EE 6886: Topics in Signal Processing
-- Multimedia Security System

Lecture 7: Multimedia Forensics

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Outline -- Introduction

- Multimedia Security :
  - Multimedia Standards – Ubiquitous MM
  - Encryption – Confidential MM
  - Watermarking – Uninfringible
  - Authentication – Trustworthy MM
- Security Applications of Multimedia:
  - Audio-Visual Person Identification – Access Control, Identifying Suspects
  - Surveillance Applications – Abnormality Detection
  - Media Sensor Networks – Event Understanding, Information Aggregation

Multimedia Forensics

- Video Tape Enhancement
- Audio Tape Enhancement
- Facial Recognition
- Handwriting Comparison
- Speaker Recognition / Identification
- Image / Art Authentication

DNA Technologies for Forensic Investigations

- Restriction Fragment Length Polymorphism (RFLP)
  - Analyzing the variable lengths of DNA fragments that result from digesting a DNA sample with a special kind of enzyme.
- Polymerase Chain Reaction (PCR)
  - Used to make millions of exact copies of DNA.
  - Allows DNA analysis on biological samples as small as a few skin cells.
- Short Tandem Repeat (STR)
  - Evaluate specific regions within nuclear DNA.
  - CODIS: An FBI standard set of 13 specific STR regions
  - The probability that two individuals will have the same profile: 1 in 1 billion.
- Mitochondrial DNA Analysis (mtDNA)
  - Extract DNA from another cellular organelle – mitochondrion.
  - Can extract from hair, bones, and teeth.
- Y-Chromosome Analysis

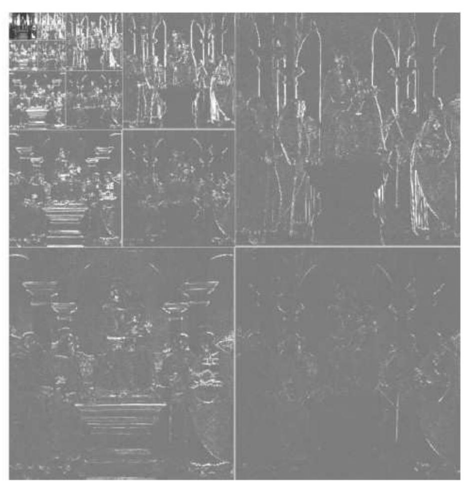
Art Authentication

- Perugino (1446-1523):
  - Great Renaissance painters may only painted a portion of the work and apprentices did the rest.
  - Experiment: “Madonna with Child” – at the Hood Museum of Art, Dartmouth College ➔ color 16852x18204 pixel image.
  - Face Region of each of the six characters was manually localized.
  - Each face was partitioned into nonoverlapping 256 x 256 regions. ➔ 189, 171, 189, 43, 81, and 144 regions).

This work was done by S. Lyu, D. Rockmore and H. Farid, Dartmouth College
“A digital technique for art authentication,” PNAS, Dec. 2004.

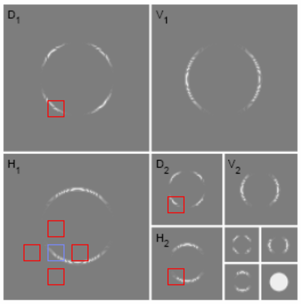
Wavelet Transform

- Multi-scale transformation
- In each scale, images are decomposed into 4 bands – LL, LH, HL, and HH.
- Example: 5-level wavelet decomposition.



Feature Extraction of an 256x256 block

- Use 72-dimensional Feature Vector for each 256x256 block.



Compute the *mean, variance, skewness and kurtosis* of the coefficients of each subband

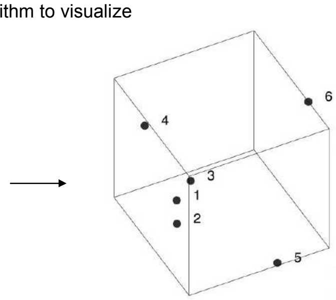
Predict the Green coefficient from Red coefficients, and compute the prediction error

