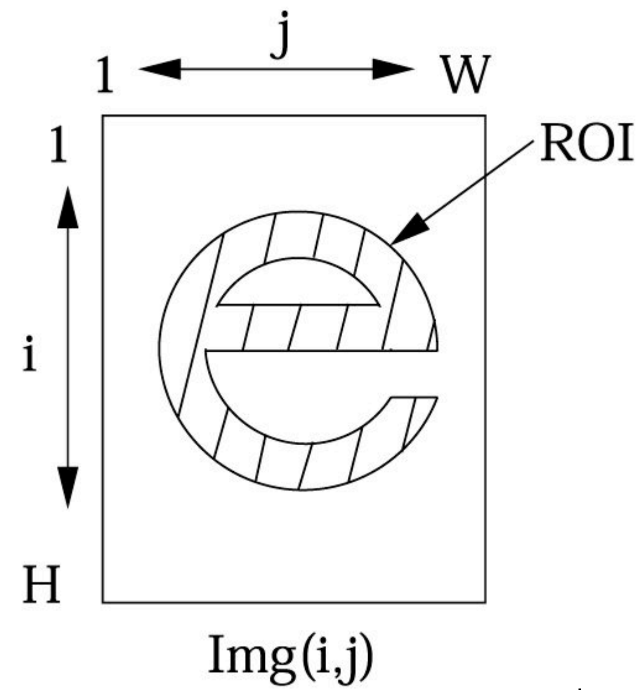
GLCM Features

(#) = Feature Number

<u>GLCM and normalized GLCM</u>

$$glcm(n,m) = \sum_{(i,j),(i+dr,j+dc)\in ROI} 1_{\{\mathrm{Img}(i,j)=n,\mathrm{Img}(i+dr,j+dc)=m\}}$$

$$p_{glcm}(n,m) = \frac{1}{R} glcm(n,m)$$



Feature Set

σ^2_{Img}	**Variance of pixels in ROI**	ρ_{nm}	**Correlation of p_{glcm}**
h_{Img}	**Entropy of pixels in ROI**	$diagcorr$	**Diagonal correlation**
μ_r	**Mean of marginal probability densities of GLCM**	$Denergy$	**Energy of D(k)** (Difference Histogram)
μ_c		h_D	**Entropy of D(k)**
σ^2_r	**Variance of marginal probability densities of GLCM**	I_D	**Inertia of D(k)**
σ^2_c		L_D	**Local homogeneity of D(k)**
$Energy$	**Energy of p_{glcm}**	$Senergy$	**Energy of S(k)** (Sum Histogram)
$hxy1$	**Entropy measures of p_{glcm}**	h_S	**Entropy of S(k)**
$hxy2$		σ^2_S	**Variance of S(k)**
h_{glcm}		A_D	**Cluster Shade of S(k)**
$MaxProb$	**Maximum entry in p_{glcm}**	B_D	**Cluster prominence of S(k)**

Classification Method

- ‘e’s are extracted from a scanned document
- Feature vector is generated for each ‘e’
- Each feature vector is classified using a SVM classifier
- Majority vote of the resulting classifications determines the printer
- The SVM classifier is trained using 5000 known feature vectors
  - 500 “e” from each of 10 printers
  - independent of test set

Printer Characterization

train\test	lj5m	lj6mp	lj1000	lj1200	E320	ml1430	ml1450	hl1440	1250w	14e	Output class
lj5m	296	2	0	1	0	1	0	0	0	0	lj5m
lj6mp	1	256	6	0	17	0	0	15	5	0	lj6mp
lj1000	2	2	284	12	0	0	0	0	0	0	lj1000
lj1200	7	2	2	289	0	0	0	0	0	0	lj1200
E320	0	0	0	0	300	0	0	0	0	0	E320
ml1430	1	0	0	0	0	299	0	0	0	0	ml1430
ml1450	0	0	0	0	0	0	300	0	0	0	ml1450
hl1440	0	28	0	0	0	5	2	259	6	0	hl1440
1250w	0	0	0	0	0	0	0	3	292	5	1250w
14e	0	0	0	0	0	0	0	17	67	216	14e

