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

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

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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

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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):
  - A normalized bispectrum, a 3rd order moment spectra

Numerator: Bispectrum

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

Magnitude

Phase

Normalization according to Cauchy-Schwartz Inequality

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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 $\omega_1,\ \omega_2$ and $\omega_1+\omega_2$ (**Quadratic Frequency Coupling - QFC**), with respective phase being $\phi_1,\ \phi_2$ and $\phi_1+\phi_2$
  - At $(\omega_1,\ \omega_2)$ 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

$$\text{If } Y(t)=X_O(t)+X_O{}^2(t)$$
$$\Rightarrow Y(t)=\tfrac{1}{2}\cos(2\omega_1 t+2\phi_1)+\tfrac{1}{2}\cos(2\omega_2 t+2\phi_2)+\cos((\omega_1+\omega_2)t+(\phi_1+\phi_2))$$
$$+\cos((\omega_1-\omega_2)t+(\phi_1-\phi_2))+\cos(\omega_1 t+\phi_1)+\cos(\omega_2 t+\phi_2)+1$$

$$\text{If } X(t)=X_O(t)+X_C(t)+X_{UC}(t)\Rightarrow\left|BIC_X(\omega_1,\omega_2)\right|^2=\frac{C_C{}^2}{C_C{}^2+C_{UC}{}^2}$$

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

Prior work using BIC to detect speech splicing

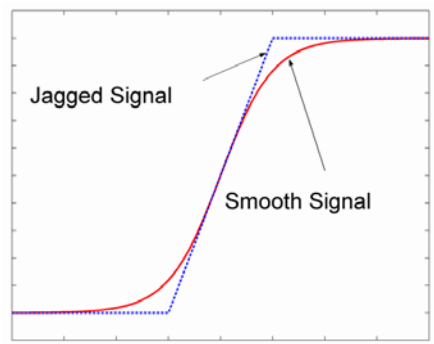
- [Farid99]
  - Assuming that speech signal is originally low in QPC
  - Nonlinearity associated with splicing causes increase of BIC magnitude
  - BIC features used for detecting the increase of QPC in spliced human speech signal are:
    - average BIC magnitude
    - Variance of the BIC phase histogram

Applications of Bicoherence (BIC) and Bispectrum (BIS)

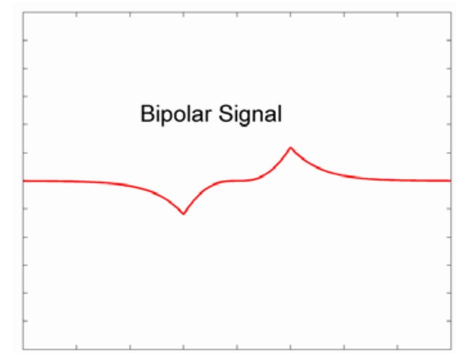
- BIC/BIS detects QPC/QFC as one form of non-linearity:
  - [Bullock97] Studying non-linearity in intracranial EEG signal
  - [KimPowers79] Application in plasma physics
  - [SatoSasaki77] Application in manufacturing
  - [Hasselman63] Application in oceanography
  - [Fackrell95a] Detecting fatigue crack 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

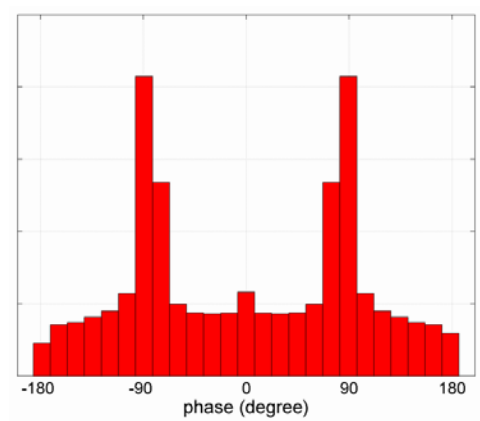
- **[NgChang ICIP04]** $bipolar = k_1\delta(x-x_o)+k_2\delta(x-x_o-\Delta)$ with $k_1 \cdot k_2 < 0$
  - Image splicing introduces rough edges at splicing interface
  - Image splicing can be considered as a bipolar perturbation on an authentic signal.



