WIFS'13

The Watchful Forensic Analyst: Multi-Clue Information Fusion with Background Knowledge

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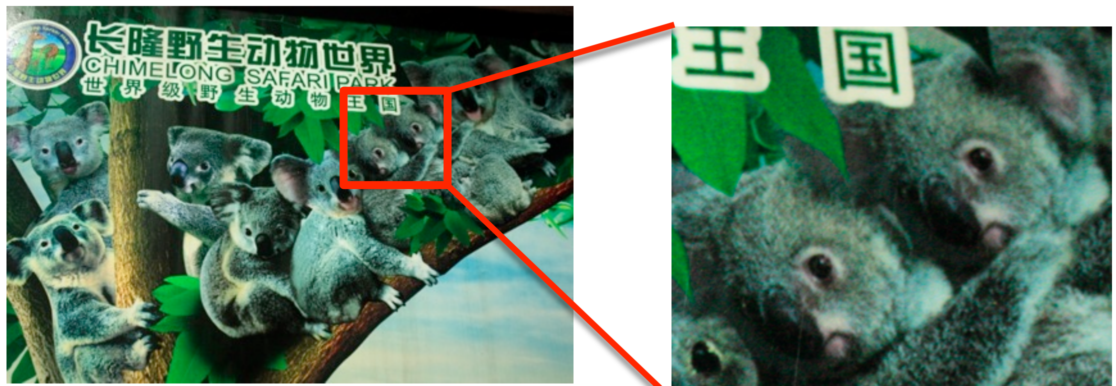
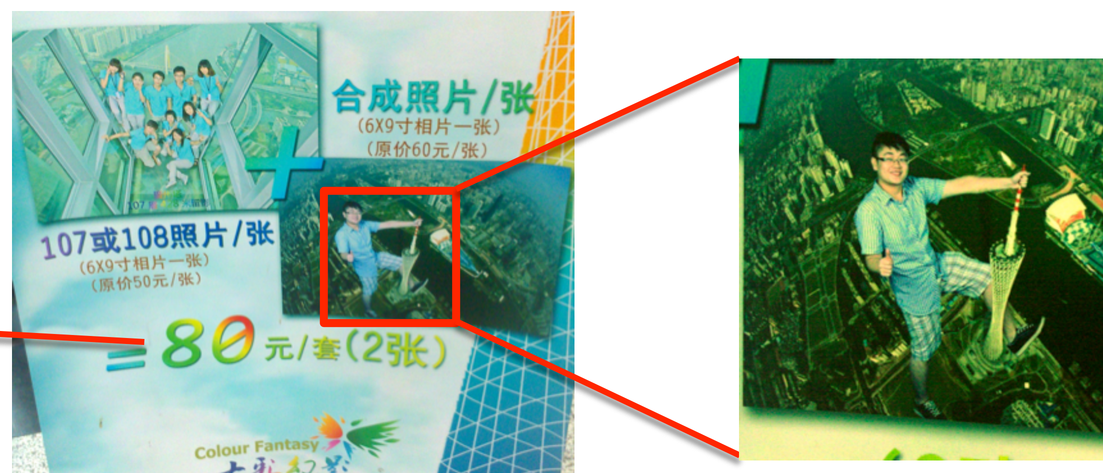
Multimedia Forensics

- Creating forged contents is nowaday easy…



- And also cheap!

~13$



Addressed Problem

- More and more multimedia forensics algorithms
- Based on on different footprints:
  - Different detection capabilities
  - Sensitive to different characteristics of analyzed content

