A Model for Image Splicing

Tian-Tsong Ng, Shih-Fu Chang

Department of Electrical Engineering

Columbia University, New York, USA

Outline

- Review
  - Problem and Motivation
  - Our Approach
  - Definition: Bicoherence
  - Why Bicoherence good for splicing detection? Previous Hypothesis
- Bicoherence Features
  - Magnitude feature
  - Phase feature
- Proposed Image Splicing Model
  - Bipolar Perturbation Hypothesis
  - Bicoherence of bipolar signal
  - Bipolar perturbation effect on magnitude feature
  - Bipolar perturbation effect on phase feature

Columbia University
in the City of New York
dvmm
DIGITAL VIDEO MULTIMEDIA LAB

Problem & Motivation: How much can we trust digital images?

- General problem: Image Forgery Detection
- Image Forgery: Images with manipulated or fake content
- (In)Famous examples:
  - March 2003: A Iraq war news photograph on LA Times front page was found to be a photomontage
  - Feb 2004: A photomontage showing John Kerry and Jane Fonda together was circulated on the Internet
- Adobe Photoshop: 5 million registered users


Fonda Speaks To Vietnam Veterans At Anti-War Rally

Definitions: Photomontage and Spliced Image

- Specific problem: Image Splicing Detection

- Photomontage: A paste-up produced by sticking together photographic images, possibly followed by post-processing (e.g. edge softening and adding noise).
- Spliced Image (see figures): Splicing of image fragments without post-processing. A simplest form of photomontage.

spliced

- Why interested in detecting image splicing?
  - Image splicing is a **basic and essential** operation in the creation of photomontage
- Therefore, a comprehensive solution for photomontage detection includes detection of post-processing operations and intelligent techniques for detecting internal scene inconsistencies

spliced

Columbia University in the City of New York

dvmm DIGITAL VIDEO MULTIMEDIA LAB

Image Forgery Detection Approaches

Active approach:

- Fragile/Semi Fragile Digital Watermarking: Inserting digital watermark at the source side and verifying the mark integrity at the detection side.
- Authentication Signature: Extracting image features for generating authentication signature at the source side and verifying the image integrity by signature comparison at the receiver side.
- Effective when there is
  - A secure trustworthy camera
  - A secure digital watermarking algorithm
  - A widely accepted watermarking standard

Passive and blind approach:

- Without any prior information (e.g. digital watermark or authentication signature), verifying whether an image is authentic or fake.
- Advantages: No need for watermark embedding or signature generation at the source side

What are the qualities of authentic images?

- Image Authenticity
  - Natural-imaging Quality
    - Entailed by natural imaging process with real imaging devices, e.g. camera and scanner
    - Effects from optical low-pass, sensor noise, lens distortion, demosicking, nonlinear transformation.
  - Natural-scene Quality
    - Entailed by physical light transport in 3D real-world scene with real-world objects
    - Results are real-looking texture, right shadow, right perspective and shading, etc.
- Examples:
  - Computer graphics and photomontages lack in both qualities.

Computer Graphics

photomontage

Columbia University in the City of New York

dvmm DIGITAL VIDEO MULTIMEDIA LAB

Definition: Bicoherence

- Bicoherence = normalized bispectrum (3rd order moment spectra)
- **Definition (Bicoherence)** The bicoherence of a signal x(t) with its Fourier transform being X(ω) is given by:

Numerator = Bispectrum

$$b(\omega_1,\omega_2)=\frac{E_X[X(\omega_1)X(\omega_2)X^*(\omega_1+\omega_2)]}{\sqrt{E_X[|X(\omega_1)X(\omega_2)|^2]E_X[|X(\omega_1+\omega_2)|^2]}}=|b(\omega_1,\omega_2)|e^{j\Phi(b(\omega_1,\omega_2))}$$

Magnitude

Phase

Normalized by the Cauchy-Schwartz Inequality upper bound

Cauchy-Schwartz Inequality

Hilbert space, $\mathrm{K}=\{x : x \text{ is a random variable satisfying } E[|x|^2]<\infty\}$

$$E[xy^*]\le\sqrt{E[|x|^2]}\sqrt{E[|y|^2]}\qquad (x,y\in\mathrm{K})$$

Notations:

$|\cdot| = magnitude$

$\Phi(\cdot) = phase$

Why BIC is Good for Splicing Detection? Hypothesis I [Farid99]

- Quadratic Phase Coupling (QPC)
  - A phenomena where quadratic related frequencies $\omega_1,\ \omega_2$ and $\omega_1+\omega_2$ has the same quadratic relationship $\phi_1,\ \phi_2$ and $\phi_1+\phi_2$

Phases are quadratic coupled (not independent)!

