

Efficient Detection of Additive Watermarking in the DWT-Domain

Roland Kwitt, Peter Meerwald, Andreas Uhl

August 28, 2009

Agenda

- ▶ Blind Watermark Detection
- ▶ Host Signal Model
- ▶ Lightweight Watermark Detection
- ▶ (Fast) Parameter Estimation
- ▶ Estimation Accuracy and Impact on Detection Performance
 - ▶ Compare LRT-GGD, LRT-Cauchy, Rao-GGD, Rao-Cauchy Detector
- ▶ Observations and Conclusions

Blind Watermark Detection

- ▶ Embed an imperceptible yet detectable additive, bipolar spread-spectrum sequence w in multimedia content:
$$y = x + \alpha w$$
- ▶ x is vector of host signal DWT coefficients, y is watermarked signal, $\alpha > 0$ determines embedding strength
- ▶ Problem: detect presence of w in signal without knowledge of x (blind detection)
- ▶ Host signal x acts as noise; performance of the detector depends on the distribution of the noise
- ▶ Simple linear correlation is optimal for Gaussian host signal, however, DCT and DWT coefficients do not obey Gaussian law

Watermarking Domain

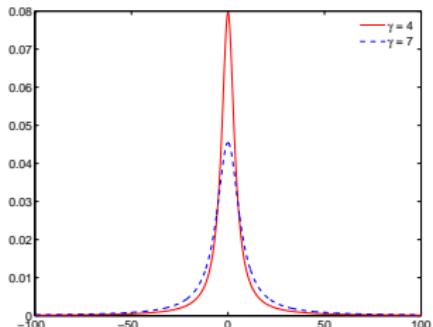
- ▶ Use DWT domain details subband coefficients for embedding
- ▶ Perceptual models available for DWT to control embedding strength and judge visual distortion
- ▶ Select coefficients of a DWT detail subband (eg. HL_2) as host signal vector \mathbf{x}
- ▶ Assume \mathbf{x} is a realization of i.i.d. random variables, formulate statistical model
- ▶ Derive watermark detectors based on statistical model

GGD and Cauchy Host Signal Model

Cauchy distribution PDF

$$p(x|\gamma, \delta) = \frac{1}{\pi} \frac{\gamma}{\gamma^2 + (x - \delta)^2},$$

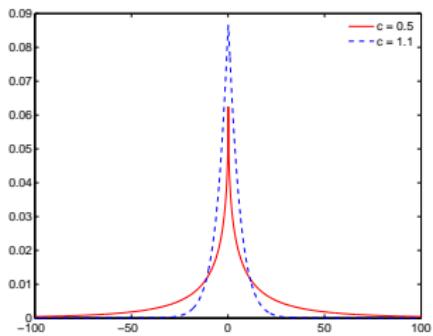
with location parameter $-\infty < \delta < \infty$ and shape parameter $\gamma > 0$



Generalized Gaussian PDF

$$p(x|b, c) = \frac{c}{2b\Gamma(1/c)} \exp\left(-\left|\frac{x}{b}\right|^c\right)$$

with $-\infty < x < \infty$ and $b, c > 0$



Detection Statistics

Linear Correlation

$$\rho(\mathbf{y}) = \frac{1}{N} \sum_{t=1}^N y[t]w[t]$$

LRT-GGD [Hernández et al., 2000]

$$\rho(\mathbf{y}) = \frac{1}{\hat{b}^{\hat{c}}} \sum_{t=1}^N \left(|y[t]|^{\hat{c}} - |y[t] - \alpha \cdot w[t]|^{\hat{c}} \right)$$

Rao-GGD [Nikolaidis and Pitas, 2003]

$$\rho(\mathbf{y}) = \frac{\sum_{t=1}^N \text{sgn}(y[t]) \cdot w[t] \cdot |y[t]|^{\hat{c}}}{\sum_{t=1}^N |y[t]|^{2\hat{c}}}$$

LRT-Cauchy [Briassouli et al., 2005]

$$\rho(\mathbf{y}) = \sum_{t=1}^N \log \left(\frac{\hat{\gamma}^2 + y[t]^2}{\hat{\gamma}^2 + (y[t] - \alpha \cdot w[t])^2} \right)$$