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 ±90°



An example of BIC phase histogram

Extract Plain BIC Features

1

128

2

Overlapping segments

64

3

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

4

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

5

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

6

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

5

Negative Phase Entropy (P)*

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

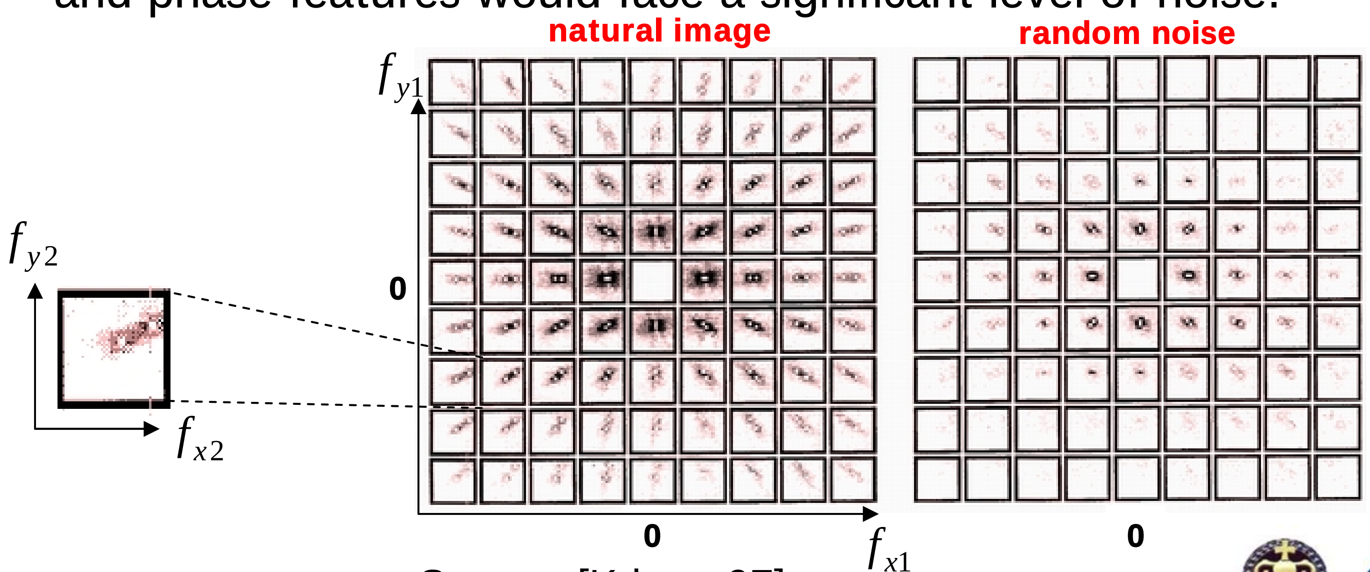
6

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

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

Challenges of Applying BIC to 2D images

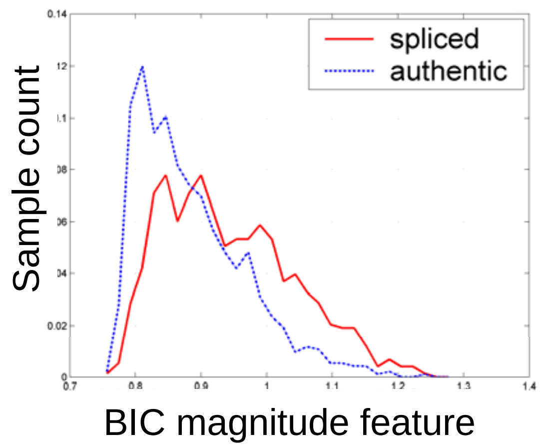
- [Krieger97]
  - Due to the predominant image edge features, natural images exhibit concentration of energy in 2-D BIS at regions with frequencies corresponding to $f_{x1} / f_{y1} = f_{x2} / f_{y2}$
  - With phase randomization assumption [Fackrell95b, Zhou96] , BIS energy implies QPC. Hence, Krieger97's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

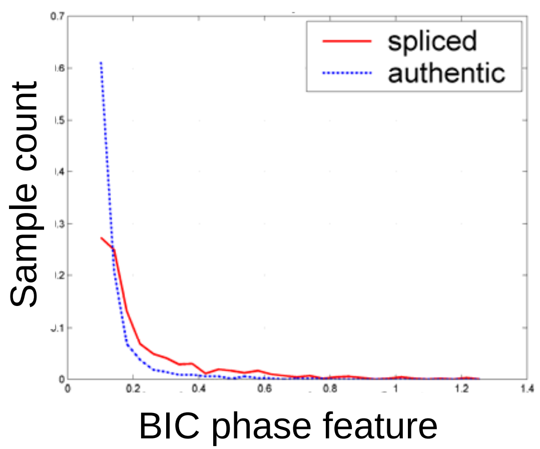


Source: [Krieger97]