Compute the *mean, variance, skewness and kurtosis* of the prediction errors

$$
\begin{aligned}
|V_i(x,y)| = {} & w_1|V_i(x-1,y)| + w_2|V_i(x+1,y)| \\
& + w_3|V_i(x,y-1)| + w_4|V_i(x,y+1)| \\
& + w_5\left|V_{i+1}\left(\frac{x}{2},\frac{y}{2}\right)\right| + w_6|D_i(x,y)| \\
& + w_7\left|D_{i+1}\left(\frac{x}{2},\frac{y}{2}\right)\right|,
\end{aligned}
$$

Authentication of Perugino's Painting

- Calculate the distance faces in the feature space:
  - For each face subimage -> partition to 256x256 blocks → 189, 171, 189, 43, 81, and 144 regions).
  - For each region, calculate 72 dimensional feature vector.
  - Calculate the Hausdorff distance of two subimages.
  - Use Multidimensional Scaling (MDS) algorithm to visualize clusters.

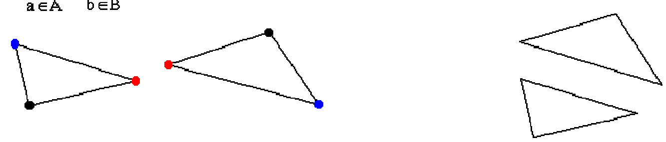


MDS representation of Hausdorff Distance of these 6 face subimages

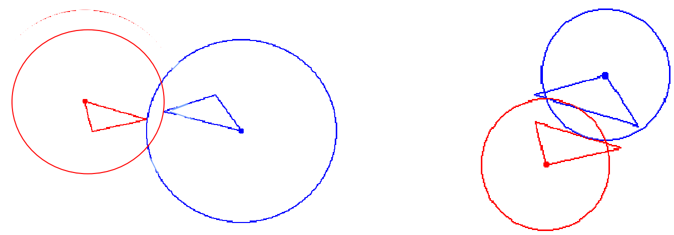
Hausdorff Distance

- Calculate the distance of two sets.

$$D(A,B) = \min_{a \in A} \{ \min_{b \in B} \{ d(a,b) \} \}$$



$$h(A,B) = \max_{a \in A} \{ \min_{b \in B} \{ d(a,b) \} \}$$



➔ *Hausdorff Distance: H (A, B) = max { h (A, B), h (B, A) }*

Authentication – Distinguish the author and imitator

- 13 art works from MOMA

Table 1. Authentic and imitation works of art

MMA cat. no.	Title	Artist
Authentic		
3	Pastoral Landscape	Bruegel
4	Mountain Landscape with Ridge and Valley	Bruegel
5	Path through a Village	Bruegel
6	Mule Caravan on Hillside	Bruegel
9	Mountain Landscape with Ridge and Travelers	Bruegel
11	Landscape with Saint Jerome	Bruegel
13	Italian Landscape	Bruegel
20	Rest on the Flight into Egypt	Bruegel
Imitation		
7	Mule Caravan on Hillside	—
120	Mountain Landscape with a River, Village, and Castle	—
121	Alpine Landscape	—
125	Solicitudo Rustica	—
127	Rocky Landscape with Castle and a River	Savery

Authentication – Distinguish the author and imitator

- Clustering Result

Table 1. Authentic and imitation works of art

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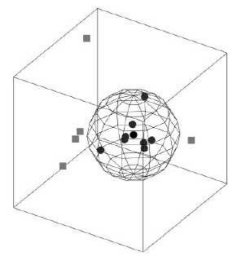

Authentic works by Bruegel and imitations. An authentic work (*Top*) and an imitation (*Middle*) (nos. 6 and 7, respectively, in Table 1). (*Bottom*) The results of analyzing eight authentic Bruegel drawings (●) and five imitations (■). Note how the imitations lie significantly outside the bounding sphere of authentic drawings.