Rao-Cauchy [Kwitt et al., 2008]

$$\rho(\mathbf{y}) = \left[\sum_{t=1}^N \frac{y[t]w[t]}{\hat{\gamma}^2 + y[t]^2} \right]^2 \frac{8\hat{\gamma}^2}{N}$$

Watermark Detection Effort

Number of arithmetic operations to compute detection statistic for signal of length N

Detector	Operations			
	+,-	\times, \div	pow, log	abs, sgn
Linear Correlation	N	N		
LRT-GGD [Hernández et al., 2000]	3N	2	2N+1	2N
Rao-GGD [Nikolaidis and Pitas, 2003]	2N	3N+2	N	2N
LRT-Cauchy [Briassouli et al., 2005]	4N	5N	N	
Rao-Cauchy [Kwitt et al., 2008]	2N	2N+4		

Watermark Detection Runtime Measurement

Runtime on Intel Core2 2.66 GHz in seconds (MATLAB)

Detector	Signal Length (N)		
	100000	1000000	10000000
Linear Correlation	0.001	0.011	0.104
LRT-GGD [Hernández et al., 2000]	0.053	0.532	5.349
Rao-GGD [Nikolaidis and Pitas, 2003]	0.038	0.398	3.935
LRT-Cauchy [Briassouli et al., 2005]	0.010	0.103	1.029
Rao-Cauchy [Kwitt et al., 2008]	0.003	0.035	0.353

Parameter Estimation

To determine the MLEs for the Cauchy or GGD shape parameter, we have to solve

$$\frac{1}{N} \sum_{t=1}^N \frac{2}{1 + (x[t]/\hat{\gamma})^2} - 1 = 0 \quad (\text{Cauchy})$$

or

$$1 + \frac{\psi(1/\hat{c}) + \log\left(\frac{\hat{c}}{N} \sum_{t=1}^N |x[t]|^{\hat{c}}\right)}{\hat{c}} - \frac{\sum_{t=1}^N |x[t]|^{\hat{c}} \log(|x[t]|)}{\sum_{t=1}^N |x[t]|^{\hat{c}}} = 0 \quad (\text{GGD})$$

numerically. Approximately the same number of iterations are necessary (Newton-Raphson), however the computation effort is much higher for the GGD.

Fast Parameter Estimation

For the Cauchy parameter, we simply use the iteration starting value

$$\hat{\gamma}_1 = 0.5(x_p - x_{1-p}) \tan(\pi(1-p)),$$

with $0.5 < p < 1$ and x_p, x_{1-p} denoting the sample quantiles [Krishnamoorthy, 2006] with $p = 0.75$.

For the GGD shape parameter, [Krupinski and Purczynski, 2006] propose a piecewise approximation of the inversion function

$$\hat{c} = F^{-1} \left(\frac{E_1}{\sqrt{E_2}} \right)$$

based on the mean absolute value E_1 and variance E_2 of the data set.

Fast Parameter Estimation Effort

Detector	Operations			
	+,-,==	\times, \div	pow, log	abs, sgn
Fast GGD [Krupinski et al., 2006]	$3N+1$	$N+8$	$N+3$	N
Fast Cauchy	$N\log(N)+3$	3	1	