If (ω_1 , ω_2 , $\omega_1+\omega_2$) have statistically independent phase,

1) $|b(\omega_1,\omega_2)|$ would be 0 due to statistical averaging

2) $\Phi[b(\omega_1,\omega_2)]$ would be random

$$b(\omega_1,\omega_2)=\frac{E_X[X(\omega_1)X(\omega_2)X^*(\omega_1+\omega_2)]}{\sqrt{E_X[|X(\omega_1)X(\omega_2)|^2]E_X[|X(\omega_1+\omega_2)|^2]}}$$

If (ω_1 , ω_2 , $\omega_1+\omega_2$) are quadratic phase coupled,

1) $\Phi[b(\omega_1,\omega_2)]$ would be 0

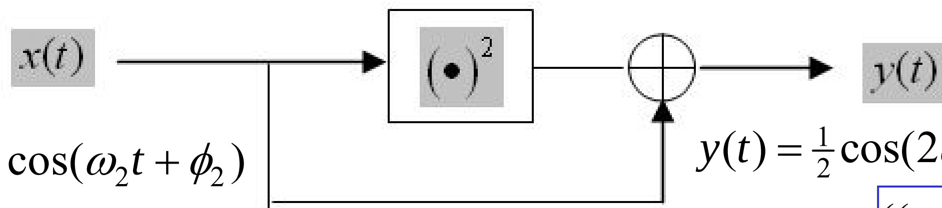
$$\Phi[X(\omega_1)X(\omega_2)X^*(\omega_1+\omega_2)]$$
$$=\Phi[X(\omega_1)]+\Phi[X(\omega_2)]-\Phi[X(\omega_1+\omega_2)]$$
$$=\phi_1+\phi_2-(\phi_1+\phi_2)=0$$

2) $|b(\omega_1,\omega_2)|$ would be close to unity (imagine X now becomes positive RV)

Hypothesis I (cont.)

Quadratic linear Operation

$$y(t) = x(t)^2 + x(t)$$



$$x(t) = \cos(\omega_1 t + \phi_1) + \cos(\omega_2 t + \phi_2)$$

$$\begin{aligned} y(t) &= \tfrac{1}{2}\cos(2\omega_1 t + 2\phi_1) + \tfrac{1}{2}\cos(2\omega_2 t + 2\phi_2) \\ &+ \cos\boxed{((\omega_1 + \omega_2)t + (\phi_1 + \phi_2))} \\ &+ \cos((\omega_1 - \omega_2)t + (\phi_1 - \phi_2)) + \\ &\cos\boxed{(\omega_1 t + \phi_1)} + \cos\boxed{(\omega_2 t + \phi_2)} + 1 \end{aligned}$$

Argument [Farid99]: Quadratic-linear operation gives rise to QPC and a nonlinear function, in Taylor expansion, contains quadratic-linear term. As splicing is a nonlinear operation, hence bicoherence is good at detecting splicing.

Problems:

1. No detailed analysis was given.
2. The quadratic-linear operation here is a point-wise operation, it is not clear how splicing can be related to a point-wise operation?

Outline

- Review
  - Problem and Motivation
  - Our Approach
  - Definition: Bicoherence
  - Why Bicoherence good for splicing? Quadratic Phase Coupling Hypothesis
- Bicoherence Features
  - Magnitude feature
  - Phase feature
- Proposed Image Splicing Model
  - Bipolar Perturbation Hypothesis
  - Bicoherence of bipolar signal
  - Bipolar perturbation effect on magnitude feature
  - Bipolar perturbation effect on phase feature