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



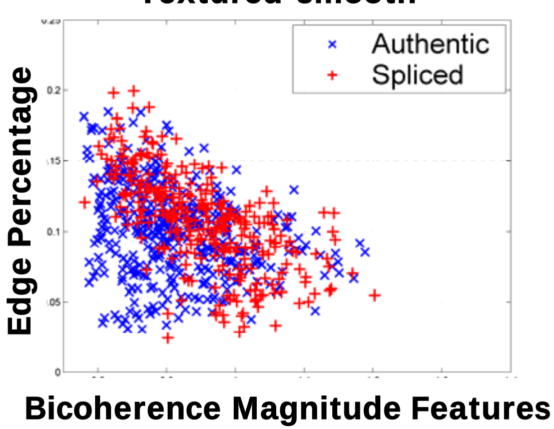


- Proposed Solutions
  - To model the image-edge effect on BIC
  - To capture splicing-invariant features

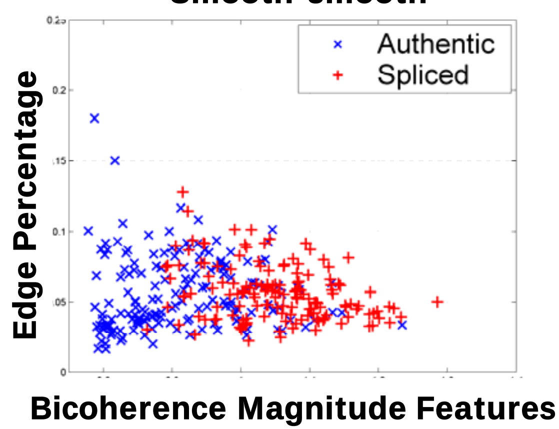
Modeling Image-edge Effect on BIC

- 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

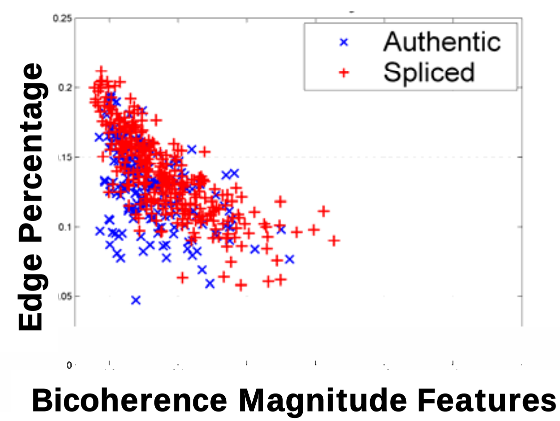
Textured-smooth



Smooth-smooth



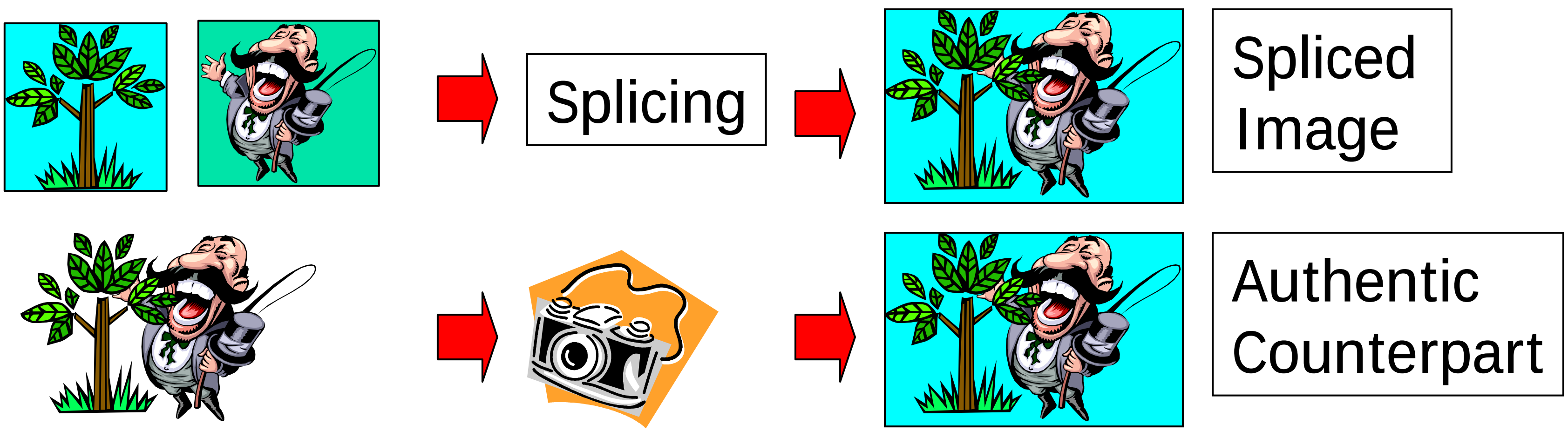
Textured-textured



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



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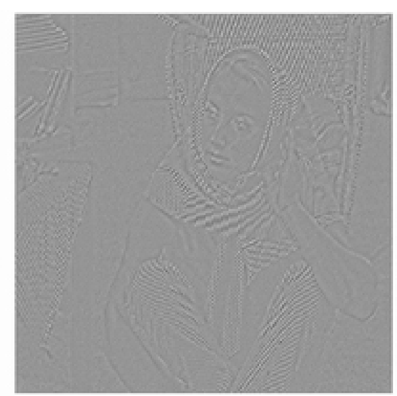
Texture Decomposition with Total Variation Minimization Framework

