



Blind Detection of Photomontages Using Higher Order Statistics

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Motivation: How much can we trust digital images?

- **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



Activists And Anti-War Activists Jane Fonda speaks to a crowd of Vietnam Veterans as Activist and former Vietnam vet John Kerry (LEFT) listens and prepares to speak next concerning the war in Vietnam. (AP Photo)

Passive and Blind Approach for Image Authentication

■ Active and blind 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.
- **Disadvantages:**
 - Need a fully-secure trustworthy camera
 - Need a common algorithm for the source and the detection side.
 - Watermark degrades image quality

■ 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

Definitions: Photomontage and Spliced Image

- **Photomontage:** [Mitchell 94]
 - A paste-up produced by sticking together photographic images
- **Spliced Image (see figure):**
 - A simplest form of photomontage
 - Splicing of image fragments without post-processing, e.g. edge softening, etc.
- **Why interested in detecting image splicing?**
 - Image splicing is a **basic and essential** operation for all photomontages and photomontaging is one of the main techniques for creating fake images with new semantics.
 - A comprehensive solution for photomontage detection would include detection of post-processing operations and computer graphics techniques for detecting scene internal inconsistencies



spliced



spliced

Definition: What is the quality of authentic images?

■ Natural-imaging Quality

- Entailed by natural imaging process with real imaging devices, e.g. camera
- Effects from optical low-pass, sensor noise, lens distortion, etc.

■ Natural-scene Quality

- Entailed by physical light transport in 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

Approach: Passive Authentication by Natural-imaging Quality (NIQ)

- **NIQ:** Authentic images comes directly from camera and have low-pass property due to camera optical low-pass
- Image splicing introduces rough edges → deviate from NIQ
- We characterize such NIQ using bicoherence
- **Bicoherence (BIC):**

Numerator:
Bispectrum

- A normalized bispectrum, a 3rd order moment spectra

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

↑ Phase

Normalization according to
Cauchy-Schwartz Inequality

Magnitude

Phase



Properties of BIC

- For signals of low-order moments like Gaussian, BIC magnitude = 0
- [Fackrell95b] Quadratic Phase Coupling (QPC) vs. BIC
 - A simultaneous occurrence of frequency harmonics at ω_1 , ω_2 and $\omega_1 + \omega_2$ (**Quadratic Frequency Coupling - QFC**), with respective phase being ϕ_1 , ϕ_2 and $\phi_1 + \phi_2$
 - At (ω_1, ω_2) with QPC, BIC phase = 0 & BIC magnitude = ratio of QPC energy

Linear quadratic operation induces QPC

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

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

$$X_{uc}(t) = C_{uc} \cos((\omega_1 + \omega_2)t + \phi_3)$$

where ϕ_3 is uncoupled with ϕ_1 and ϕ_2



$$\text{If } Y(t) = X_o(t) + X_o^2(t)$$

$$\Rightarrow Y(t) = \frac{1}{2} \cos(2\omega_1 t + 2\phi_1) + \frac{1}{2} \cos(2\omega_2 t + 2\phi_2) + \cos((\omega_1 + \omega_2)t + (\phi_1 + \phi_2))$$

$$+ \cos((\omega_1 - \omega_2)t + (\phi_1 - \phi_2)) + \cos(\omega_1 t + \phi_1) + \cos(\omega_2 t + \phi_2) + 1$$



$$\text{If } X(t) = X_o(t) + X_c(t) + X_{uc}(t) \Rightarrow |BIC_X(\omega_1, \omega_2)|^2 = \frac{C_c^2}{C_c^2 + C_{uc}^2}$$



$$\text{If } X(t) = X_o(t) + X_c(t) \Rightarrow \angle BIC_X(\omega_1, \omega_2) = 0$$