Passive-blind Image Forensics: A Review

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dvmm DIGITAL VIDEO | MULTIMEDIA LAB

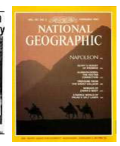
Background
Passive-blind Image Forensics

- Digital images is pliable to manipulation.
- [WSJ 89] 10% of color images published in US were altered.
- Image forensic: to find out the condition of an image without any prior information.
- Two main functions of image forensics:
  - Image Forgery Detection
  - Image Source Identification

Image Forgery Hall of Fame


LA Times '03

Internet '04



Nat. Geo. '92

Times '96

Problem I
Image Forgery Detection

- Image forgery: Photomontage, images with removed objects, retouched images, etc.
- Adobe Photoshop – 5 million registered users (2004)
- Photoshop altered images are common – 178,582 images on www.worth1000.com (2005)

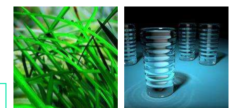
www.worth1000.com (scandal category)

Problem II
Image Source Identification

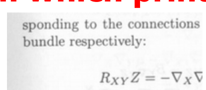
- Identify image production devices: camera, computer graphics, printer and scanner, etc.
- Identify nature of the image scene: 2D photo or 3D scene
  - A face recognition system should not be fooled when being shown a 2D face photo of someone.

From which camera?

CG Or Photo?



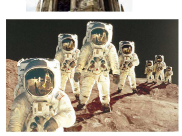
From which printer?


sponding to the connections
bundle respectively:

$R_{XY}Z = -\nabla_X\nabla$

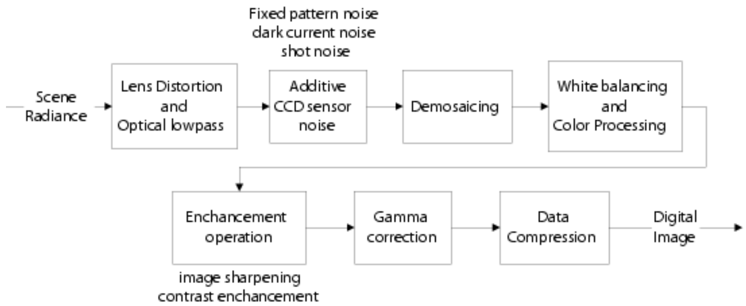
Image Authenticity

- The idea of image authenticity is at the core of image forensics.
- The role of image authenticity
  - Define an authentic image for image forgery detection.
  - Define images of a specific source for image source identification.
- In image forensics, image authenticity can be defined through:
  - Imaging device characteristics.
  - Natural-scene characteristics.

		camera-authentic	**scene-authentic**
Computer Graphics		✗	✓
Photomontage		✓	✗

Camera Authenticity

- A result of the camera operation pipeline.
  - **Local effect**: optical low-pass, color filter array interpolation, CCD sensor noise, white-balancing and non-linear gamma correction.
  - **Global effect**: lens distortion

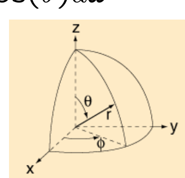


Natural-scene Authenticity

- A physical constraint from the light transport in a real world scene.
  - **Global effect**: the orientation of a shadow is related to the lighting direction.
  - **Local effect**: the complex reflectance properties of real-world objects.

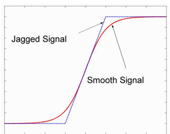
Global Illumination Equation

$$\underbrace{L(x,\theta_0,\phi_0)}_{\text{Scene Radiance}} = \underbrace{L_e(x,\theta_0,\phi_0)}_{\text{Emitted Radiance}} + \int_\Omega \underbrace{f(x,\theta_0,\phi_0,\theta,\phi)}_{\text{Bidirectional Reflectance Distribution Function (BRDF)}} \underbrace{L_i(x,\theta,\phi)}_{\text{Incident Radiance}} \cos(\theta)\, d\omega$$



Prior Work in Image Forgery Detection – by Camera Authentic Characteristics

- Optical Low-pass property [Ng et al. 04]
  - Image splicing (simple cut-&-paste) introduces abrupt discontinuities – violates the optical low-pass property.
  - Use bicoherence (a third order moment spectrum).
  - Propose a model for image splicing and show why bicoherence is sensitive to image splicing.



- Demosaicing [Popescu et al. 05]
  - Demosaicing introduces an interpolation pattern, image compositing may disrupt the pattern.
  - Propose an EM algorithm to estimate the interpolation pattern.
  - Experiment shows the capability of distinguishing image regions with demosaicing and without demosaicing.