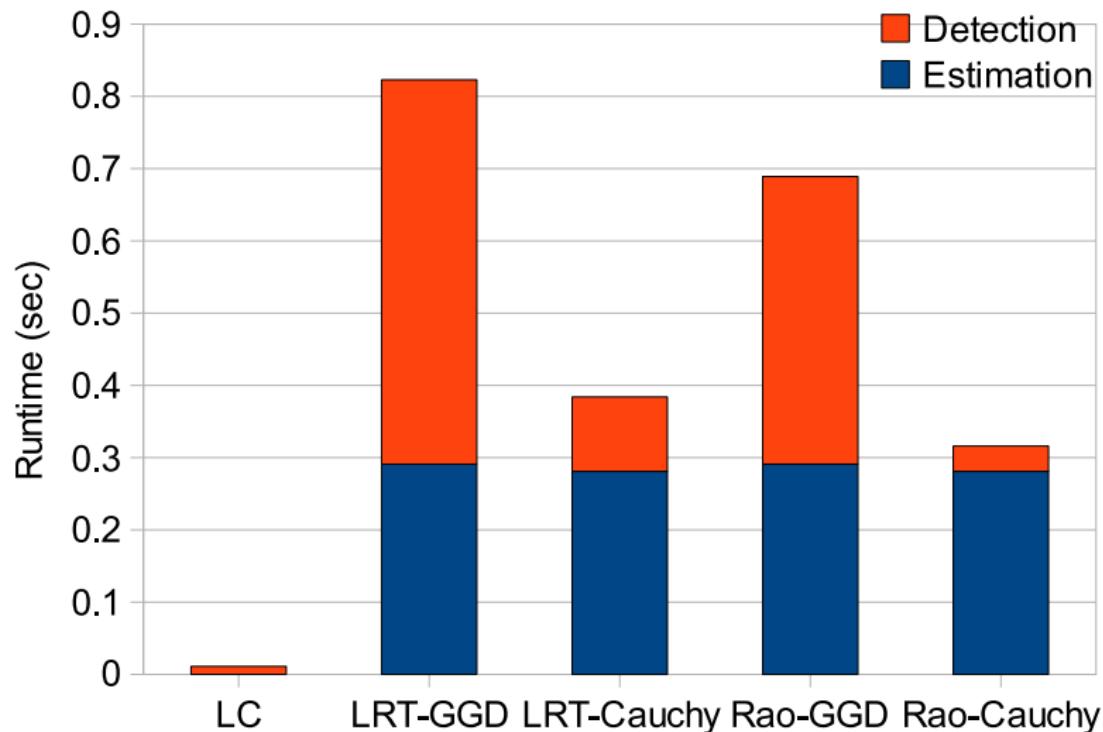
Note: Cauchy parameter estimation requires sorting the data.

Parameter Estimation Runtime Measurement

Approximate MATLAB runtime on Intel Core2 2.6 GHz averaged over 10 runs

Estimation	Signal Length (N)		
	100000	1000000	10000000
Fast GGD [Krupinski et al., 2006]	0.029	0.291	2.899
Fast Cauchy	0.024	0.281	3.069
GGD MLE [Do and Vetterli, 2002]	0.139	1.019	10.154
GGD Fitting	14.108	141.319	-
Cauchy Fitting	0.422	4.261	-

Runtime Measurements



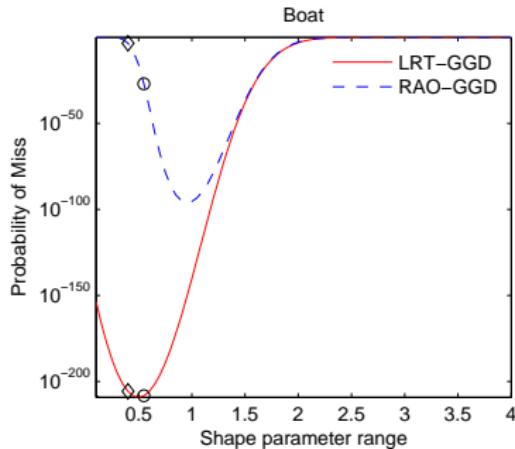
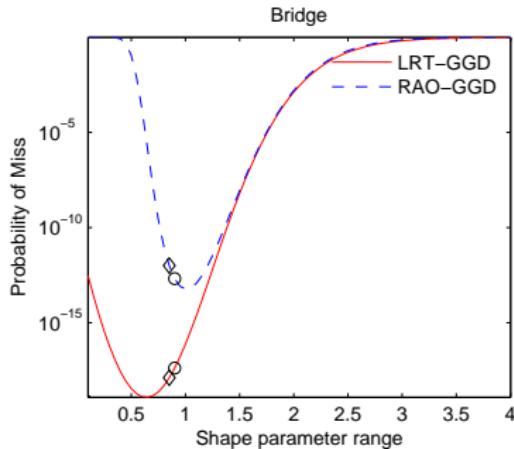
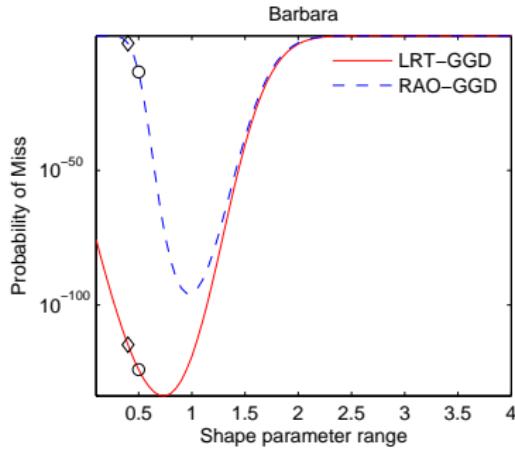
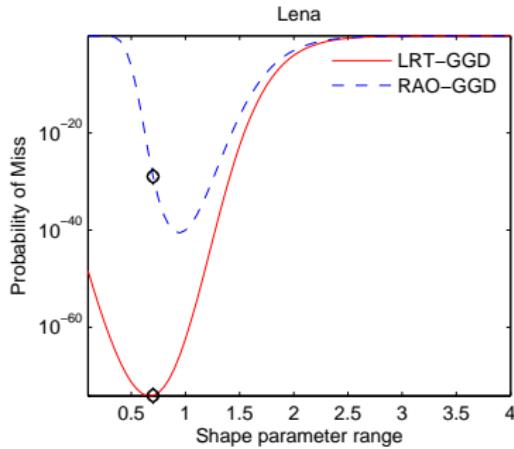
Estimation Accuracy and Impact on Detection Performance