Prior work using BIC to detect speech splicing

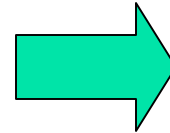
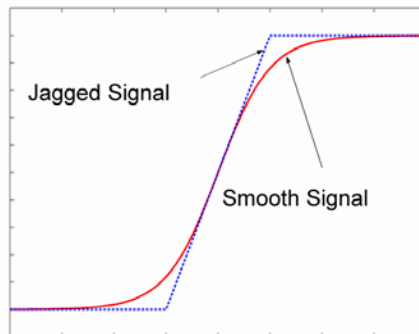
- [Farid99]
 - Assuming that speech signal is originally low in QPC
 - Nonlinearity associated with splicing causes increase of BIC magnitude
 - BIC features used for detecting the increase of QPC in spliced human speech signal are:
 - average BIC magnitude
 - Variance of the BIC phase histogram

Applications of Bicoherence (BIC) and Bispectrum (BIS)

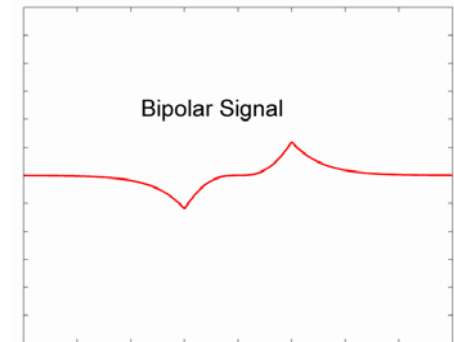
- BIC/BIS detects QPC/QFC as one form of non-linearity:
 - [Bullock97] Studying non-linearity in intracranial EEG signal
 - [KimPowers79] Application in plasma physics
 - [SatoSasaki77] Application in manufacturing
 - [Hasselmann63] Application in oceanography
 - [Fackrell95a] Detecting fatigue crack in structure through vibration
- BIC/BIS detect signal non-gaussianity
 - [Santos02] Detecting non-gaussianity in the cosmic microwave background data

Theoretical Basis for Bicoherence for Image Splicing Detection

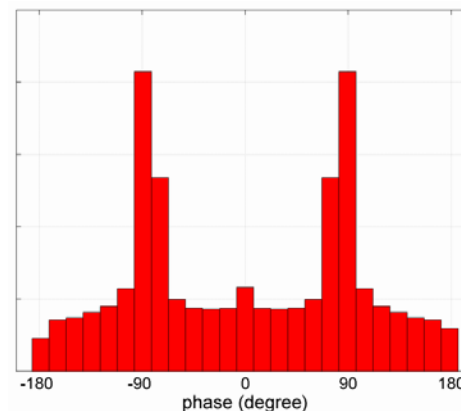
- **[NgChang ICIP04]** *bipolar* = $k_1\delta(x - x_o) + k_2\delta(x - x_o - \Delta)$ with $k_1 \cdot k_2 < 0$
 - Image splicing introduces rough edges at splicing interface
 - Image splicing can be considered as a bipolar perturbation on an authentic signal.



Difference between the jagged and the smooth signal



- **Theoretical analysis** shows that bipolar perturbation of a signal results in an increase in BIC magnitude and phase concentration at $\pm 90^\circ$



An example of BIC phase histogram

Extract Plain BIC Features



128



Overlapping segments 64



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



Negative Phase Entropy (P)

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



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



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



$$fP = \sqrt{\left(\frac{1}{N_h} \sum_i P_i^{Horizontal}\right)^2 + \left(\frac{1}{N_v} \sum_i P_i^{Vertical}\right)^2}$$