- [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

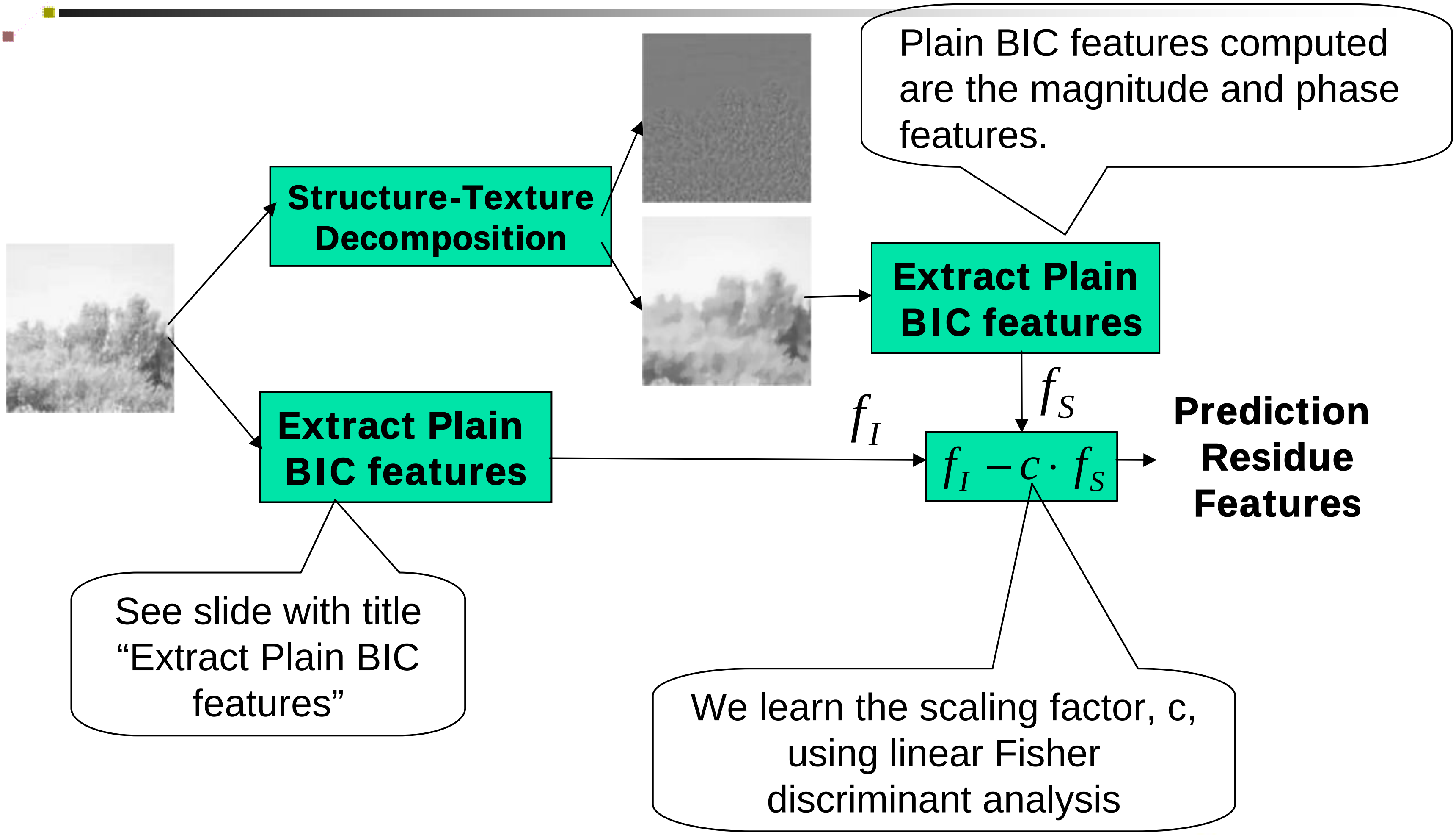

Structure


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: $M_{accuracy} = \frac{1}{100}\sum_i (N^i_{S|S} + N^i_{A|A}) \big/ (N^i_{\bullet|S} + N^i_{\bullet|A})$
  - Average precision: $M_{precision} = \frac{1}{100}\sum_i N^i_{S|S} / N^i_{S|\bullet}$
  - Average recall $M_{recall} = \frac{1}{100}\sum_i N^i_{S|S} / N^i_{\bullet|S}$