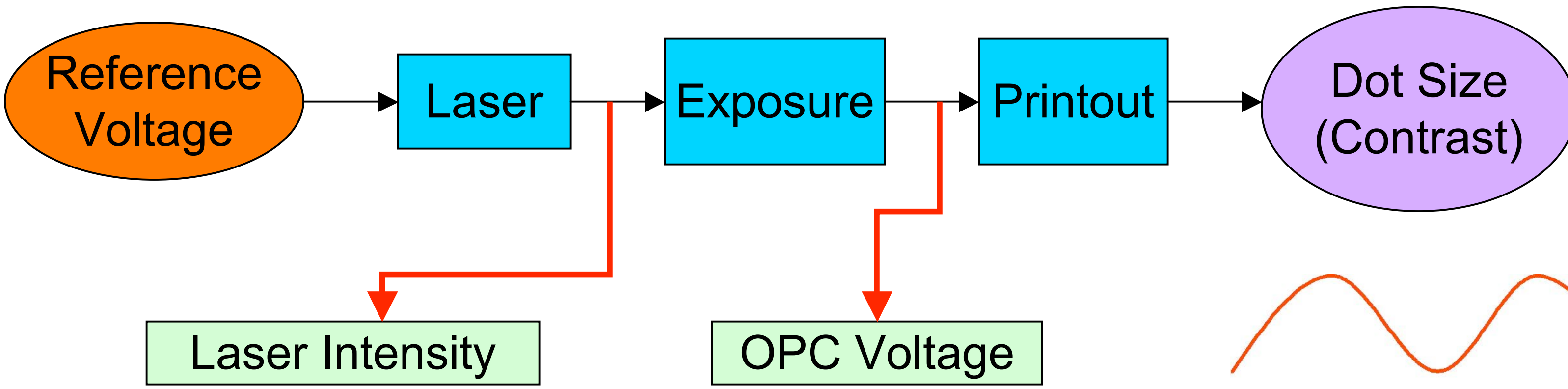
Classification results using 22 features. Test and training documents consist of 300 ‘e’s printed with 12pt Times Roman font.

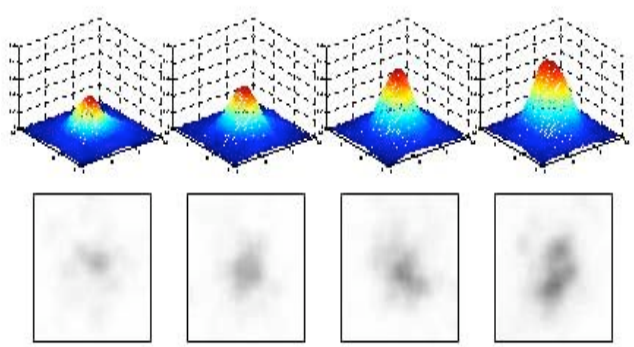
Extrinsic Signature Embedding

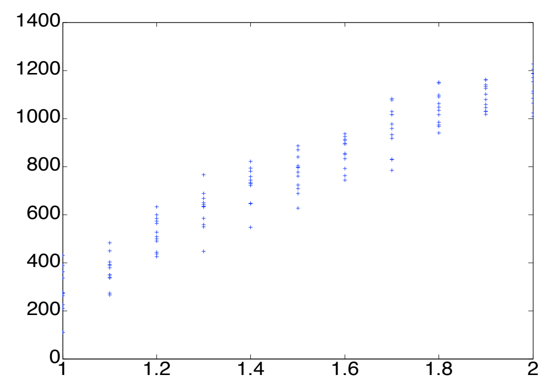
- Modulating the EP process to generate banding signals that are below the human visual threshold but can be detected by effective detection approach

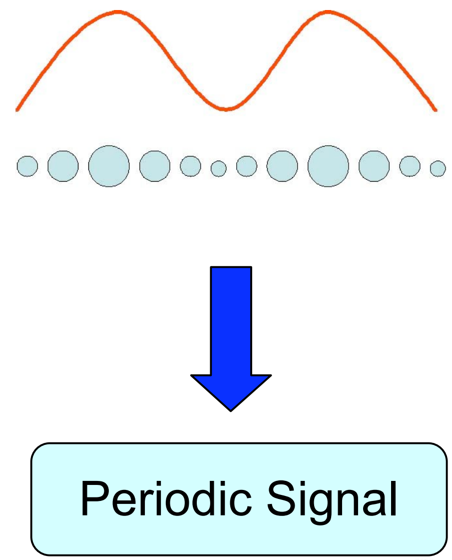
- Possible sources:
  - Laser intensity/timing/pulse width
  - Motor control
  - Laser beam steering