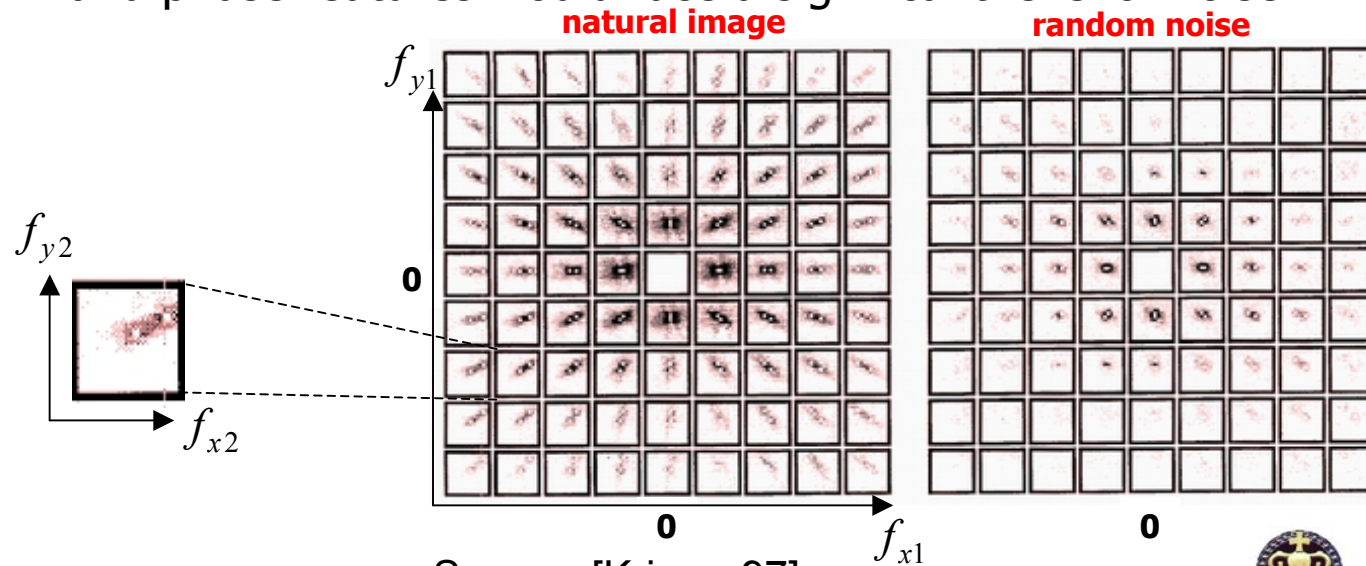
$$fM = \sqrt{\left(\frac{1}{N_h} \sum_i M_i^{Horizontal}\right)^2 + \left(\frac{1}{N_v} \sum_i M_i^{Vertical}\right)^2}$$

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

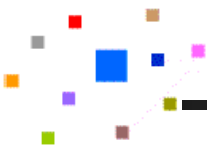
Challenges of Applying BIC to 2D images

[Krieger97]

- Due to the predominant image edge features, natural images exhibit concentration of energy in 2-D BIS at regions with frequencies corresponding to $f_{x1} / f_{y1} = f_{x2} / f_{y2}$
- With phase randomization assumption [Fackrell95b, Zhou96], BIS energy implies QPC. Hence, Krieger97's empirical observation predicts that image splicing detection using bicoherence magnitude and phase features would face a significant level of noise.

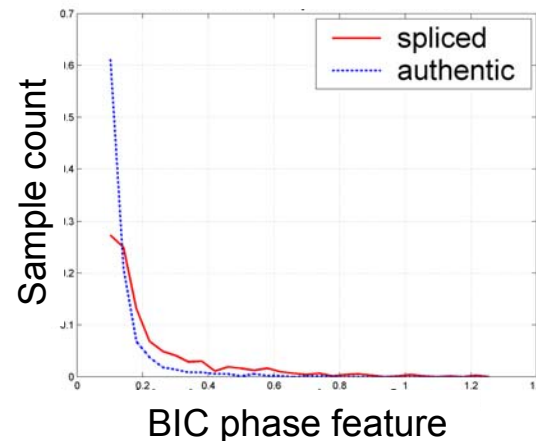
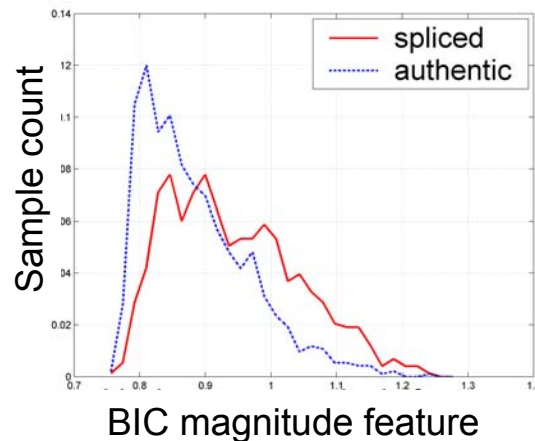