Estimate detection performance for 4 sample images as a function of host model parameter

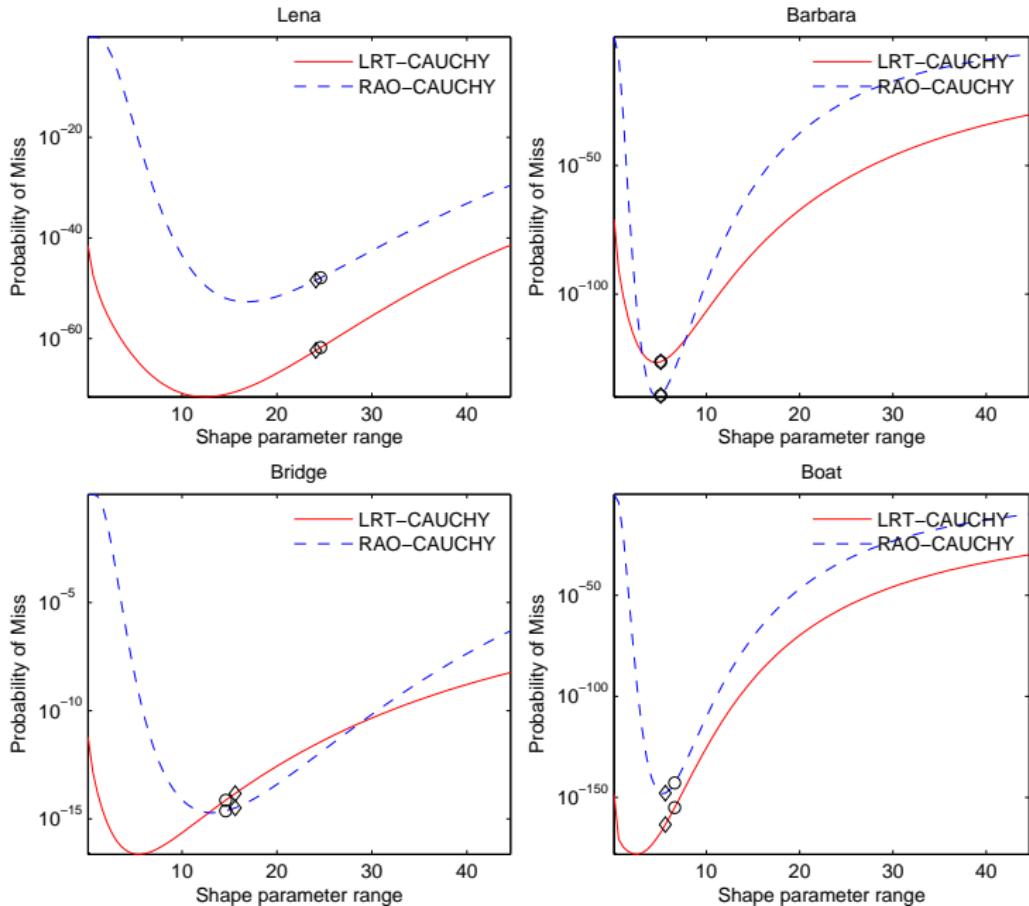
- ▶ Performance at MLE and fast approx. MLE of host parameter
- ▶ Optimal performance