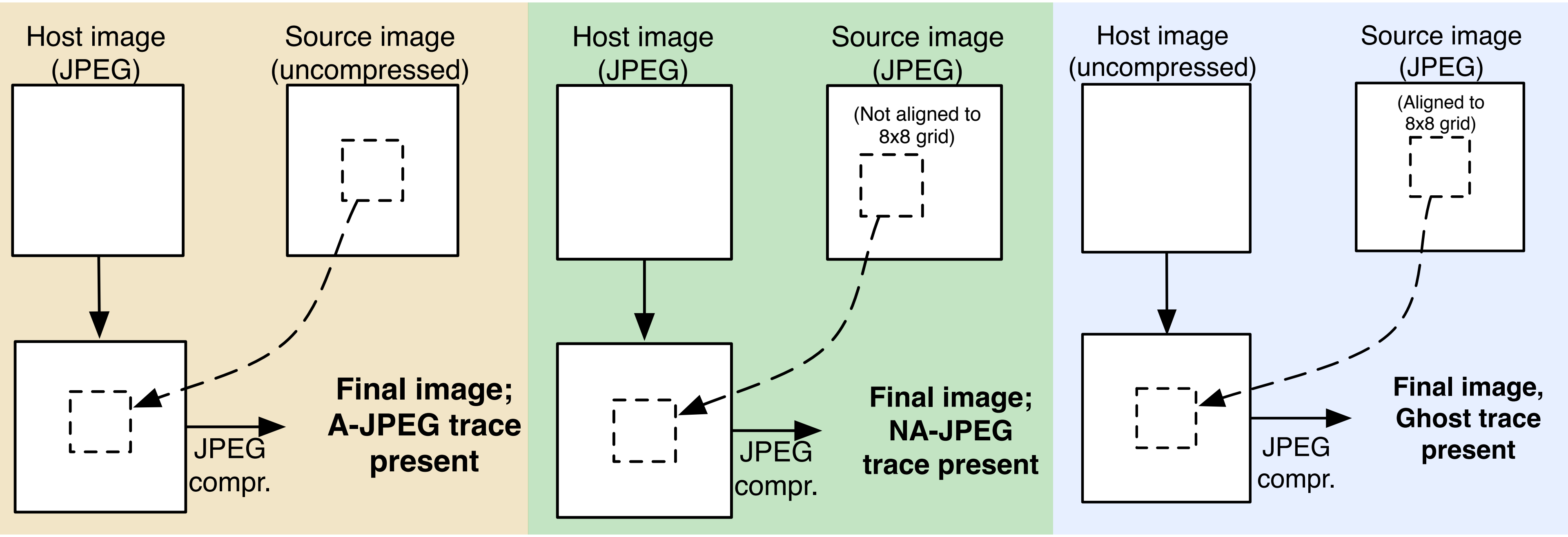
Goal:
to fuse all the available information

Contribution

- We focus on image forensics, and investigate:
  - **What** background information can serve
  - **How** to fruitfully exploit it to improve overall performance of decision fusion systems
- We provide:
  1. An evidence-based approach to quantify the influence of a given characteristic
  2. A way to include such information in
     - A Dempster-Shafer based decision fusion system
     - A SVM based decision fusion system

Case Study 1/2

- JPEG Image Forgery Detection:
  - Many possible kinds of splicing



Case Study 1/2

- JPEG Image Forgery Detection:
  - Many possible kinds of splicing
  - Plenty of tools, based on complementary footprints

Aligned Double JPEG compr.

- Z. Lin, J. He, X. Tang, and C. Tang. *Fast, automatic and fine-grained tampered JPEG image detection via DCT coefficient analysis*. Pattern Recognition, 42(11):2492–2501, 2009.
- T. Bianchi, A. De Rosa, and A. Piva. *Improved DCT coefficient analysis for forgery localization in jpeg images*. In ICASSP, pp 2444–2447. IEEE, 2011.

Non – Aligned Double JPEG compr.

- W. Luo, Z. Qu, J. Huang, and G. Qiu. *A novel method for detecting cropped and recompressed image blocks*. In IEEE Conference on Acoustics, Speech, and Signal Processing (ICASSP), 2007.
- T. Bianchi and A. Piva. *Detection of non-aligned double jpeg compression with estimation of primary compression parameters*. In ICIP, 2011.

JPEG Ghost Effect

- H. Farid. *Exposing digital forgeries from JPEG ghosts*. IEEE Transaction on Information Forensics and Security, 4:154–160, 2009.

Case Study 2/2

- We generated a dataset of 50600 spliced images
  - Four different cut-&-paste procedures
  - Various size for the spliced region (64x64, 128x128, … 1024x1024)
  - Various combinations of compression quality
  - Heterogeneous contents

Background Information

- Tools search for footprints left by processing
- Footprint less detectable ➔ tool less reliable
- Defining the "detectability" of a footprint in general is hard to do
- We propose an evidence-based approach:

$$\mathcal{P} = \mathcal{P}_1 \times \mathcal{P}_2 \times \cdots \times \mathcal{P}_P$$ Set of analyzed properties

$$\mathcal{R}_j = \mathcal{P}_1 \times \ldots \mathcal{P}_{j-1} \times \{\mathcal{P}_j \cap \mathcal{R}\} \times \ldots \mathcal{P}_P$$