Source: [Krieger97]



Experiment with Plain BIC features

- We compute the plain BIC features and look at the feature distribution for our data set (described later)
- We find that the distribution for magnitude and phase are greatly overlapped

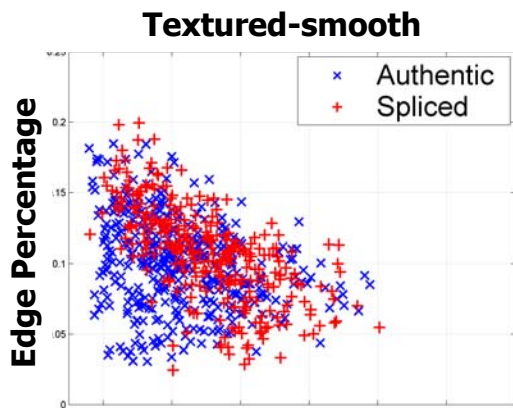


- Proposed Solutions
 - To model the image-edge effect on BIC
 - To capture splicing-invariant features

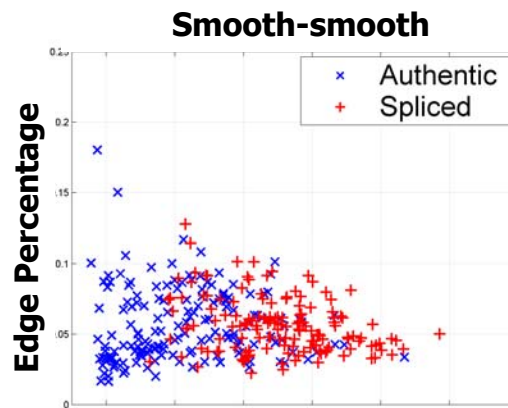
Modeling Image-edge Effect on BIC

BIC depends on the image characteristics

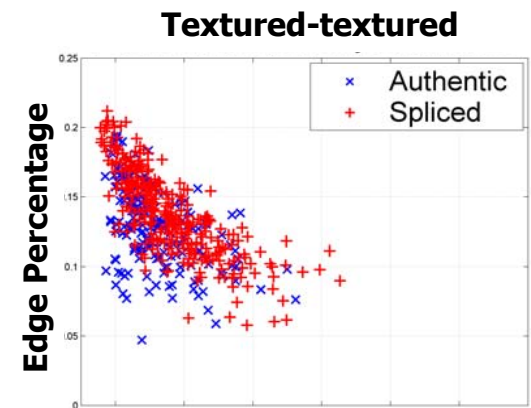
- [Krieger97] shows image edges result in high BIC energy.
- Classifier needs to consider image types
- We categorize images according to region interface types – textured-textured, textured-smooth and smooth-smooth
- Experiment shows that BIC features have different separability for different interface types
- We use canny edge pixel percentage (one of many ways) for determining interface types