GGD Host Model



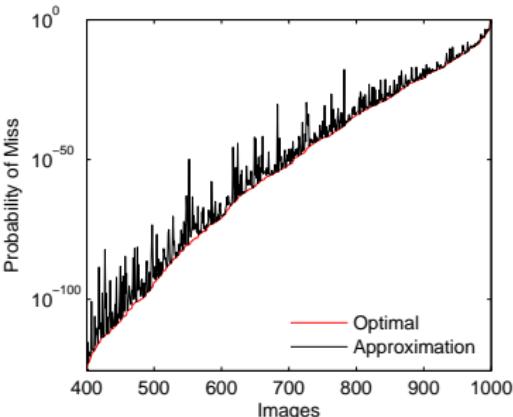
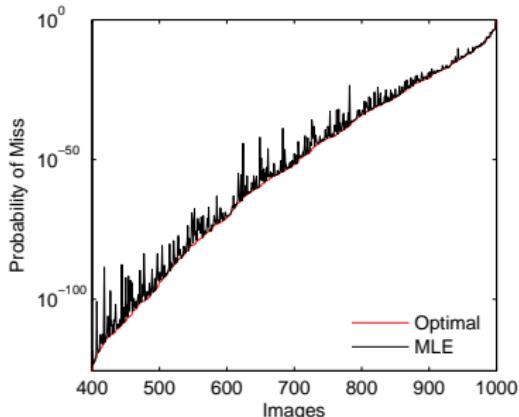
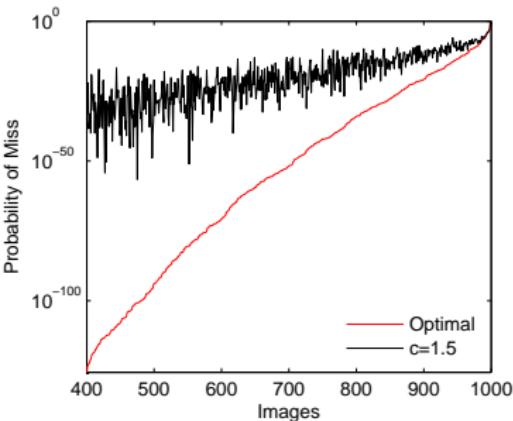
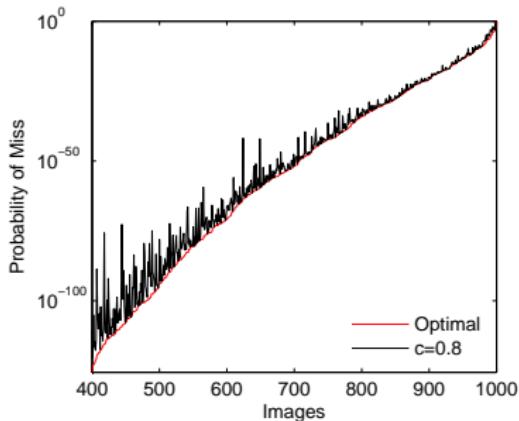
Cauchy Host Model