Restricted set for the j-th property

Background Information

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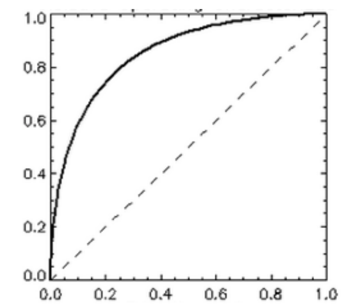
$$P_D^f(\mathcal{R}_j) = \int_{\Lambda_1(\tau)\cap\mathcal{R}_j} p(x|\mathcal{H}_1)\ \mathrm{d}x$$

$$P_{FA}^f(\mathcal{R}_j) = \int_{\Lambda_1(\tau)\cap\mathcal{R}_j} p(x|\mathcal{H}_0)\ \mathrm{d}x$$

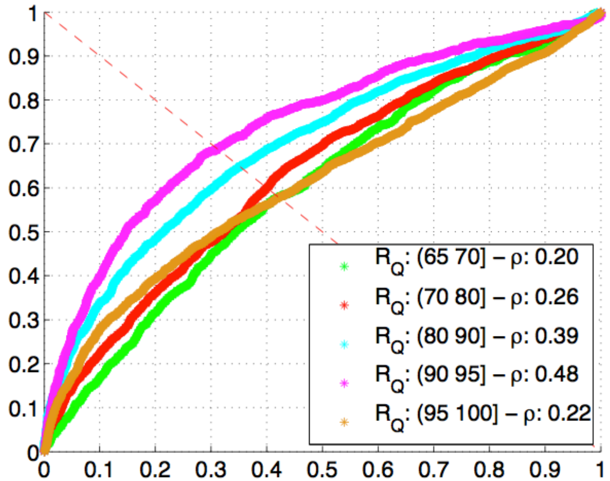
(Restricted) Acceptance Region of the Tool



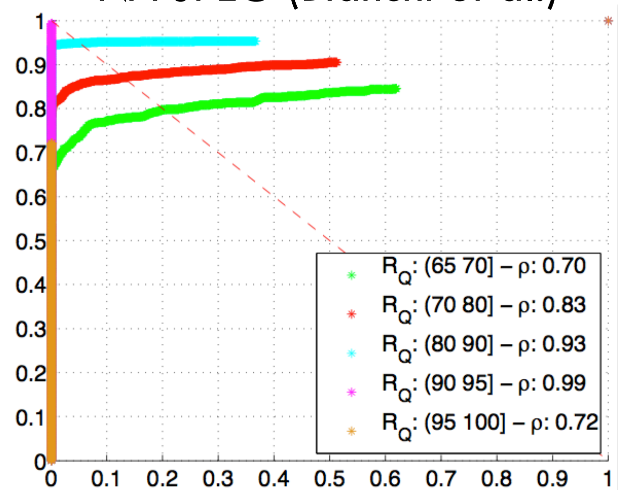
Gini coefficient:
$\rho = 2 \times \mathrm{AUC} - 1$

Influence of Image Properties

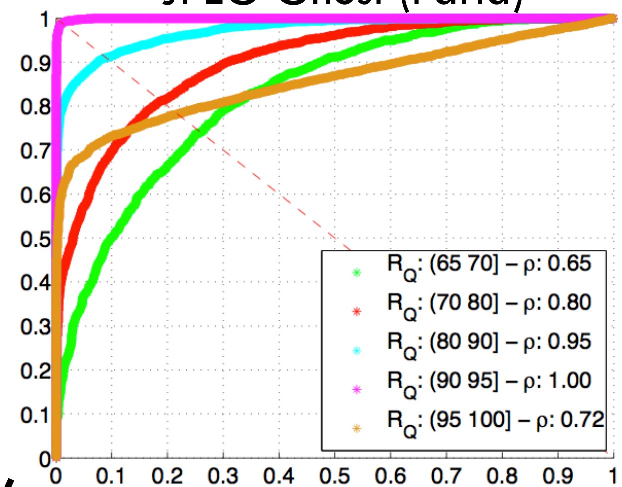
NA-JPEG (Luo et al.)



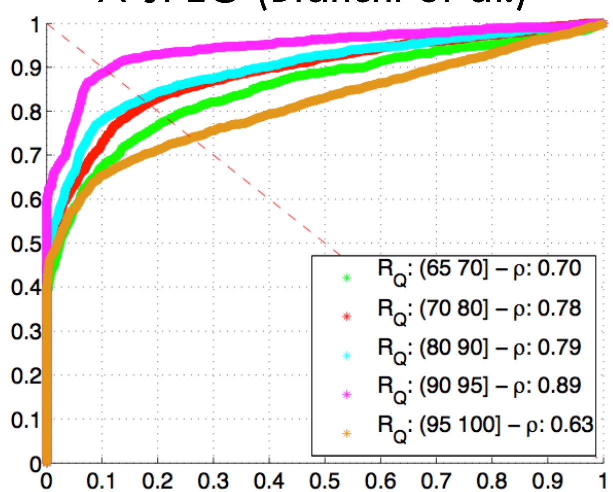
NA-JPEG (Bianchi et al.)