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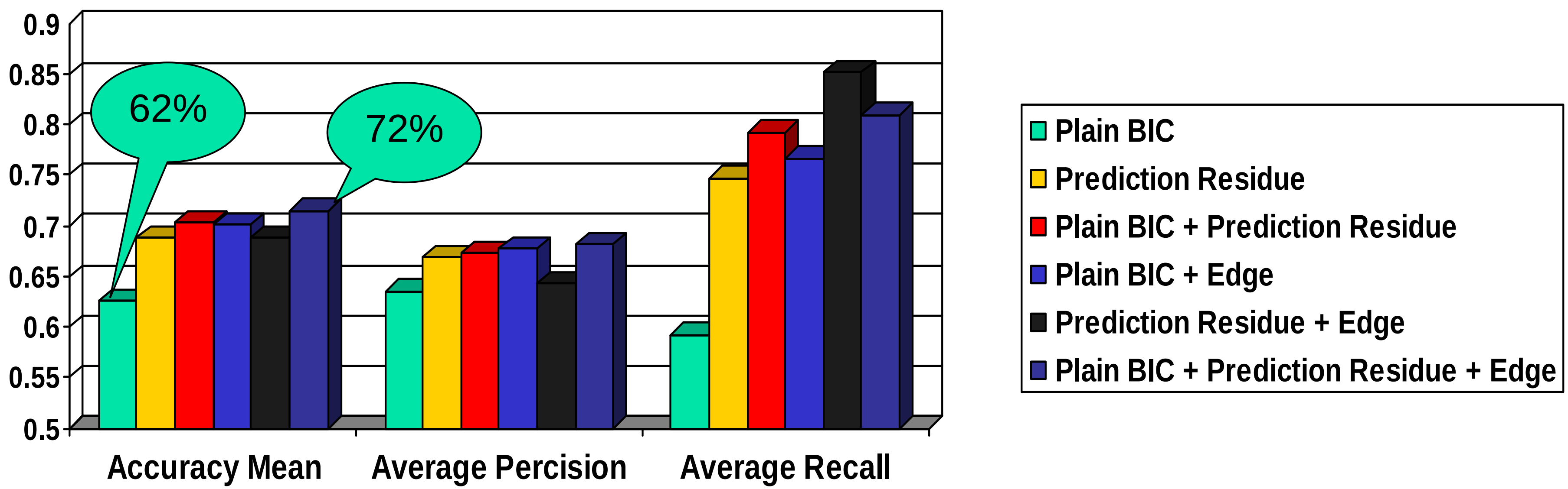
Classification Results

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

  } Plain BIC features
  - BIC magnitude predication residue
  - BIC phase prediction residue

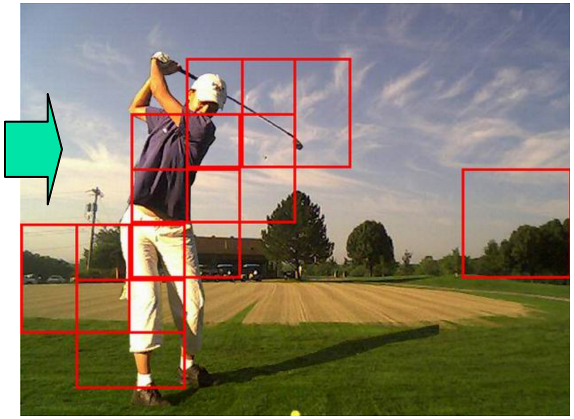
  } Prediction residue features
  - Edge pixel percentage } Edge feature