Bicoherence Magnitude Features



Bicoherence Magnitude Features

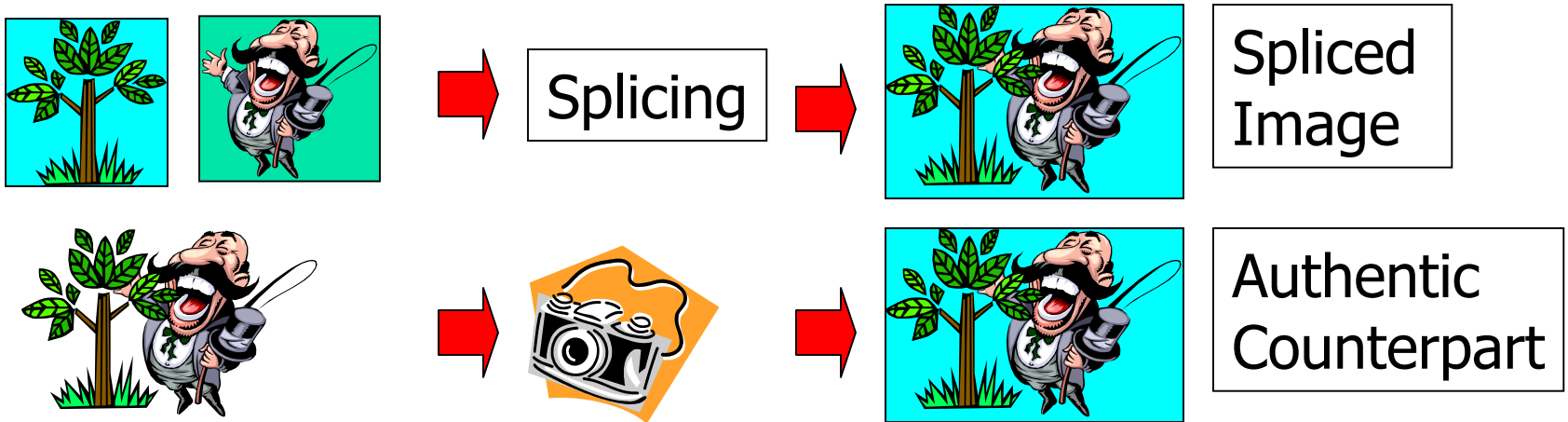


Bicoherence Magnitude Features

The scatter plot for BIC phase feature is similar!

Splicing-invariant Features – Authentic Counterpart (AC)

- **AC** is similar to the spliced image except that it is authentic



Texture Decomposition with Total Variation Minimization Framework

■ [VeseOsher02]

- An image f is decomposed as $u+v$:
 - u = structure component (a edge-preserving function of bounded variation) $u \in BV(\mathbb{R}^2)$
 - v = fine-texture component (a oscillating function) $v \in G(\mathbb{R}^2)$
- Decomposition is by a total variation minimization framework formulated as:

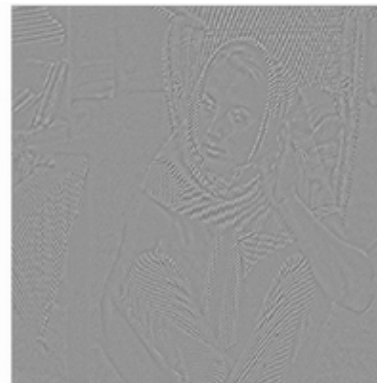
$$\inf_u \left\{ E(u) = \|u\|_{BV} + \lambda \|f - u\|_G ; f = u + v, f \in L_2(\mathbb{R}^2), u \in BV(\mathbb{R}^2), v \in G(\mathbb{R}^2), \|u\|_{BV} = \int_{\mathbb{R}^2} |\nabla u| \right\}$$