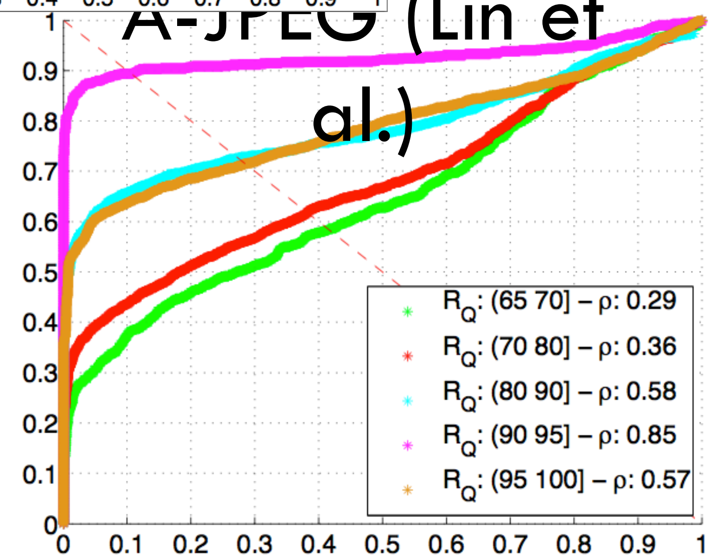
JPEG Ghost (Farid)



A-JPEG (Bianchi et al.)



A-JPEG (Lin et al.)



Application to our Case Study

Size

Tool	$\mathbf{R}_Z^1$: (0,64]	$\mathbf{R}_Z^2$: (64,128]	$\mathbf{R}_Z^3$: (128,256]	$\mathbf{R}_Z^4$: (256,512]	$\mathbf{R}_Z^5$: (512,1024]
JPGH	0.63	0.67	0.71	0.75	0.80
JPDQ	0.37	0.62	0.72	0.75	0.78
JPLC	040	0.39	0.36	0.31	0.21
JPNA	0.74	0.75	0.74	0.73	0.72
JPBM	0	0.08	0.21	0.31	0.40

Average

	$\mathbf{R}_A^1$: (0,30]	$\mathbf{R}_A^2$: (30,60]	$\mathbf{R}_A^3$: (60,150]	$\mathbf{R}_A^4$: (150,230]	$\mathbf{R}_A^5$: (230,255]
JPGH	0.49	0.68	0.73	0.62	0.20
JPDQ	0.50	0.63	0.70	0.54	0.04
JPLC	0.09	0.35	0.38	0.25	0.19
JPNA	0.58	0.78	0.80	0.60	0.36
JPBM	0.15	0.19	0.23	0.14	-0.23

Std. Dev.

	$\mathbf{R}_S^1$: (0,5]	$\mathbf{R}_S^2$: (5,10]	$\mathbf{R}_S^3$: (10,15]	$\mathbf{R}_S^4$: (20,40]	$\mathbf{R}_S^5$: (40,60]
JPGH	0.51	0.69	0.70	0.73	0.74
JPDQ	0.31	0.60	0.65	0.71	0.73
JPLC	0.28	0.28	0.34	0.38	0.33
JPNA	0.46	0.65	0.76	0.79	0.80
JPBM	0.07	0.13	0.18	0.21	0.30

Dempster-Shafer Theory

- Alternative to classical Bayesian theory
  - Good for modeling missing information
  - No need for prior probabilities
- Information is represented through *belief assignments*
- **Dempster's Combination Rule**: fuse information from multiple sources
- See the paper for more details and references

Dempster's Combination Rule

- A rule to combine two BBAs coming from independent sources into a single one.
- Given m_1 and m_2 two BBAs defined over the same frame, their orthogonal sum m_{12} is defined as:

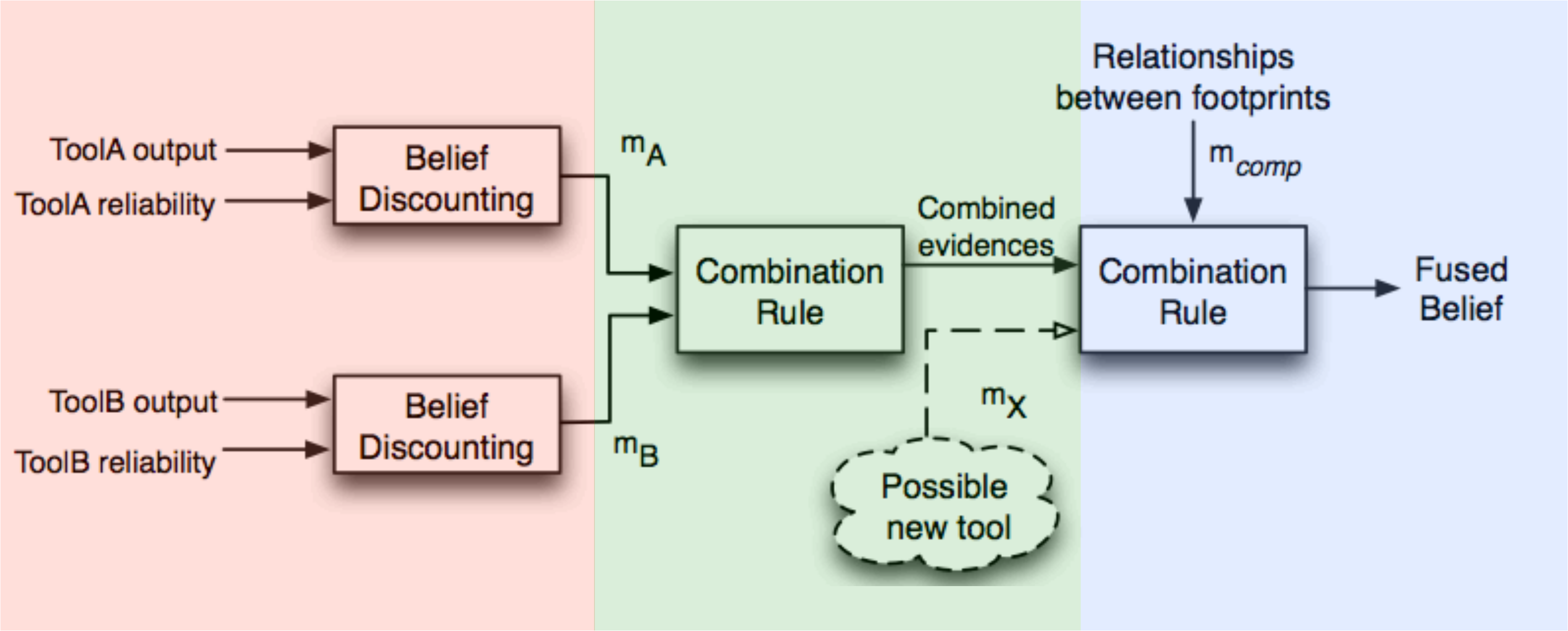
$$m_{12}(X) = m_1(X) \oplus m_2(X) = \frac{1}{1-K} \cdot \sum_{\substack{A,B \subseteq \Theta: \\ A \cap B = X}} m_1(A) m_2(B)$$

Notice

- Can be used directly only for tool looking for the same trace
- Merging heterogeneous tools requires more theoretical steps…

Embedding Background Information: DST fusion framework

- Starting point: DST fusion framework for image forensic:



Interpretation of Tools Output (mapping to BBA)