Color Filter: Bayer Pattern

R	G	R	G
G	B	G	B

Prior Work in Image Forgery Detection – by Camera Authentic Characteristics

- Camera Response Function (CRF)
  - The CRF estimated from an authentic image should be similar over all spatial location.
  - The challenge is to estimate CRF from a single image.
  - [Popescu et al. 04] estimate CRF using bicoherence.
  - [Lin et al. 05] estimate CRF by the linear pixel blending property, assumed to be uniform over the RGB channel.

Image Irradiance

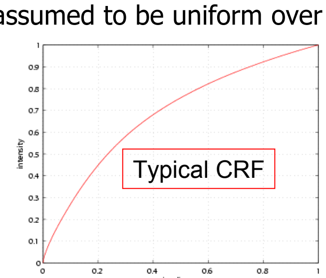


Image Intensity

Prior Work in Image Forgery Detection – by Natural-scene Authentic Characteristics

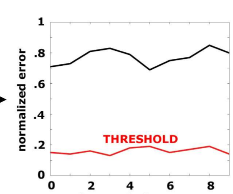
- 2D Lighting Consistency [Johnson et al. 05]
  - It is difficult to estimate 3D point light source direction with unknown object geometry (i.e., surface normal).
  - The surface normal on the occlusion contours can be easily estimated from image appearance (i.e., z-component = 0, x-y component = occlusion contour normal).
  - Assuming Lambertian surface, constant reflectance (albedo), single distant point light source, scene radiance can be estimated by a least square method.

$$\underbrace{R(x,y)}_{\text{Scene Radiance}} = \underbrace{\rho}_{\text{Reflectance}}\underbrace{\mathbf{N}(x,y)}_{\text{Surface Normal}} \cdot \underbrace{\mathbf{L}}_{\text{Lighting Direction}} + \underbrace{A}_{\text{Ambient Lighting}}$$

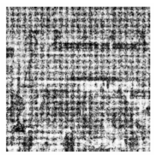
Prior Work in Image Forgery Detection – by Natural-scene Authentic Characteristics

- Implicit Lighting Consistency Checking
  - [Dhruv et al. (in review)] Checking lighting consistency without explicitly estimating lighting.
  - Propose a theory of spherical harmonics invariants.
  - Work for complex lighting but assume known object geometry.

→ **Lighting Consistency Checking Module** →



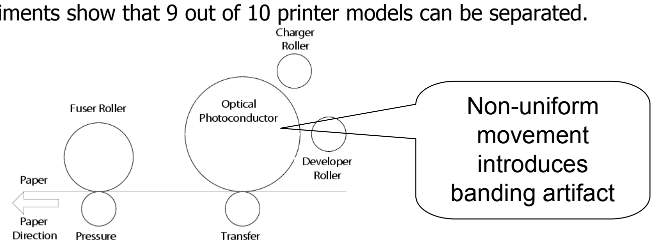
Prior Work in Image Forgery Detection – by Image Forgery Artifacts



- Resampling [Popescu et al. 05]
  - Image fragments may be rescaled, before being pasted onto another image. Rescaling may result in resampling of some image pixels.
  - Resampling (interpolation) pattern can be estimated by an EM algorithm (as in the case of demosaicing).
- Imaging noise, Double JPEG compression, Duplicate image regions [Popescu et al. 04]
- Brightness, contrast adjustment [Avcibas et al. 04]

Prior Work in Image Source Identification

- CG vs. Photo
  - Will be described later…
- Identify Models of Camera [Mehdi et al. 04]
  - Exploit the differences in color processing (e.g., white balancing, etc.).
  - Achieve 88% of classification accuracy for 4 models of camera.
- Identify Printer Models from Scanned Documents [Mikkilineni et al. 04]
  - Exploit the banding artifact of laser printers as intrinsic printer signature.
  - Banding artifact non-uniform light and dark lines in the print-process direction.
  - Capture the banding artifact using co-occurrence matrix on characters.
  - Experiments show that 9 out of 10 printer models can be separated.



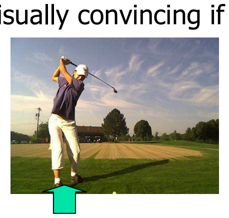
Passive-blind Image Forensics Work in Columbia University

- (1) Image forgery detection
  - Address image splicing detection using bicoherence.
  - Theoretical explanations for why bicoherence is sensitive to image splicing.
- (2) Image source identification
  - Address Photo/CG classification by analyzing the physical image generative process.