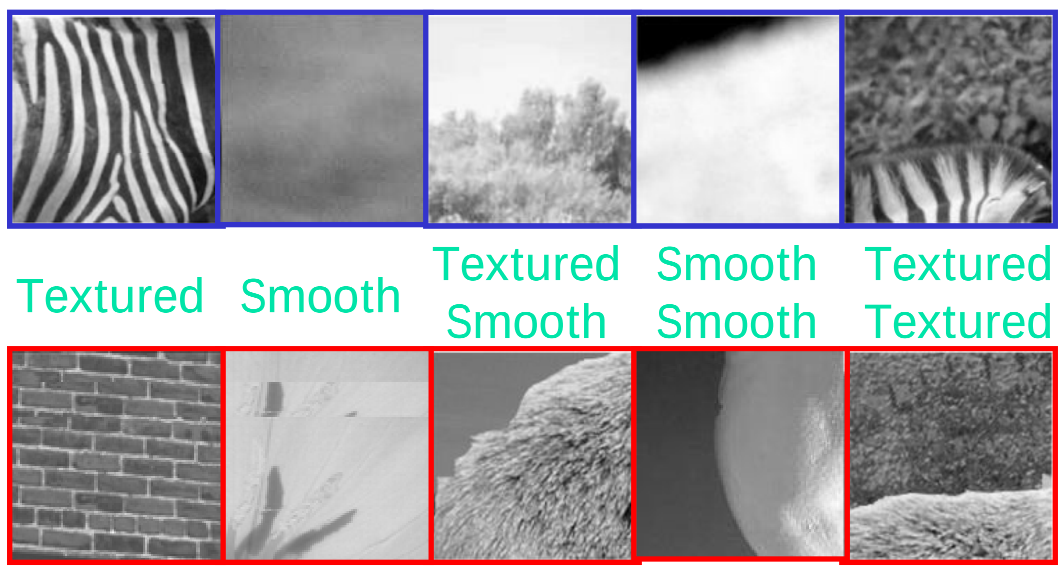
Columbia Image Splicing Detection Evaluation Dataset

- 933 authentic and 912 spliced image blocks (128x128 pixels)
- Extracted from
  - Berkeley's CalPhotos images (contributed by photographers) which we assume to be authentic
- Splicing is done by cut-and-paste of arbitrary-shaped objects and also vertical/horizontal strip.

- Authentic

Samples

- Spliced



Download URL:
http://www.ee.columbia.edu/dvmm/newDownloads.htm

Columbia University in the City of New York

dvmm DIGITAL VIDEO MULTIMEDIA LAB

Definition: Phase Histogram

- Phase histogram (normalized)

$$p(\Psi_i) = \frac{1}{M^2} \sum_{\Omega} 1\{\Phi[b(\omega_1, \omega_2)] \in \Psi_i\},\ i = -N, \ldots, N$$

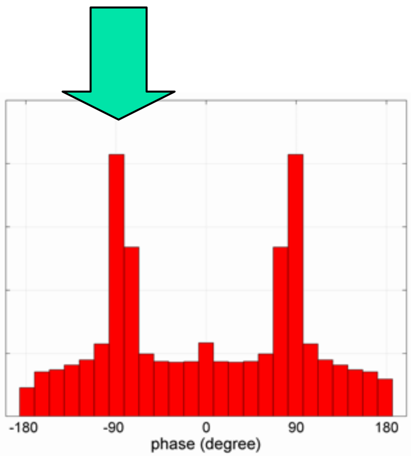
where

$$1\{true\} = 1 \text{ otherwise } 0$$

$$\Omega = \{\omega_1, \omega_2 \mid \omega_1 = \frac{2\pi m_1}{M}, \omega_2 = \frac{2\pi m_2}{M}; m_1, m_2 = 0, \ldots, M-1\}$$

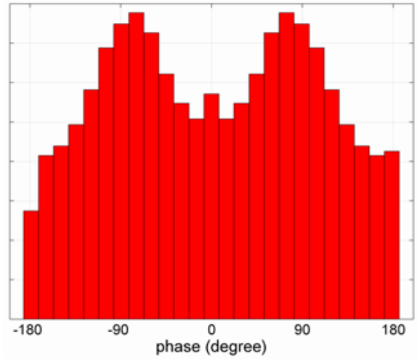
$$\Psi_i = \{\phi \mid \frac{(2i-1)\pi}{(2N+1)} \leq \phi \leq \frac{(2i+1)\pi}{(2N+1)}\}$$

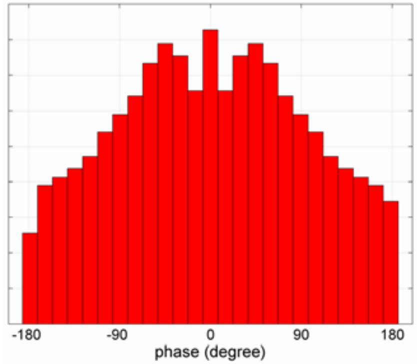
Strong phase concentration at ±90°



- Symmetry Property: For real-valued signal, bicoherence phase histogram is symmetrical, i.e.,