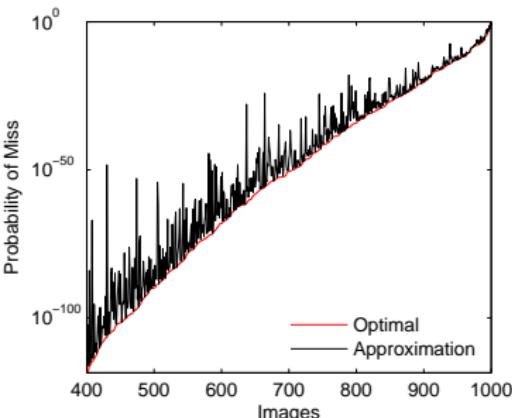
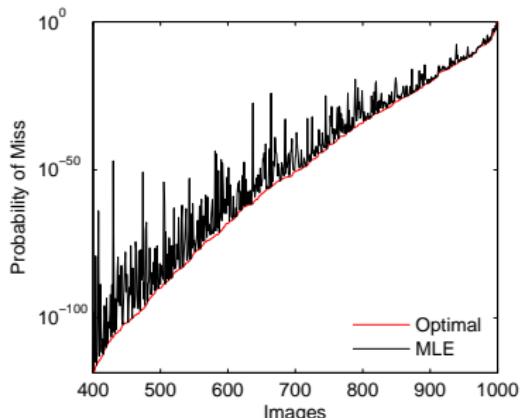
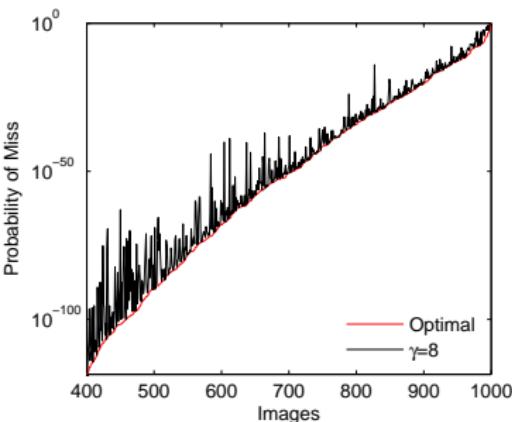
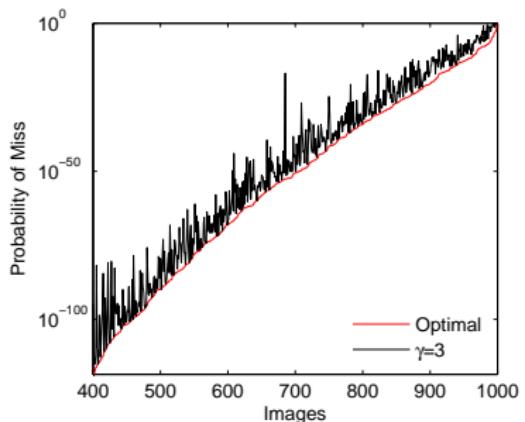
Detection Performance over Larger Image Sets

- ▶ First 1000 images of UCIID [Schaefer and Stich, 2004]
512 × 384 color image database
- ▶ Compare detection performance
 - ▶ Optimal host signal parameter setting
 - ▶ Fixed parameter settings
 - ▶ GGD shape parameter $c:0.8,1.5$
 - ▶ Cauchy γ parameter: 3,8
 - ▶ MLE parameter setting & fast approximation
- ▶ BOWS-2 512 × 512 grayscale images yield very similar results