(1) Image Splicing Detection
Motivation & Problem

- Photomontage is an important and common type of image forgery.
- Two major steps in photomontage creation:
  - Cut-and-paste (i.e., image splicing)
  - Post-processing (e.g., blending, matting, smoothing, etc.)
- From image operation perspective, the effects of the above operations are the tell-tale signs of photomontage.
- In this work, we focus on the most basic operation – image splicing.
- Spliced images can be visually convincing if carefully done.


spliced


spliced

(1) Image Splicing Detection
Related Work

- Detecting other image operations related to photomontage:
  - Double JPEG compression, region duplicating, resampling [Popescu et al. 04/05]
  - Brightness, contrast adjustment [Avcibas et al. 04]
- Detecting inconsistent image authenticity properties among image regions:
  - Demosaicing [Popescu et al. 05]
  - Camera Transfer Function [Popescu et al. 04] [Lin et al. 05]
  - Lighting [Johnson et al. 05] [Dhruv et al.]

(1) Image Splicing Detection
Our Approach

- Detect image splicing using bicoherence, a third-order moment spectrum:

bicoherence

$$b(\omega_1,\omega_2) = \frac{E\left[X(\omega_1)X(\omega_2)X^{\star}(\omega_1+\omega_2)\right]}{\sqrt{E\left[|X(\omega_1)X(\omega_2)|^2\right] E\left[|X(\omega_1+\omega_2)|^2\right]}}$$

$X(\omega)$ is the Fourier spectrum of a 1D signal.

- Properties of bicoherence:
  - It is complex-valued.
  - Unlike power spectrum, it captures the phase information of a Fourier spectrum.
  - When there exists (ω_1,θ_1), (ω_2, θ_2) and $(\omega_1+\omega_2, \theta_1+\theta_2)$
    - The phase of $b(\omega_1,\omega_2)$ is 0
    - $|b(\omega_1,\omega_2)|$ is large, due to the expectation of a constant-phase random variable.

Quadratic Phase Coupling

(1) Image Splicing Detection
Why Bicoherence? – Previous Theory

- [Farid 99] Image splicing can be considered as a point-wise non-linear function, f(r).
- By Taylor expansion of f(r), we obtain a linear-quadratic term.

$$f(r) = f(0) + \boxed{r f'(0) + \frac{r^2}{2!} f''(0)} + \cdots$$

- Linear-quadratic operation on a signal introduces **quadratic phase coupling**.

Linear-quadratic operation

Quadratic Phase Coupling

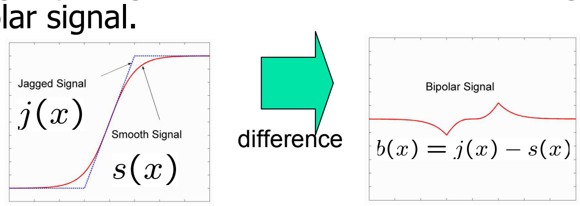
$$r(x) = a_1 \cos(\omega_1 x + \theta_1) + a_2 \cos(\omega_2 x + \theta_2)$$

$$r(x) + \alpha r(x)^2 = a_1 \boxed{\cos(\omega_1 x + \theta_1)} + a_2 \boxed{\cos(\omega_2 x + \theta_2)}$$

$$+ a_1 a_2 \boxed{\cos((\omega_1 + \omega_2)x + (\theta_1 + \theta_2))} + \cdots$$

(1) Image Splicing Detection
Why Bicoherence? – Our Proposed Theory

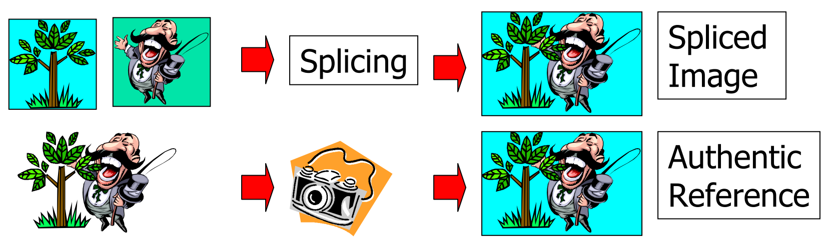
- Image splicing can be modeled as the adding of a bipolar signal.