$$p(\Psi_i) = p(\Psi_{-i})$$





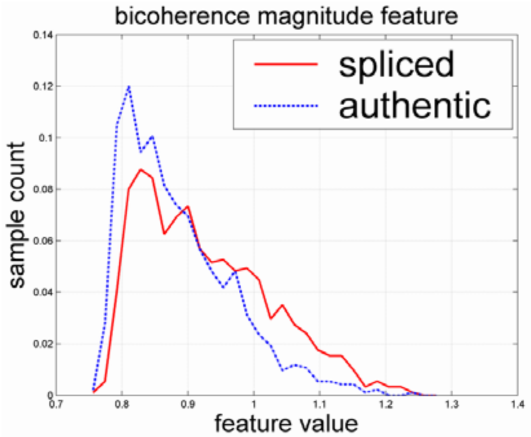
Bicoherence Features

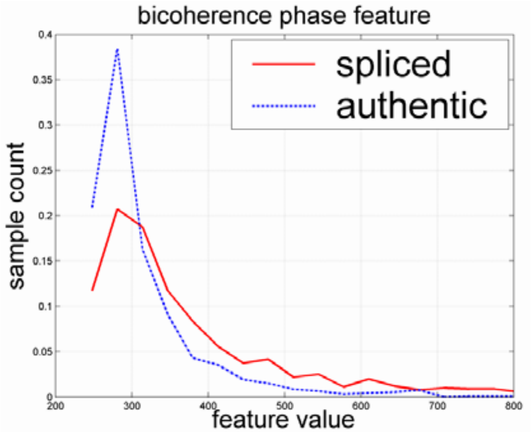
- Definition: Phase feature

$$f_P = \sum_i p(\Psi_i) \log p(\Psi_i) \quad \text{where } p(\Psi_i) \text{ is phase histogram}$$

- Definition: Magnitude feature

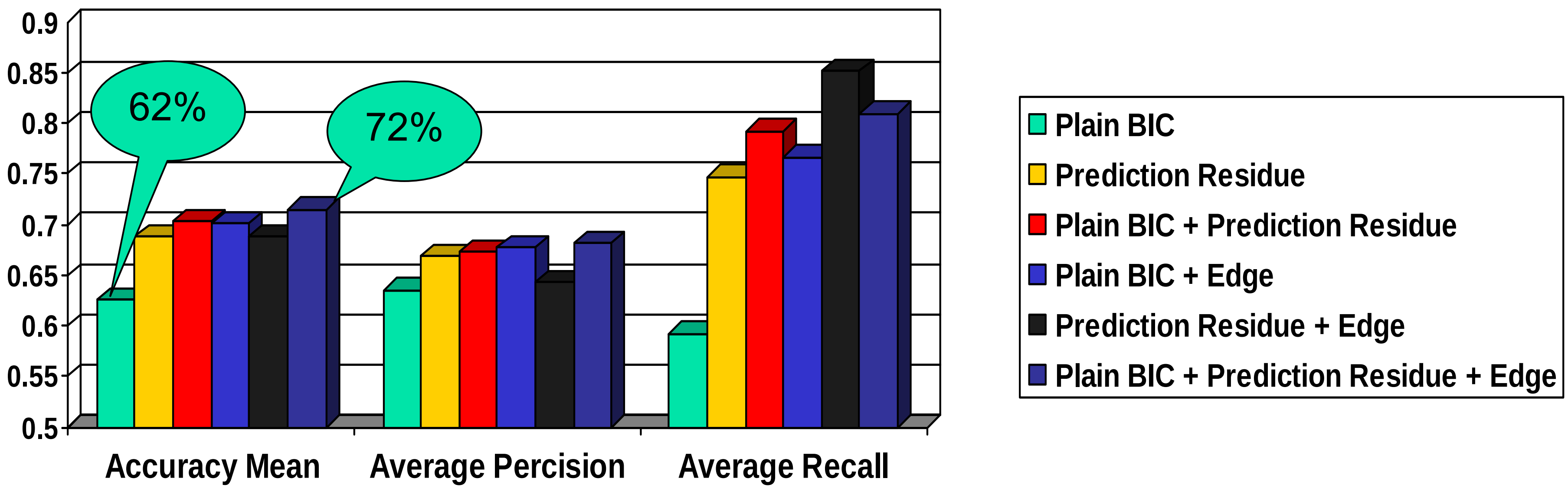
$$f_M = \frac{1}{M^2} \sum_{(\omega_1, \omega_2) \in \Omega} \left| b(\omega_1, \omega_2) \right|$$





Columbia University in the City of New York
dvmm DIGITAL VIDEO MULTIMEDIA LAB

Additional Results on Bicoherence Features [ISCAS'04]