Combine BBAs from different tools

Account for traces compatibility

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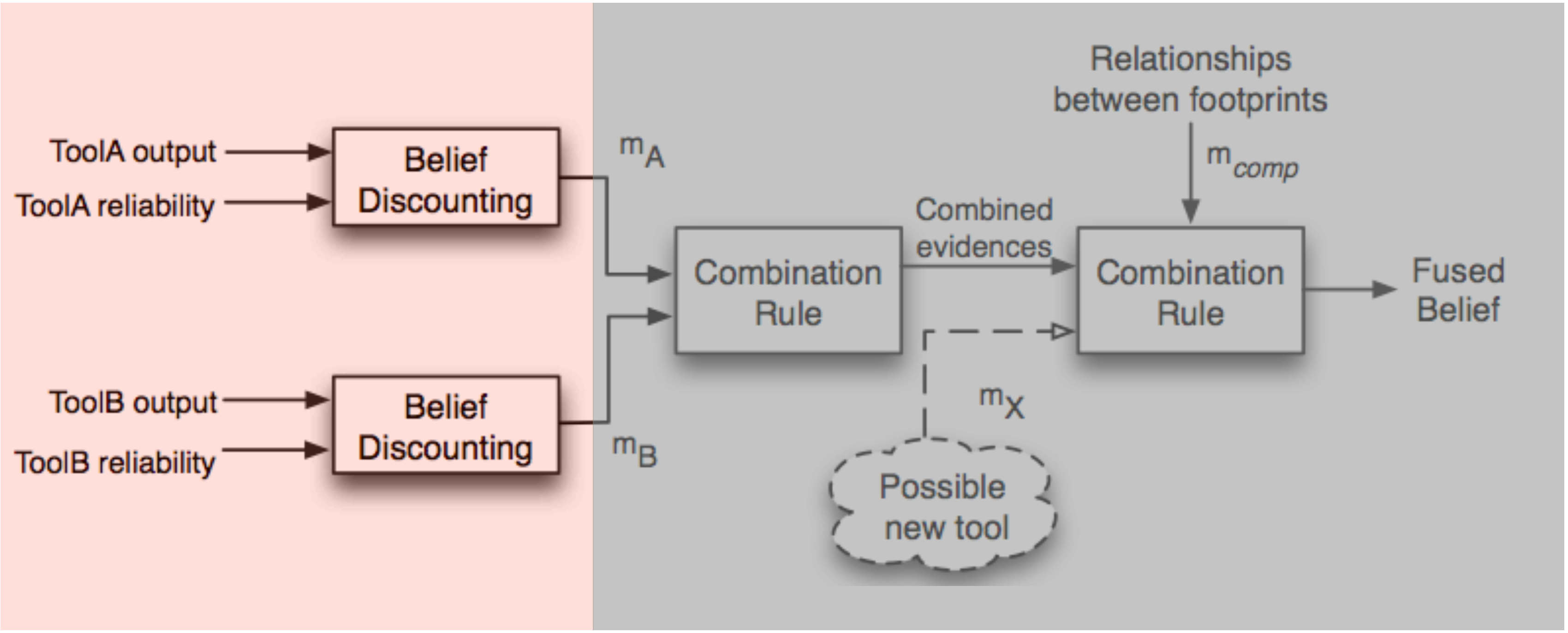

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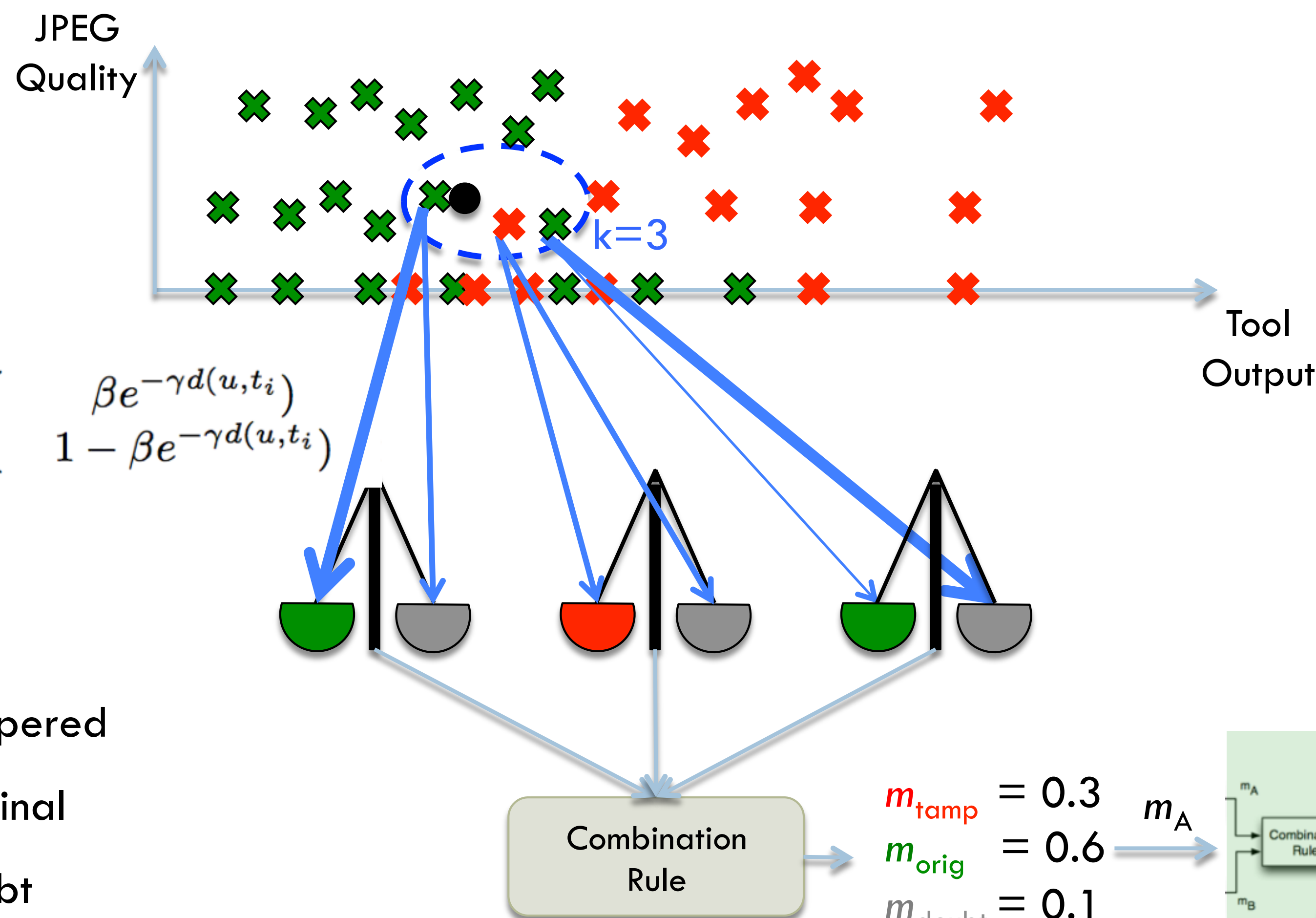
Multi-Clue Belief Assignment