- Theoretical results:
  - Bicoherence of a bipolar signal has a constant ±90° phase.
  - Addition of a bipolar signal induces an increase in ±90° phase in bicoherence (different from the QPC case!).
  - Addition of a bipolar signal increases $|b(\omega_1,\omega_2)|$
- The theoretical results are validated experimentally.

(1) Image Splicing Detection
Improving Bicoherence Method

- Using the basic bicoherence magnitude and phase features, the classification rate is only 62%.
- [Krieger et al. 97] Natural images originally have a certain amount of bicoherence energy – making detection difficult.
- We introduce the idea of "authentic reference image" – improve the classification to 72%.



(1) Image Splicing Detection
Functional Texture Decomposition

- [Vese et al. 02] Functional texture decomposition separates an image f into:
  - u, gross structure component (homogenous regions with sharp boundaries).
  - v, fine texture component (small-scale repeated details) .


original Structure Fine-texture

A bipolar signal can be considered a local oscillating function.

$$\inf_u \left(E(u) = \int |\nabla u| + \lambda ||v||_*, \quad f = u + v \right)$$

$u \in BV(\mathbf{R}^2)$, bounded variation function space.
$v \in G$, oscillating function space.

(2) CG vs. Photo
Motivation & Prior Work

- CG nowadays can produce convincing fake photos.

CG Or Photo?

- [Ianeva et al. 03] Classify photo and general CG (including drawing and cartoon).
  - For the purpose of improving video key-frame retrieval.
- [Lyu et al. 05] Classify photo and photorealistic CG.
  - Using wavelet statistics.
  - 67% photo detection rate (1% false alarm).
  - provides little insight into the physical differences between photo and CG.

(2) CG vs. Photo
Our Approach & Outcome

- We analyze the differences in the image generative process for Photo and CG
  - Capture the differences with features derived from fractal geometry, differential geometry and local patch statistics.
- The geometry features provide a classification model
  - Outperforms the methods in prior work.
- An open dataset
  - Avoids repeated data collection effort.
  - As a benchmark dataset.
- An online evaluation system.
  - Allows users to test the system.

(2) CG vs. Photo
Photo Generative Process

- Photographic Images

Light source

(1) Complex surface model
- Subsurface scattering of human skin.
- Color dependency.

(2) Complex object geometry
- Human skin texture follows biological system.
- Building surface formed by air erosion.

(3) Non-linear camera Transfer function
- Not an arbitrary transform.

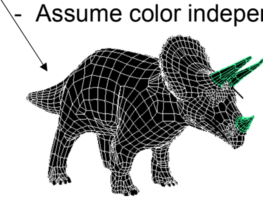
(2) CG vs. Photo
CG Generative Process

- Computer Graphics

3 Differences for Photo and CG
(1) Surface Model Difference.
(2) Object Model Difference.
(3) Acquisition Difference.

Light source

(1) Simplified surface model
- Assume color independence.

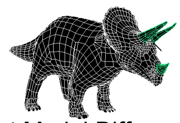


(2) Polygonal object geometry
- Reduced mesh resolution for computational efficiency.
- Without care, it introduces sharp structures in rendered images.

(3) Non-standard Post-processing
- Subject to the artist's taste.
- May different from camera transform.

Post-processing

(2) CG vs. Photo
Geometry Features


	Acquisition Difference	Object Model Difference	Surface Model Difference
Differential Geometry	Image Gradient	Quadratic Form	Surface Laplacian
Fractal Geometry		Distribution of the Local Fractal Dimension	
Local Patch Statistics	Distribution of the 3x3-pixels Local patches		

Differential Geometry I
Image Gradient

- Non-linear camera transform has effects on image Gradient!