Columbia University in the City of New York

DIGITAL VIDEO MULTIMEDIA LAB

Outline

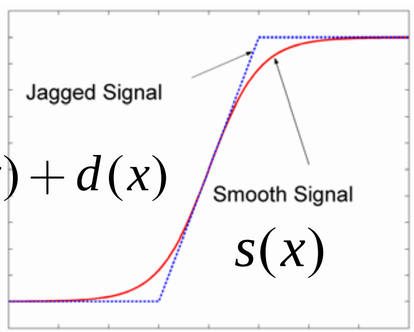
- Review
  - Problem and Motivation
  - Our Approach
  - Definition: Bicoherence
  - Why Bicoherence good for splicing? Quadratic Phase Coupling Hypothesis
- Bicoherence Features
  - Magnitude feature
  - Phase feature
- Proposed Image Splicing Model
  - Bipolar Perturbation Hypothesis
  - Bicoherence of bipolar signal
  - Bipolar perturbation effect on phase feature
  - Bipolar perturbation effect on magnitude feature

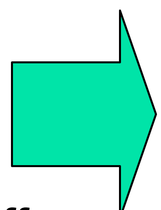
Hypothesis II: Bipolar perturbation model

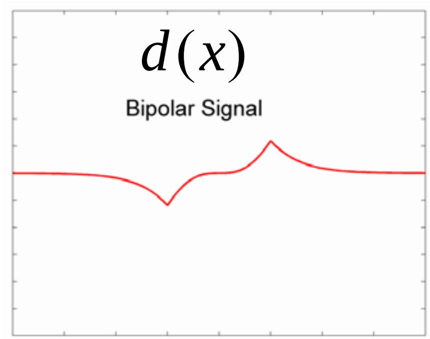
- Original image signal is relatively smooth due to the low-pass anti-aliasing operation in camera or scanner.
- Spliced image signal can have arbitrary discontinuity

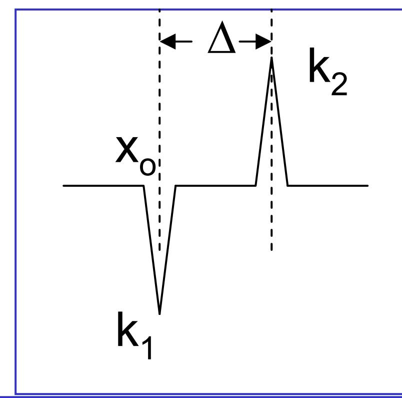
$s_p(x)$

$= s(x) + d(x)$









Definition (Bipolar signal):

$$d(x) = k_1\delta(x - x_o) + k_2\delta(x - x_o - \Delta) \underset{\substack{Fourier\\transform}}{\Leftrightarrow} D(\omega) = k_1 \exp(-jx_o\omega) + k_2 \exp(-j(x_o + \Delta)\omega)$$

where $\delta(\cdot)$ is a delta function, $k_1 k_2 < 0,\ \Delta > 0$

Columbia University in the City of New York

dvmm DIGITAL VIDEO MULTIMEDIA LAB

Bicoherence of Bipolar Signal

- Results: Bicoherence phase of bipolar signal is concentrated at ±90°:

$$D(\omega_1)D(\omega_2)D^*(\omega_1+\omega_2) = 2k^3 j\left[\sin(\Delta\omega_1)+\sin(\Delta\omega_1)-\sin(\Delta(\omega_1+\omega_2))\right]$$

Resulting in ±90° phase bias

- When there is phase coherency, bicoherence magnitude is close to unity

Columbia University in the City of New York

dvmm DIGITAL VIDEO MULTIMEDIA LAB

Bipolar Perturbation Effect on Phase Feature

- Bipolar perturbation

$$s_p(x) = s(x) + d(x) \underset{\substack{\text{Fourier} \\ \text{Transform}}}{\Leftrightarrow} S_p(\omega) = S(\omega) + D(\omega)$$

Consistently contributing to the $\pm 90°$ phase, for every (ω_1, ω_2) frequency pair.

The contribution depends on k, the magnitude of the bipolar

Numerator of the perturbed signal bicoherence:

$$S_p(\omega_1)S_p(\omega_2)S_P^*(\omega_1+\omega_2) = S(\omega_1)S(\omega_2)S^*(\omega_1+\omega_2) +$$

$$C(\omega_1,\omega_2,k,\Delta) + \boxed{2k^3 j\left[\sin(\Delta\omega_1) + \sin(\Delta\omega_1) - \sin(\Delta(\omega_1+\omega_2))\right]}$$