TRAINING DATASET



$$m_i^u(X) = \begin{cases} \beta e^{-\gamma d(u,t_i)} \\ 1 - \beta e^{-\gamma d(u,t_i)} \end{cases}$$

tampered

original

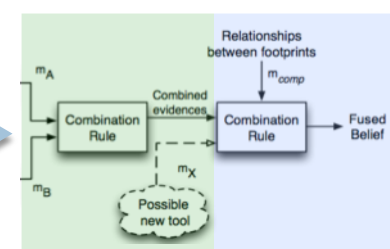
doubt

$m_{tamp} = 0.3$

$m_{orig} = 0.6$

$m_{doubt} = 0.1$

m_A



T.Denoeux, *A k-nearest neighbor classification rule based on Dempster-Shafer theory* - Systems, Man and Cybernetics, IEEE Transactions on, vol. 25, no. 5, pp. 804–813, 1995.

Formally

- Each training sample works as an expert about his class
- We use Dempster-Shafer Theory to model its information
  1. A labeled training set is created, where each element is the concatenation of tool output and observed parameters

     $$\mathcal{T} = \{t^i = (o^i, p_1^i, \ldots, p_P^i) : i = 1 \ldots N\}$$

  2. For an unseen sample $u = (o^u, p_1^u, \ldots, p_P^u)$, each element in *T* provides a belief about u belonging to its class

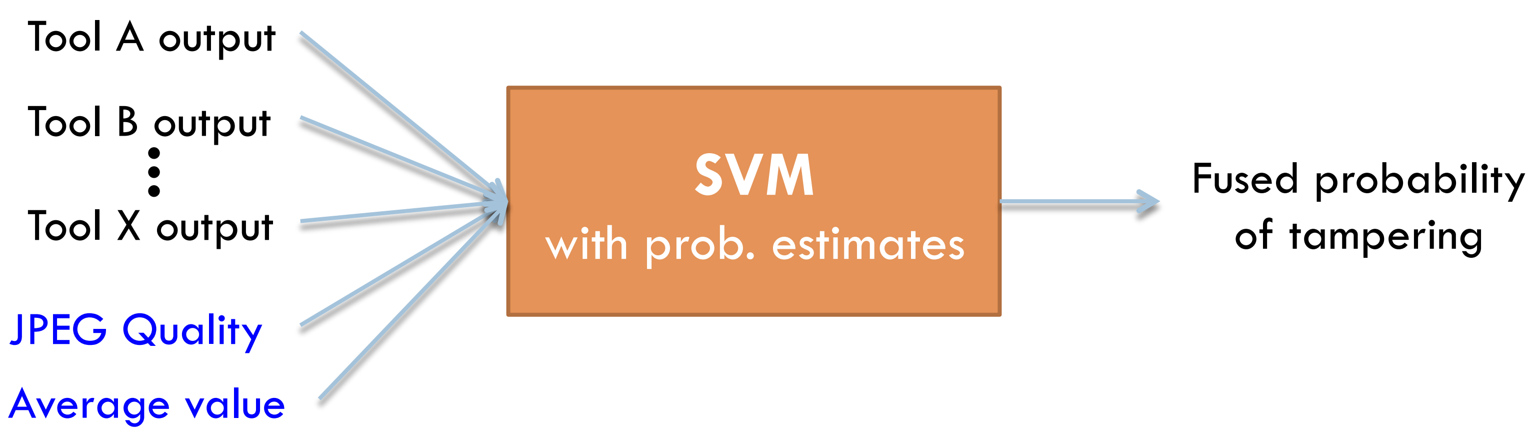
     $$m_i^u(X) = \begin{cases} \beta e^{-\gamma d(u,t_i)} \\ 1 - \beta e^{-\gamma d(u,t_i)} \end{cases}$$