original



Structure

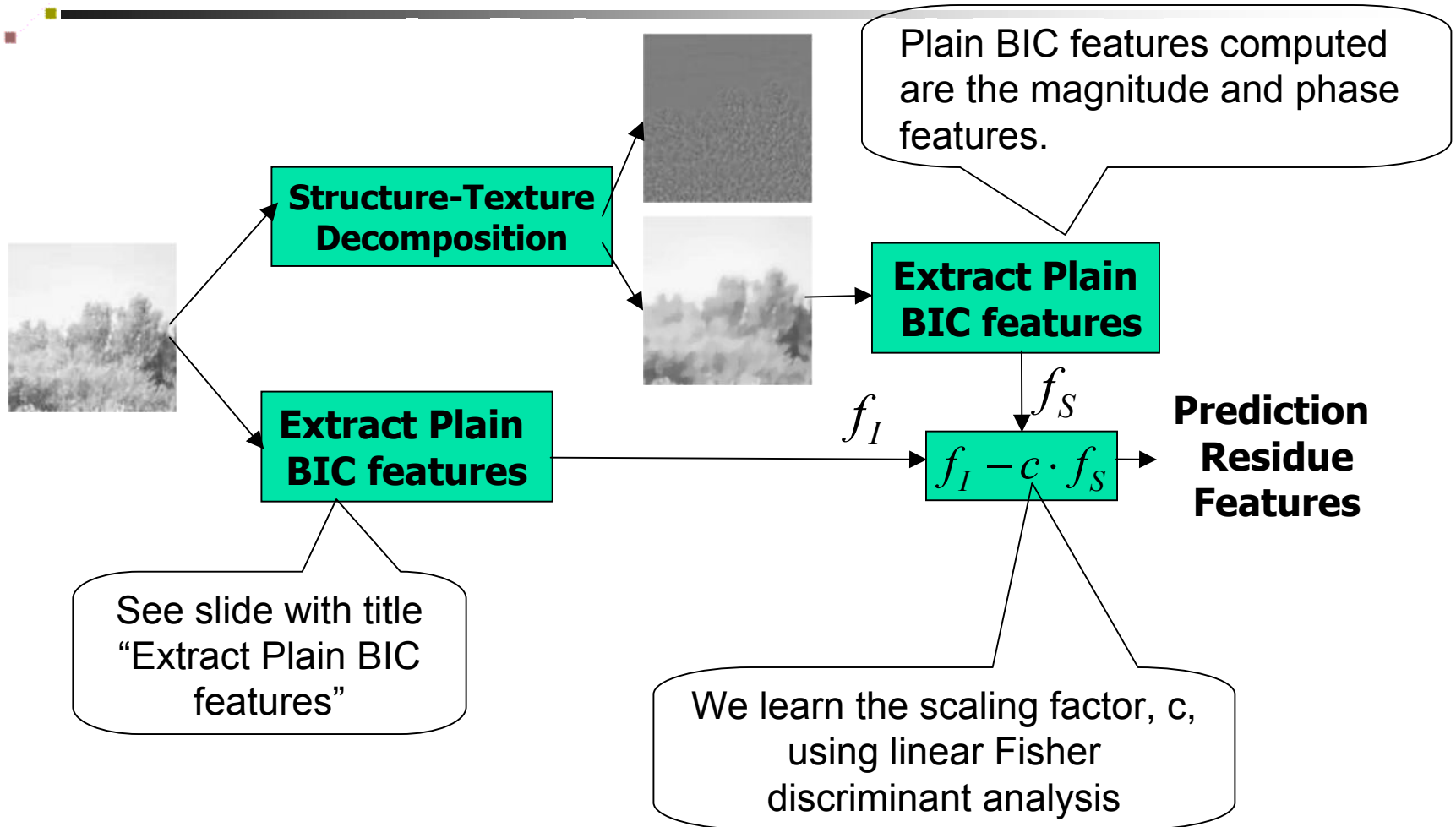


Fine-texture

Splicing Detection using Texture Decomposition

- We approximate the authentic counterpart (AC) using the structure component
 - We assume that the structure component captures the splicing invariant features, i.e., less contaminated by splicing
 - We assume that splicing artifacts (bipolar perturbation) are captured by the fine-texture component
- 2 approaches for detecting image splicing
 - Detect the presence of splicing artifacts in the fine-texture component (Does not work well because the value of BIC features of the fine-texture component vary in a very narrow range, hence not discriminative)
 - Detect the absence of splicing artifacts in the structure component. (We adopt this technique)