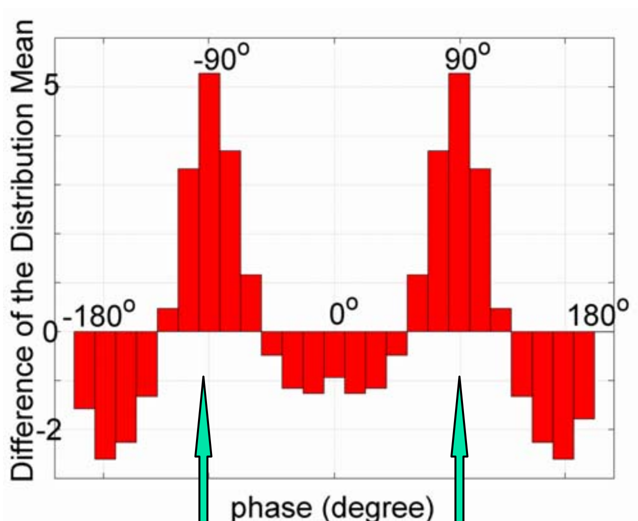
Cross term involves both S(ω) and D(ω), hence we assume that it has no consistent phase across all (ω_1, ω_2) frequency pair

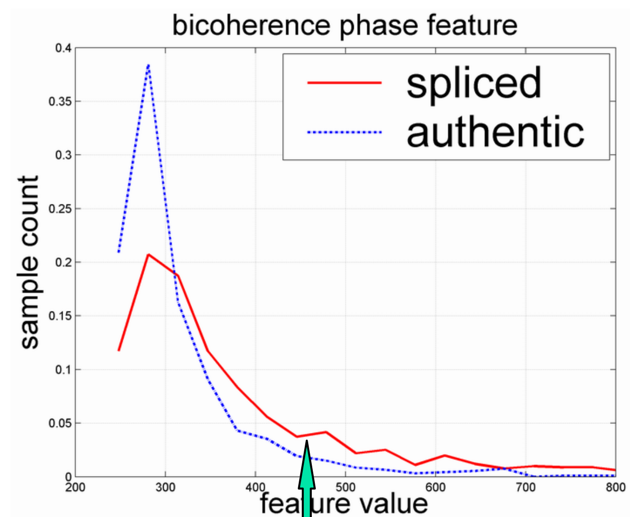
Columbia University in the City of New York

dvmm DIGITAL VIDEO MULTIMEDIA LAB

Empirical Support for Bipolar Perturbation Model

Spliced averaged phase histogram
- Authentic averaged phase histogram





Spliced average phase histogram has Significantly greater 90 deg phase bias

More Spliced image blocks have large phase feature value

Columbia University in the City of New York

dvmm DIGITAL VIDEO MULTIMEDIA LAB

Effect of Bipolar Perturbation on Magnitude Feature

$$s_p(x) = s(x) + d(x) \underset{\substack{Fourier\\ Transform}}{\Leftrightarrow} S_p(\omega) = S(\omega) + D(\omega) = \boxed{k(\frac{S(\omega)}{k} + G(\omega))}$$

$$\left|b(\omega_1,\omega_2)\right| = \frac{\left|E[k^3[\frac{S(\omega_1)}{k} + G(\omega_1)]\cdot[\frac{S(\omega_2)}{k} + G(\omega_2)]\cdot[\frac{S^*(\omega_1+\omega_2)}{k} + G^*(\omega_1+\omega_2)]]\right|}{\sqrt{E[k^4\left|[\frac{S(\omega_1)}{k} + G(\omega_1)]\cdot[\frac{S(\omega_2)}{k} + G(\omega_2)]\right|^2]E[k^2\left|\frac{S(\omega_1+\omega_2)}{k} + G^*(\omega_1+\omega_2)\right|^2]}}$$

Markov Inequality:

$$\mathrm{p}(\left|\frac{S(\omega)}{k}\right| \geq \varepsilon) \leq \frac{E[\left|S(\omega)\right|]}{k\varepsilon}$$

For energy signal (finite power)

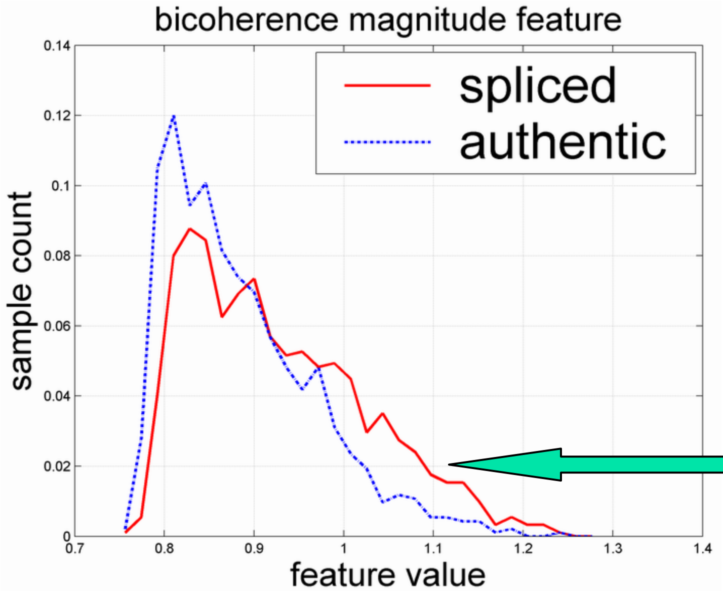
$$\sum \left|S(\omega)\right|^2 < \infty$$