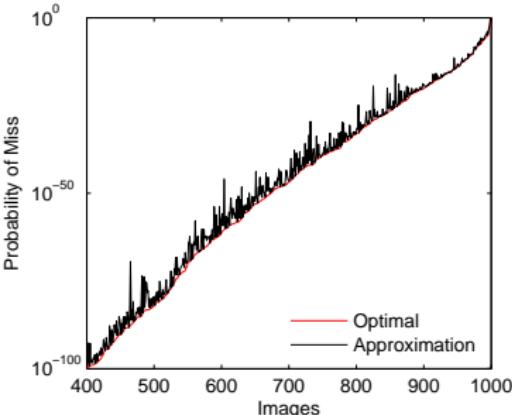
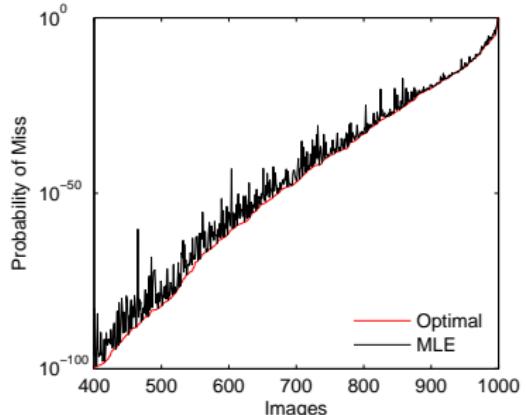
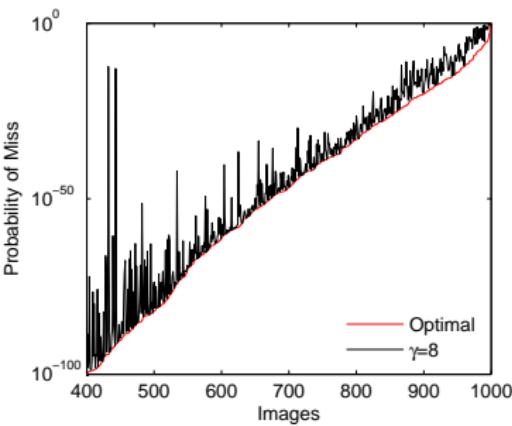
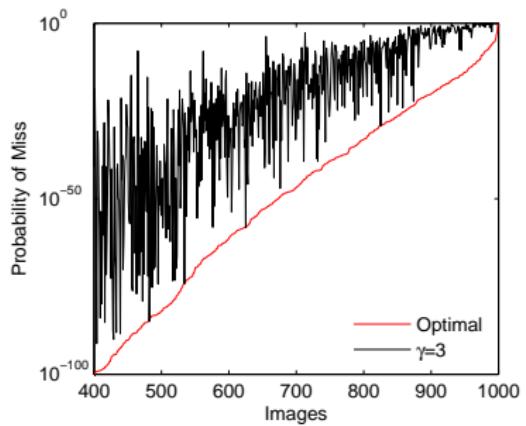
LRT-GGD Detector



LRT-Cauchy Detector



Rao-Cauchy Detector



Observations and Conclusion

- ▶ Watermark embedding does not significantly alter host signal distribution, knowledge of original signal distribution does not improve detection
- ▶ **MLE of signal parameter does not guarantee optimum detection performance!**
- ▶ Fast MLE is reasonably accurate
- ▶ GGD model is more sensitive to estimation error
- ▶ For Cauchy host model, better overestimate γ parameter
- ▶ Fixed parameters can be chosen without sacrificing much detection performance
- ▶ Fixing Cauchy $\gamma \sim 8$ provides good results
- ▶ Rao-GGD $c \sim 1.1$ beats MLE, and $c = 1$ leads to a very simple detector: $\rho(\mathbf{y}) = \frac{1}{N} \sum_{t=1}^N \text{sgn}(y[t])w[t]$

-  Briassouli, A., Tsakalides, P., and Stouraitis, A. (2005).
Hidden messages in heavy-tails: DCT-domain watermark detection using alpha-stable models.
IEEE Transactions on Multimedia, 7(4):700–715.
-  Do, M. and Vetterli, M. (2002).
Wavelet-based texture retrieval using Generalized Gaussian density and Kullback-Leibler distance.
IEEE Transactions on Image Processing, 11(2):146–158.
-  Hernández, J. R., Amado, M., and Pérez-González, F. (2000).
DCT-domain watermarking techniques for still images: Detector performance analysis and a new structure.
IEEE Transactions on Image Processing, 9(1):55–68.
-  Krishnamoorthy, K. (2006).
Handbook of Statistical Distributions with Applications.
Chapman & Hall.
-  Krupinski, R. and Purczynski, J. (2006).
Approximated fast estimator for the shape parameter of Generalized Gaussian distribution.
Signal Processing, 86(2):205–211.
-  Kwitt, R., Meerwald, P., and Uhl, A. (2008).
A lightweight Rao-Cauchy detector for additive watermarking in the DWT-domain.
In *Proceedings of the ACM Multimedia and Security Workshop, MMSEC '08*, pages 33–41, Oxford, UK. ACM.
-  Nikolaidis, A. and Pitas, I. (2003).
Asymptotically optimal detection for additive watermarking in the DCT and DWT domains.
IEEE Transactions on Image Processing, 12(5):563–571.
-  Schaefer, G. and Stich, M. (2004).
UCID - an uncompressed colour image database.
In *Proceedings of SPIE, Storage and Retrieval Methods and Applications for Multimedia*, pages 472–480, San Jose, CA, USA. SPIE.