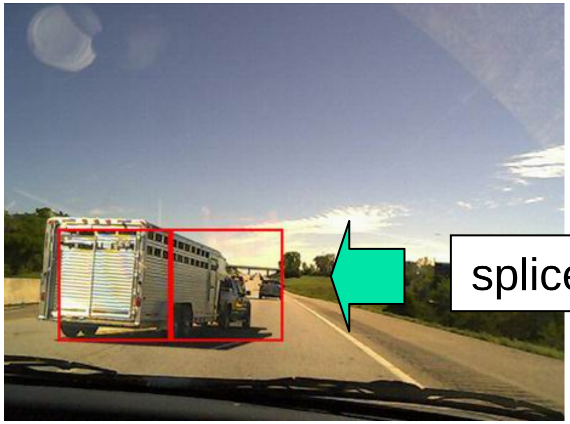


Conclusions and Future work

- 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.

spliced





spliced

References

- [Bullock97] T. H. Bullock, J. Z. Achimowicz, R. B. Duckrow, S. S. Spencer, and V. J. Iragui-Madoz, "Bicoherence of intracranial EEG in sleep, wakefulness and seizures," *EEG Clin Neurophysiol*, vol. 103, pp. 661-678, 1997.
- [Fackrell95a] J. W. A. Fackrell, P. R. White, J. K. Hammond, R. J. Pinnington, and A. T. Parsons, "The interpretation of the bispectra of vibration signals-I. Theory," *Mechanical Systems and Signal Processing*, vol. 9, pp. 257-266, 1995.
- [Fackrell95b] J. W. A. Fackrell, S. McLaughlin, and P. R. White, "Practical Issues Concerning the Use of the Bicoherence for the Detection of Quadratic Phase Coupling," IEEE-SP ATHOS Workshop on Higher-Order Statistics, Girona, Spain, Jnne 1995.
- [Farid99] H. Farid, "Detecting Digital Forgeries Using Bispectral Analysis," *MIT AI Memo* AIM-1657, MIT, 1999.
- [Hasselman63] K. Hasselman, W. Munk, and G. MacDonald, "Bispectrum of Ocean Waves," in *Time Series Analysis*, M. Rosenblatt, Ed. New York: Wiley, 1963, pp. 125-139.
- [KimPowers79] Y. C. Kim and E. J. Powers, "Digital Bispectral Analysis and its Applications to Nonlinear Wave Interactions," *IEEE Transactions on Plasma Science*, vol. PS-7, pp. 120-131, June 1997.
- [Krieger97] G. Krieger, C. Zetzsche, and E. Barth, "Higher-order statistics of natural images and their exploitation by operators selective to intrinsic dimensionality," *IEEE Signal Processing Workshop on Higher-Order Statistics*, Banff, Canada, July 21-23, 1997.
- [Mitchell94] W. J. Mitchell, "When Is Seeing Believing?," *Scientific American*, pp. 44-49, 1994.
- [NgChang04] T.-T. Ng and S.-F. Chang, "A Model for Image Splicing," *IEEE International Conference on Image Processing*, Singapore, Oct 24-27, 2004.
- [Santos02] M. e. a. Santos, "An estimate of the cosmological bispectrum from the MAXIMA-1 CMB map," *Physical Review Letters*, vol. 88, 2002.
- [SatoSasaki77] T. Sato, K. Sasaki, and Y. Nakamura, "Real-time Bispectral Analysis of Gear Noise and its Applications to Contactless Diagnosis," *Journal of the Acoustic Society America*, vol. 62, pp. 382-387, 1977.
- [VeseOsher02] L. A. Vese and S. J. Osher, "Modeling Textures with Total Variation Minimization and Oscillating Patterns in Image Processing," *UCLA C.A.M. Report* 02-19, May 2002.
- [Zhou96] G. T. Zhou and G. B. Giannakis, "Polyspectral Analysis of Mixed Processes and Coupled Harmonics," *IEEE Transactions on Information Theory*, vol. 42, pp. 943-958, May 1996.