Computing Prediction Residue Features



Experiment Data Set:

Authentic and Spliced Image Blocks

- 933 authentic and 912 spliced image blocks (128x128 pixels)
- Extracted from
 - Berkeley's CalPhotos images (contributed by photographers) which we assume to be authentic
 - A small set (10) of smooth-smooth images captured by camera
- Splicing is done by cut-and-paste of arbitrary-shaped objects and also vertical/horizontal strip.

- Authentic

Samples



Textured

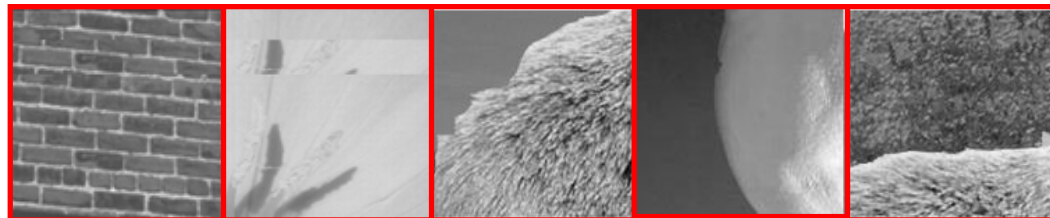
Smooth

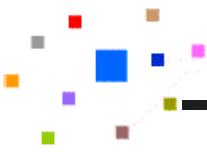
Textured
Smooth

Smooth
Smooth

Textured
Textured

- Spliced





Performance Metrics

- RBF kernel Support Vector Machine (SVM) on 933 Authentic and 912 Spliced images, 10-fold cross-validation to ensure no overfitting.
- 3 evaluation metrics over 100 runs of classification:

- Accuracy mean:
$$M_{accuracy} = \frac{1}{100} \sum_i (N_{S|S}^i + N_{A|A}^i) / (N_{\bullet|S}^i + N_{\bullet|A}^i)$$

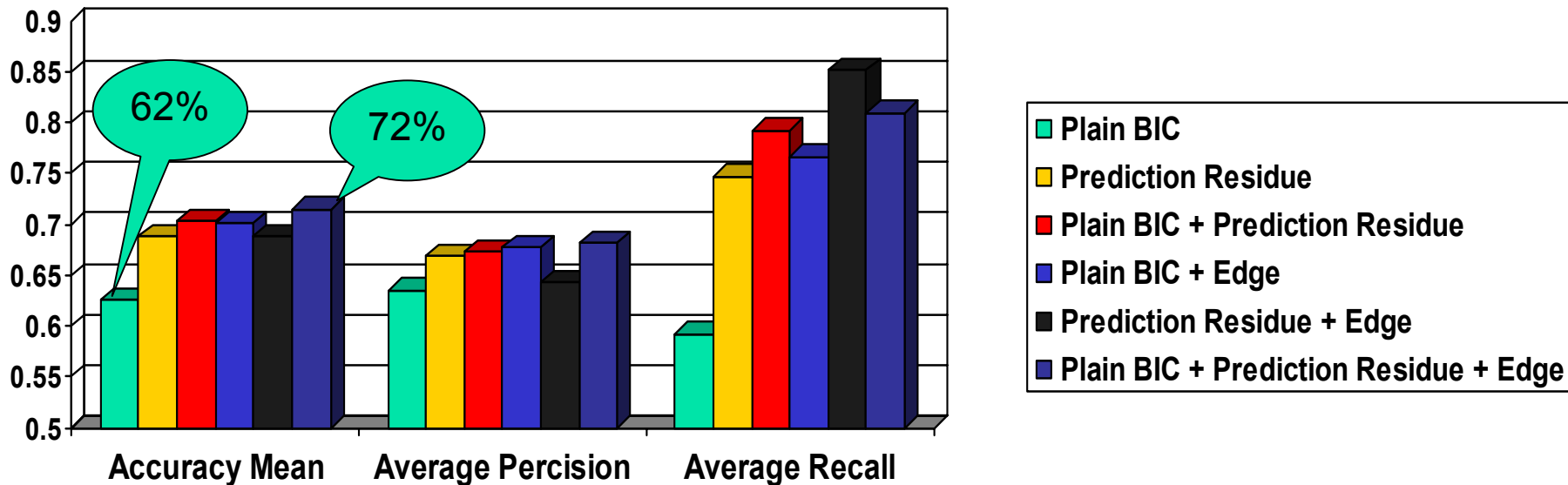
- Average precision:
$$M_{precision} = \frac{1}{100} \sum_i N_{S|S}^i / N_{S|\bullet}^i$$