$$\lim_{k\to\infty} p(\left|\frac{S(\omega)}{k}\right| \geq \varepsilon) = 0$$

Effect of Bipolar Perturbation on Magnitude Feature (cont.)

$$\lim_{k\to\infty} p\left(\left|\frac{S(\omega)}{k}\right| \geq \varepsilon\right) = 0 \quad \Rightarrow \quad \lim_{k\to\infty} P\left(\left| |b(\omega_1,\omega_2)| - \boxed{\frac{|E[D(\omega_1)D(\omega_2)D^*(\omega_1+\omega_2)]|}{\sqrt{E[|D(\omega_1)D(\omega_2)|^2]E[|D^*(\omega_1+\omega_2)|^2]}}} \right| \geq \varepsilon\right) = 0$$

Close to 1, due to phase coherency of bipolar signal



More Spliced image blocks have large magnitude feature value

Conclusions

- We propose a bipolar perturbation model for explaining the effectiveness of bicoherence in detecting image splicing
- The prediction of the model matches empirical observations (90 deg phase bias)
- **Columbia Dataset for Image Splicing Detection http://www.ee.columbia.edu/dvmm/newDownloads.htm**
- Recent related work in using image phase information for estimating perceptual image blur:
  - **Local phase coherence and the perception of blur** Z Wang and E P Simoncelli. Neural Information Processing Systems, December 2003 (NIPS 2003).

Thank You

Proof of Markov Inequality

$$p(|x| \geq \varepsilon) = \int_{|x|\geq\varepsilon} p(x)dx \leq \int_{|x|\geq\varepsilon} \frac{|x|}{\varepsilon} p(x)dx \leq \frac{1}{\varepsilon}\int_{-\infty}^{+\infty} |x|\, p(x)dx = \frac{E[|x|]}{\varepsilon}$$

Proof of Cauchy-Schwartz Inequality

$\|tf+g\|^2 = t^2\|f\|^2 + 2t\langle f,g\rangle + \|g\|^2 \geq 0$, where t is a scalar

Note, the above expression is a quadratic polynomial of t

Then:

$$4\left|\langle f,g\rangle\right|^2 - 4\|f\|^2\|g\|^2 \leq 0$$

$$\left|\langle f,g\rangle\right| \leq \|f\|\|g\| = \left|\langle f,f\rangle\right|\left|\langle g,g\rangle\right|$$

Effect of Bipolar Perturbation on Magnitude Feature

- Recall the correlation of bipolar signal:

$$D(\omega_1)D(\omega_2)D^*(\omega_1+\omega_2) = 2k^3 j\left[\sin(\Delta\omega_1)+\sin(\Delta\omega_1)-\sin(\Delta(\omega_1+\omega_2))\right]$$

$$D(\omega) = k\exp(-jx_o\omega)+k\exp(-j(x_o+\Delta)\omega) = k\exp(-jx_o)(1-\exp(-j\Delta\omega))$$

In ideal case, if bipolar signal at every segment in the averaging term is identical (having same k, x_o and Δ) …..

Then, for every (ω1, ω2) frequency pair:

$$\left|E[D(\omega_1)D(\omega_2)D^*(\omega_1+\omega_2)]\right| = \sqrt{E[\left|D(\omega_1)D(\omega_2)\right|^2]}\sqrt{E[\left|D(\omega_1+\omega_2)\right|^2]}$$

$$\Leftrightarrow\; D(\omega_1)D(\omega_2) = cD(\omega_1+\omega_2) \text{ where c=constant}$$

$$\Rightarrow \left|b(\omega_1,\omega_2)\right| = 1$$

Reach Cauchy-Schwartz Inequality Upper Bound

Bicoherence magnitude is 1!