Camera Model

r
image irradiance

↓

R=f(r)
Camera Transfer Function

↓

R
image Intensity

Chain Rule

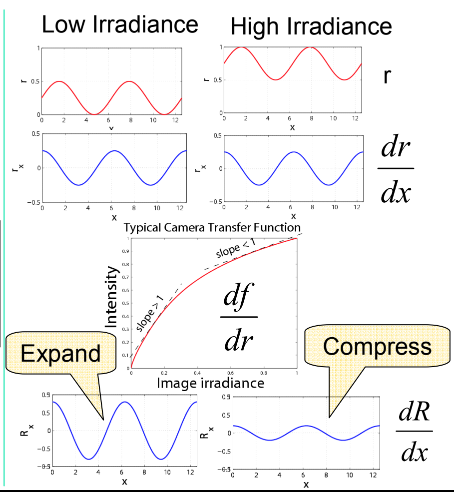
$$\frac{dr}{dx}$$

↓

$\frac{df}{dr}$
Slope of the curve

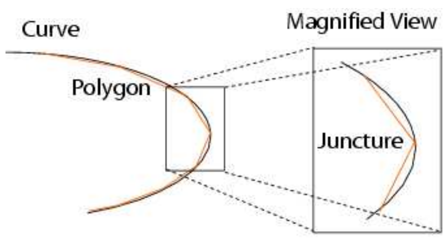
↓

$$\frac{dR}{dx} = \frac{df}{dr}\frac{dr}{dx}$$



Differential Geometry II
Quadratic Form

- Polygonal Model leads to sharp structures
  - At the junctures, the polygon is always sharper than the smooth curve.



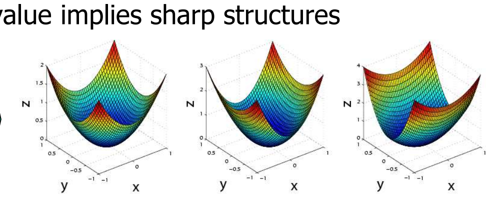
A smooth is approximated by a polygon

Unusually sharp transition

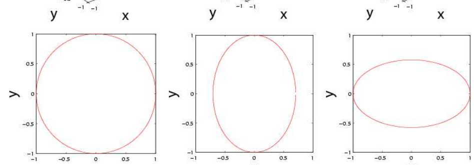
Differential Geometry II
Quadratic Form

- A graph submanifold can be locally approximated by a quadratic form.
  - Quadratic form can be characterized by 2 eigenvalues
  - The large eigenvalue implies sharp structures

3D plot of elliptic Quadratic form.



Cross-section of the quadratic form at z=1.



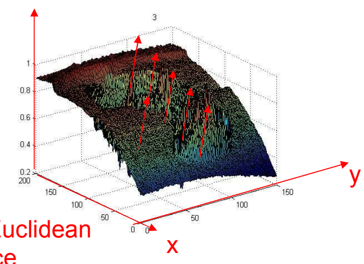
eigenvalues (1,1) (2,1) (3,1)

Differential Geometry III
Surface Laplacian

- Rendering of CG often assumes color independence in the object surface model (generally, not true for real-world object):
  - We capture the difference in the RGB correlation for Photo and CG using the surface Laplacian.
- Laplacian operator (Δ_g) on a graph surface
  - A vector pointing to the decreasing surface area direction.
  - For a submanifold in the 5D space, it measures the correlation between R, G and B.

(R,G,B)

$(\Delta_g I) = (\Delta_g I_R, \Delta_g I_G, \Delta_g I_B)$



5D Euclidean Space

Dataset
Columbia Open Dataset

- A publicly available Photo/CG dataset.
- Consists of 4 subsets, 800 images for each subset.

From a few personal collections of photo

Personal Photo | Google Photo | Internet CG | Recaptured CG

Downloaded from Google Image Search

Downloaded from the 3D artist websites

Recaptured from a LCD screen by a Canon G3 camera

Available at http://www.ee.columbia.edu/trustfoto

Experimental Results I
SVM Classification

- SVM classification with radial basis function (RBF) kernel.
- Cartoon feature is the conventional feature for modeling the general computer graphics (includes cartoon or drawing)