  3. These mass assignments are combined with Dempster's rule

     $$m^u(X) = \bigoplus_{i=1}^{k} m_i^u(X)$$

Embedding Background Information: SVM

- We start from the Q-stack classifier idea [K07]
  - Give to the classifier a measure of the quality of the signal that originated the features
- Instead of quality of the signal, we provide influencing properties to the classifier



[K07] K. Kryszczuk and A. Drygajlo, *Q-stack: Uni- and multimodal classifier stacking with quality measures*, in Proc. of the 7th International Workshop on Multiple Classifier Systems, MCS, 2007, pp. 367–376.

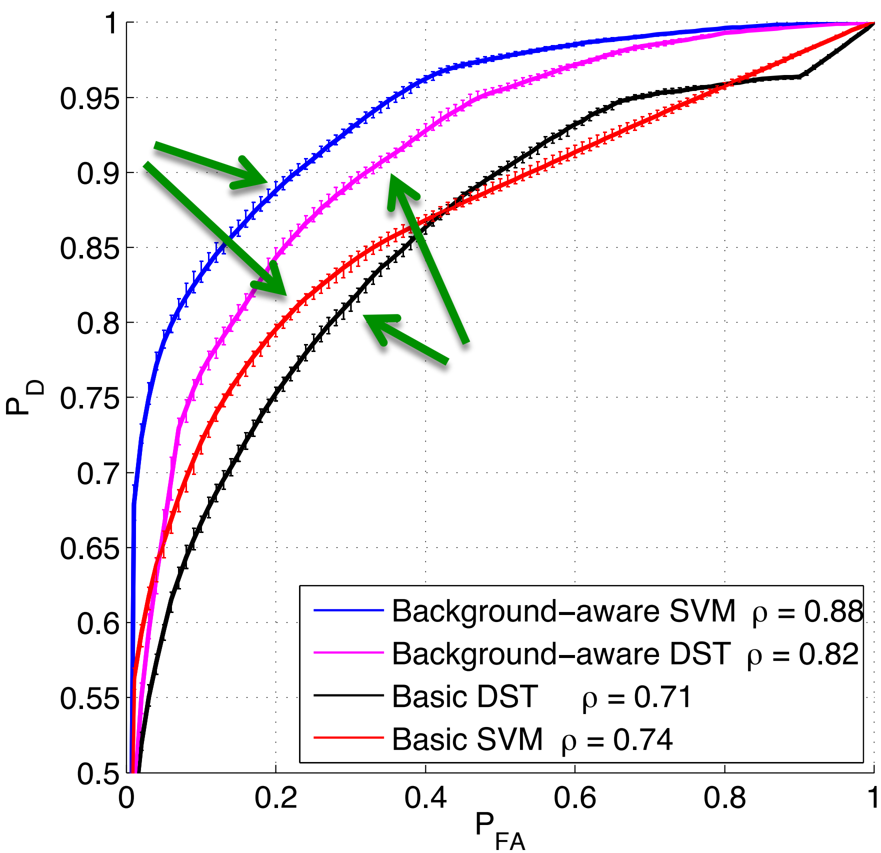
Experimental Results 1/2

- Compare performance of:
  - DST and SVM frameworks endowed with background information
  - The same frameworks without such information
- **Dataset:** the set of images in our Case Study
  - 50600 JPEG images (synthetically generated)
  - Half tampered, half original
  - Several kinds of splicing

Experimental Results 2/2

- DST framework: **+11%**
- SVM framework: **+14%**

- Pros and Cons:
  - SVM:
    - ☺ Ready-to-use
    - ☹ Requires joint training of all tools (huge datasets)
  - DST:
    - ☺ Explicitly models traces relationship
    - ☹ Exponential complexity in the number of traces



Concluding Remarks

- Background information valuable for forensics
- Especially important when different tools are available
  - Different frameworks, comparable performance gain
- Future work:
  - Widen the theoretical perspective
  - Consider more heterogeneous sets of tools
  - Extend to fusion of probability maps

Acknowledgments

REWIND

REVerse engineering of audio-VIsual coNtent Data

www.rewindproject.eu

LIFTGATE

Lifting Up the Potential of the Galician Telecomms Center

Thanks for your attention! Questions?

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