Goal: Image Splicing Detection using Natural-imaging Quality (NIQ)

- NIQ: Authentic images comes directly from camera and have low-pass property due to camera optical anti-aliasing low-pass
- Deviations from NIQ: Image splicing introduces arbitrarily rough edges/discontinuities in image signal
- We characterize such NIQ using bicoherence

Extraction of BIC Features from image

1

128

2

Overlapping segments

64

3

128-points DFT (with zero padding and Hanning windowing)

4

$$\hat{b}(\omega_1,\omega_2)=\frac{\frac{1}{k}\sum_k X_k(\omega_1)X_k(\omega_2)X_k^*(\omega_1+\omega_2)}{\sqrt{\left(\frac{1}{k}\sum_k\left|X_k(\omega_1)X_k(\omega_2)\right|^2\right)\left(\frac{1}{k}\sum_k\left|X_k(\omega_1+\omega_2)\right|^2\right)}}$$

5

Negative Phase Entropy (P) *

$$f_P=\sum_n p(\Psi_n)\log p(\Psi_n)$$

5

Magnitude mean, $f_M=\frac{1}{|\Omega|^2}\sum_{(\omega_1,\omega_2)\in\Omega}\left|b(\omega_1,\omega_2)\right|$

6

$$P=\sqrt{\left(\tfrac{1}{N_h}\sum_i f_{Pi}^{Horizontal}\right)^2+\left(\tfrac{1}{N_v}\sum_i f_{Pi}^{Vertical}\right)^2}$$

6

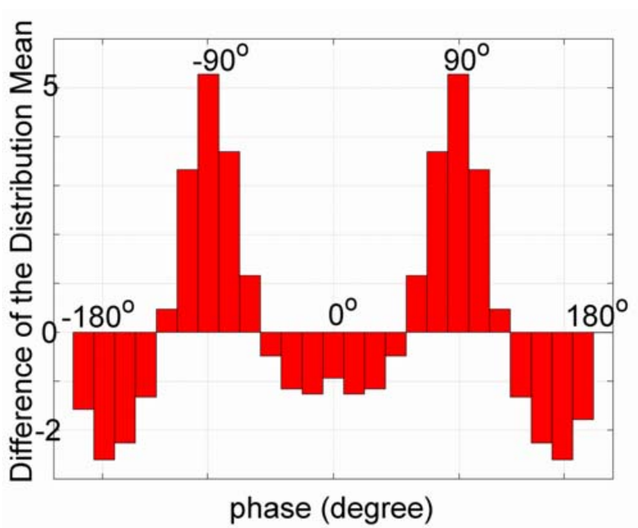
$$M=\sqrt{\left(\tfrac{1}{N_h}\sum_i f_{Mi}^{Horizontal}\right)^2+\left(\tfrac{1}{N_v}\sum_i f_{Mi}^{Vertical}\right)^2}$$

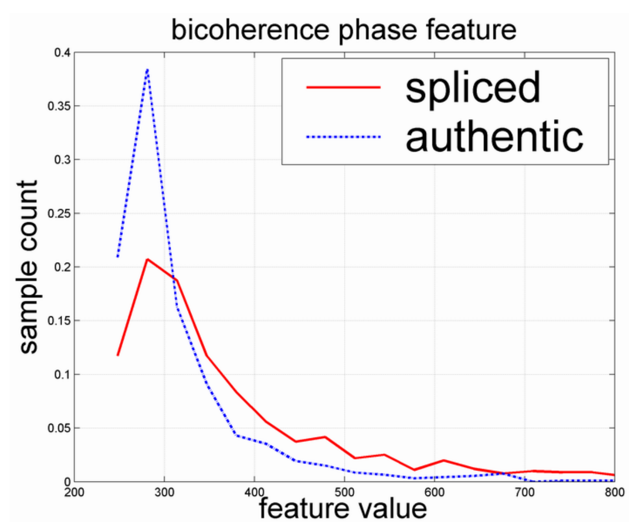
** To reduce noise effect, phase histogram is obtained from the BIC components with magnitude exceeding a threshold*

Bipolar Perturbation Effect on Phase Feature (cont.)

- Estimation: $$\hat{b}(\omega_1,\omega_2)=\frac{\frac{1}{k}\sum_k X_k(\omega_1)X_k(\omega_2)X_k^*(\omega_1+\omega_2)}{\sqrt{\left(\frac{1}{k}\sum_k\left|X_k(\omega_1)X_k(\omega_2)\right|^2\right)\left(\frac{1}{k}\sum_k\left|X_k(\omega_1+\omega_2)\right|^2\right)}}$$

- The strength of the final ±90° degree phase bias also depends on
  - % segments in the averaging term having bipolar





Columbia University in the City of New York

dvmm DIGITAL VIDEO MULTIMEDIA LAB