Features	Geometry	Wavelets	Cartoon
Accuracy	83.5%	80.3%	71.0%

Receiver operating characteristic (ROC) curve

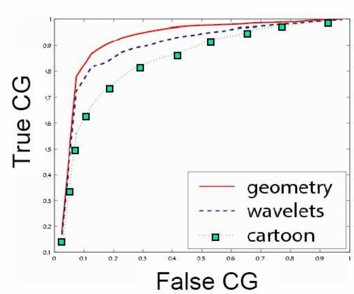
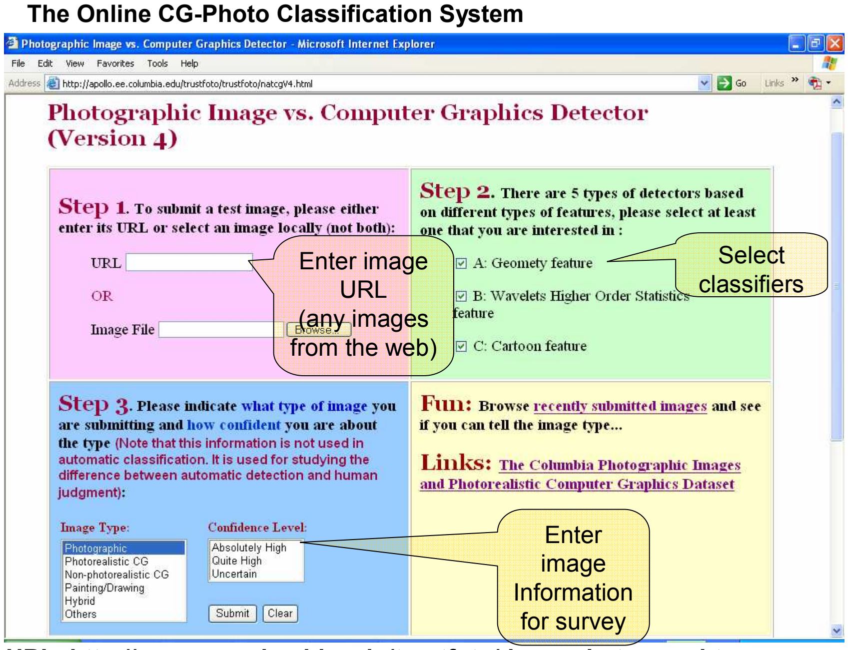


Photo
Vs
Internet CG

The Online CG-Photo Classification System



URL: http://www.ee.columbia.edu/trustfoto/demo-photovscg.htm

Thank you!

Online demo: **http://www.ee.columbia.edu/trustfoto/demo-photovscg.htm**

References

- S. Lyu, D. Rockmore and H. Farid, “A digital technique for art authentication,” PNAS, Dec. 2004.
- S. Lyu and H. Farid, “How Realistic is Photorealistic?”, IEEE Trans. on Signal Processing, 2005
- S.-S. Kim et al., Interactive Visualization of Hierarchical Clusters Using MDS and MST, 1998
- T.-T. Ng and S.-F. Chang, “A Model for Image Splicing,” ICIP 2004.
- T.-T Ng, S.-F. Chang, Q. Sun, “Blind Detection of Photomontage Using Higher Order Statistics, “ ISCAS 2004.
- T.-T Ng, S.-F. Chang, C.-Y. Lin, Q. Sun, “Passive-blind Image Forensics,” in Multimedia Security for Digital Rights Management, June 2006.

Final Project

- Team work is encouraged (1 – 3 students)
- Implement components of multimedia security systems or surveys of emerging technologies
- Oral presentations at the mid-term project proposal (4/5) and the final presentation (5/3).
- Final project report due at 5/12.

Possible Projects

- Paper study on an emerging field (1-person only):
  - Digital Rights Management in Mobile Environment
  - Steganography and steganoanalysis
  - Multimedia Forensics
  - Biometric Authentication
    - Face Recognition
    - Behavior Authentication
  - Audio/Visual Sensor Network

Possible Projects

- System Implementation (2 – 3 people):
  - Software / Hardware
  - Any topic in these fields:
    - Digital Rights Management
    - Watermarking
    - Media Authentication
    - Human Authentication / Recognition
    - Audio-Visual Sensor Network

E 6886 Topics in Signal Processing: Multimedia Security Systems

Possible Project Topics

- Human Vision Systems – implementations and experiments
- Art authentication
  - style change through time
  - Types of paintings: modern, abstract, impression, etc.
- Tampering detection, Natural / CG detection
- Video Forensics
- Face recognition in videos
- Fingerprint recognition
- Human behavior authentication:
  - Keyboard
  - Email records
- Event detection from camera(s)
- Etc.