- Average recall
$$M_{recall} = \frac{1}{100} \sum_i N_{S|S}^i / N_{\bullet|S}^i$$

Classification Results

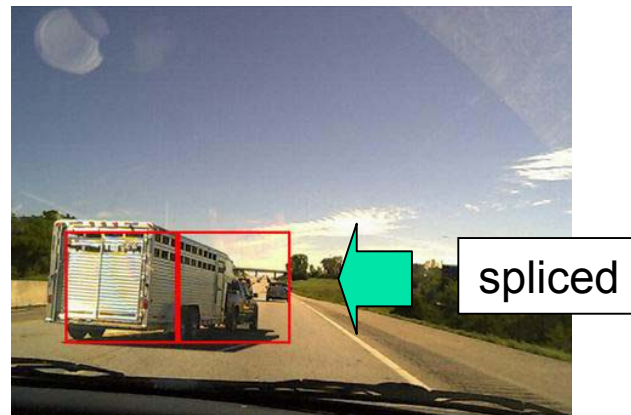
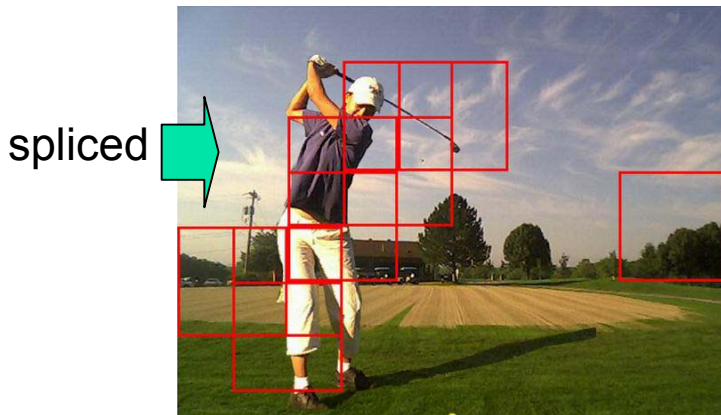
Features evaluated (*all features below are 1-D*)

- BIC magnitude feature $M = \frac{1}{|\Omega|^2} \sum_{(\omega_1, \omega_2) \in \Omega} |b(\omega_1, \omega_2)|$
 - BIC phase feature $P = \sum_n p(\Psi_n) \log p(\Psi_n)$
 - BIC magnitude predication residue
 - BIC phase prediction residue
 - Edge pixel percentage
- } Plain BIC features
 } Prediction residue features
 } Edge feature



Conclusions and Future work

- Plain BIC features do not perform well
- Need to incorporate image characteristics and the splicing invariant component with respect to BIC
 - Improve the classification accuracy from 62% to 72%
- Still a large margin for innovation and improvement
 - Possible directions:
 - Explore cross-block fusion and incorporate image structure in fusion
 - Combine with computer-vision analysis (dealing with scene and illumination consistency)
 - Other issues: explore discriminative features other than BIC.



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