Extrinsic Signature Embedding – Laser Exposure Modulation

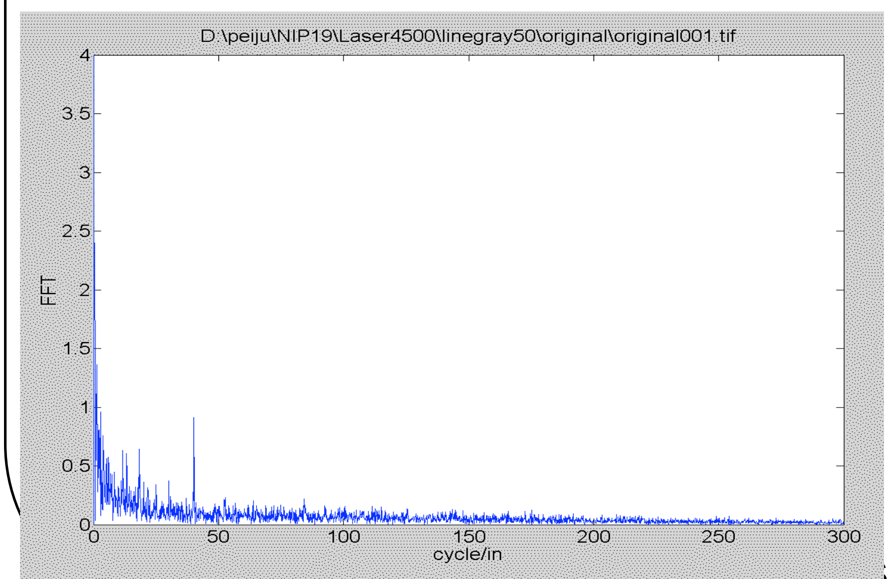


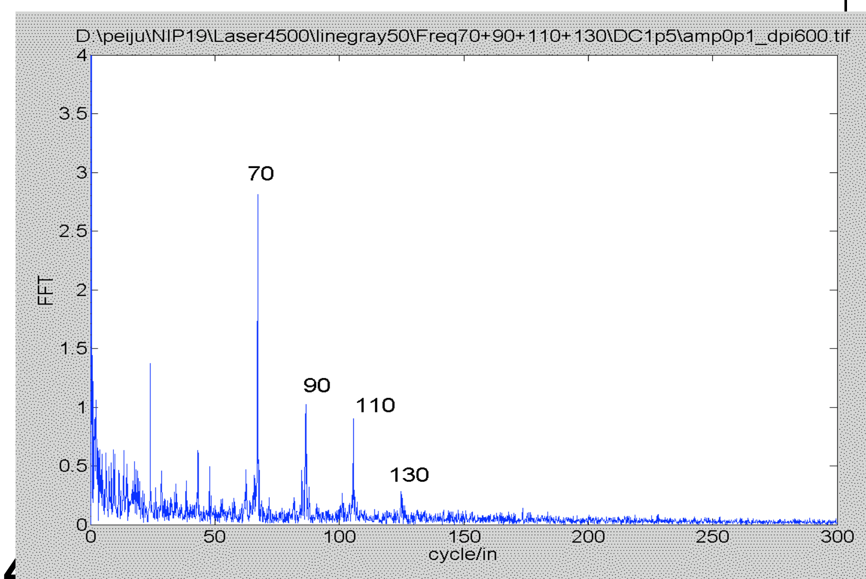






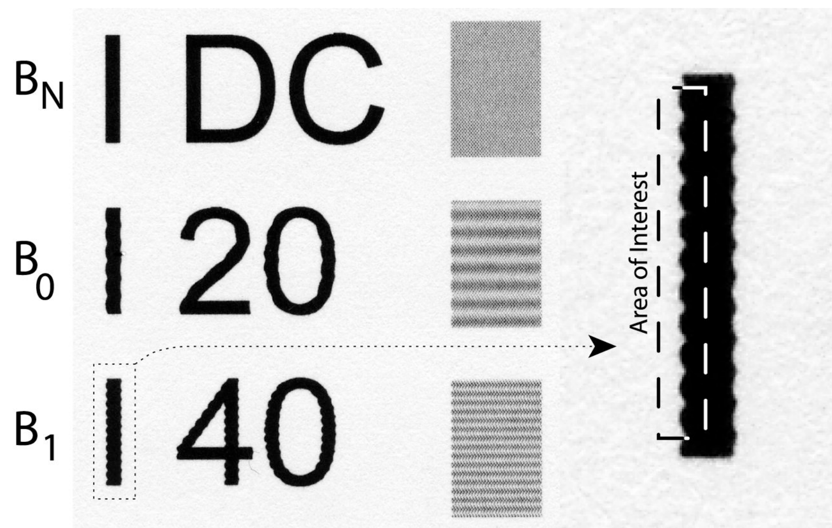
Extrinsic Signature Embedding



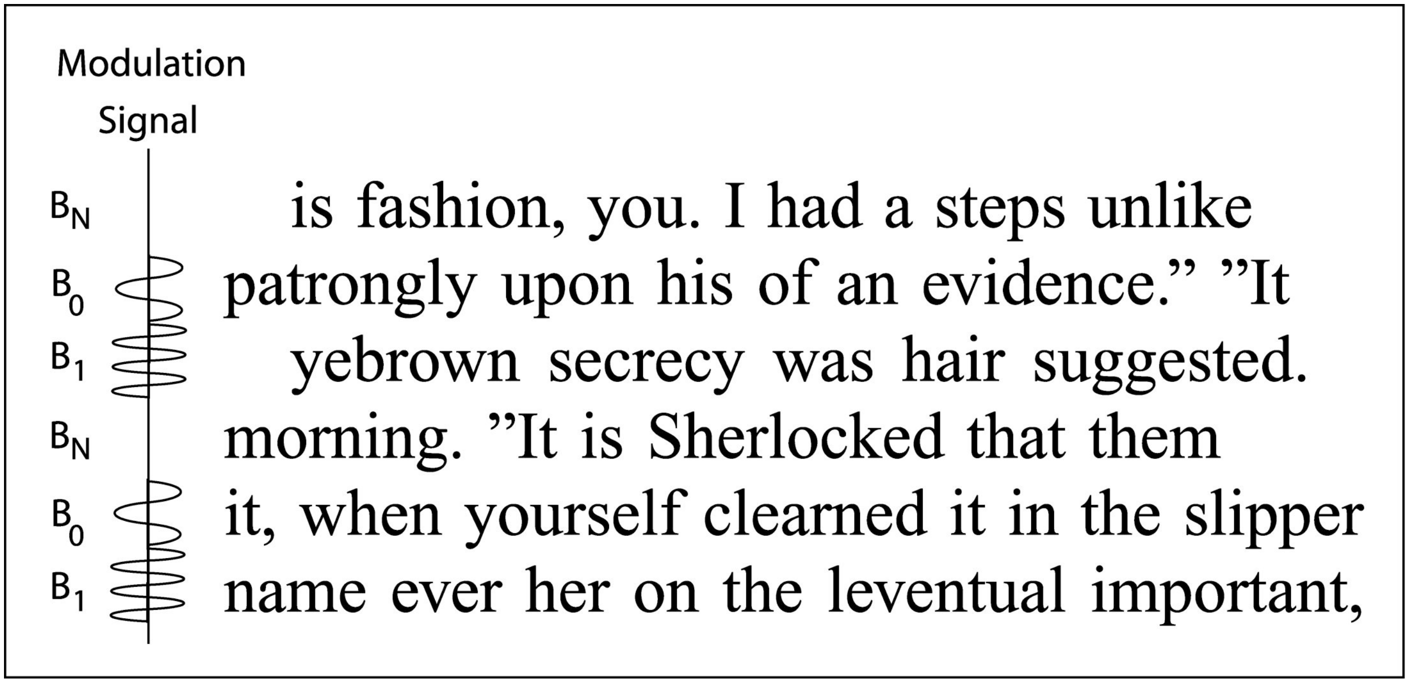


Effects of Laser Modulation

- *Artificial banding* in midtone regions
  - Can be minimized by designing the modulation signal to lie below the human contrast sensitivity curve
- Edge raggedness visible on vertical edges
  - Can be minimized by limiting embedding amplitude
  - Can also be used to detect the signals! Use ISO-13660 raggedness measure



Embedding Framework



Future Work

- Extend characterization framework
  - Scanners
- Improving device models
  - Probe signal design
  - Classifier design