

# Improved Detection of LSB Steganography in Grayscale Images

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# Summary

This presentation will tell you about:

1. A project to **evaluate** the reliability of steganalytic algorithms;
2. Some potential pitfalls in this area;
3. Improved steganalysis methods:  
*exploiting uncorrelated estimators,  
simplifying, by dropping the message length estimate,  
(applying discriminators to a segmented image);*
4. Experimental evidence of improvement.

# “Reliability”

The primary aim of an Information Security Officer (Warden) is to perform a reliable hypothesis test:

$H_0$ : *No data is hidden in a given image*

$H_1$ : *Data is hidden (for experiments we posit a fixed amount/proportion)*

(as opposed to forming an estimate of the amount of hidden data, or recovering the hidden data)

A steganalysis method is a discriminating statistic for this test; by adjusting the sensitivity of the hypothesis test, false positive (type I error) and false negative (type II error) rates may be traded.

Reliability is a “ROC” curve showing how false positives and false negatives are related.

# Distributed Steganalysis Evaluation Project

## *Applied systematically*

Over 200 variants of steganalysis statistics tested so far

## *Very large image libraries are used*

Currently over 90,000 images in total, with more to come

Images come in “sets” with similar characteristics.

## *Results are produced quickly*

Computation performed by a heterogeneous cluster of 7-50 machines

Calculations queued and results stored in a relational database

Currently over 16 million rows of data, will grow to 100+ million

# Scope of This Work

## *Covers*

Grayscale bitmaps  
(which quite likely were previously subject to JPEG compression)

## *Embedding method*

LSB steganography in the spatial domain using various proportions of evenly-spread pixels

Particular interest in very low embedding rates  
(0.01-0.1 secret bits per cover pixel)

## *Aiming to improve the closely-related steganalysis statistics*

“Pairs” [Fridrich *et al*, SPIE EI'03]

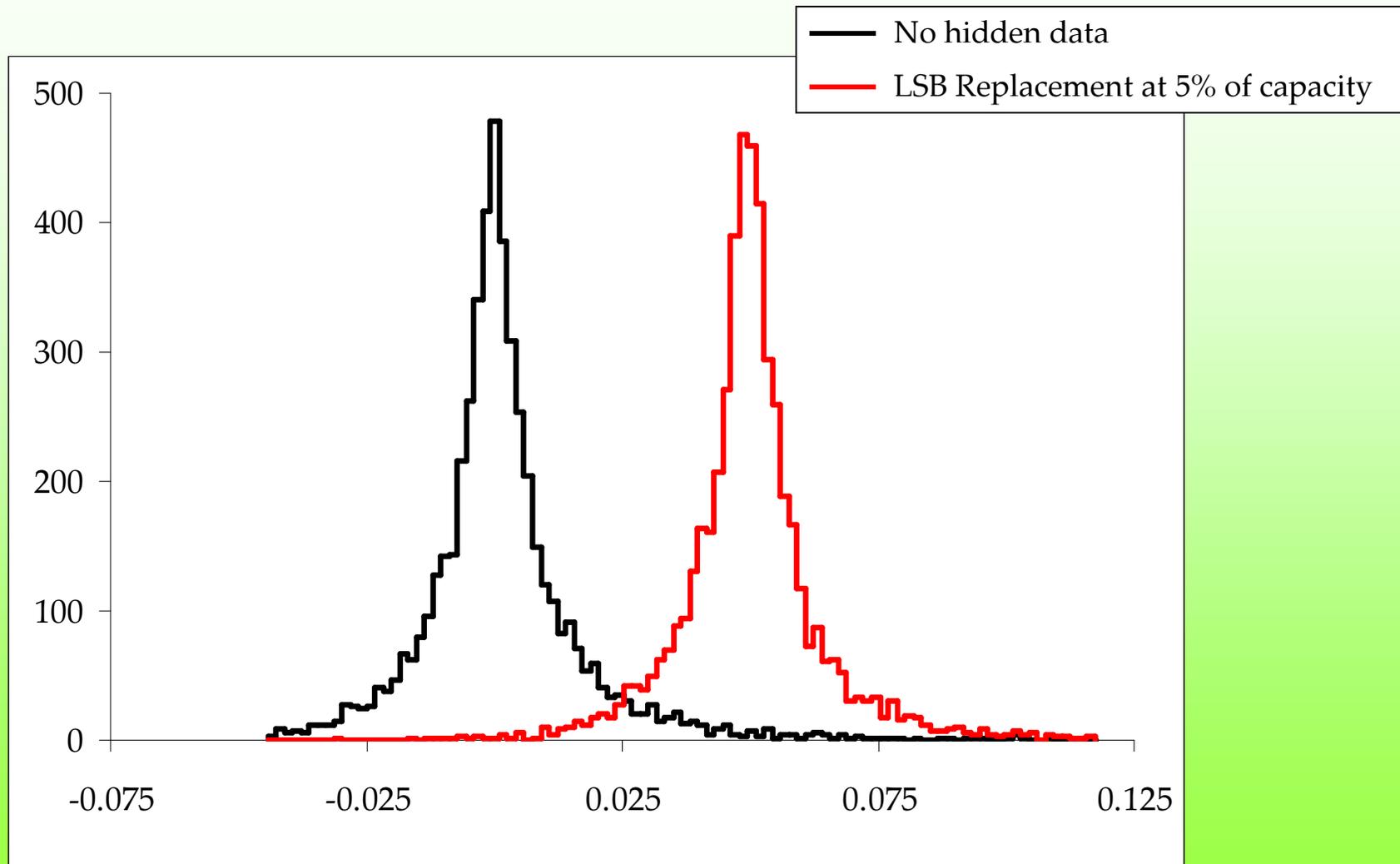
“RS” a.k.a. “dual statistics” [Fridrich *et al*, ACM Workshop '01]

“Sample Pairs” [Dumitrescu *et al*, IHW'02] a.k.a. “Couples”

# The world's smallest steganography software

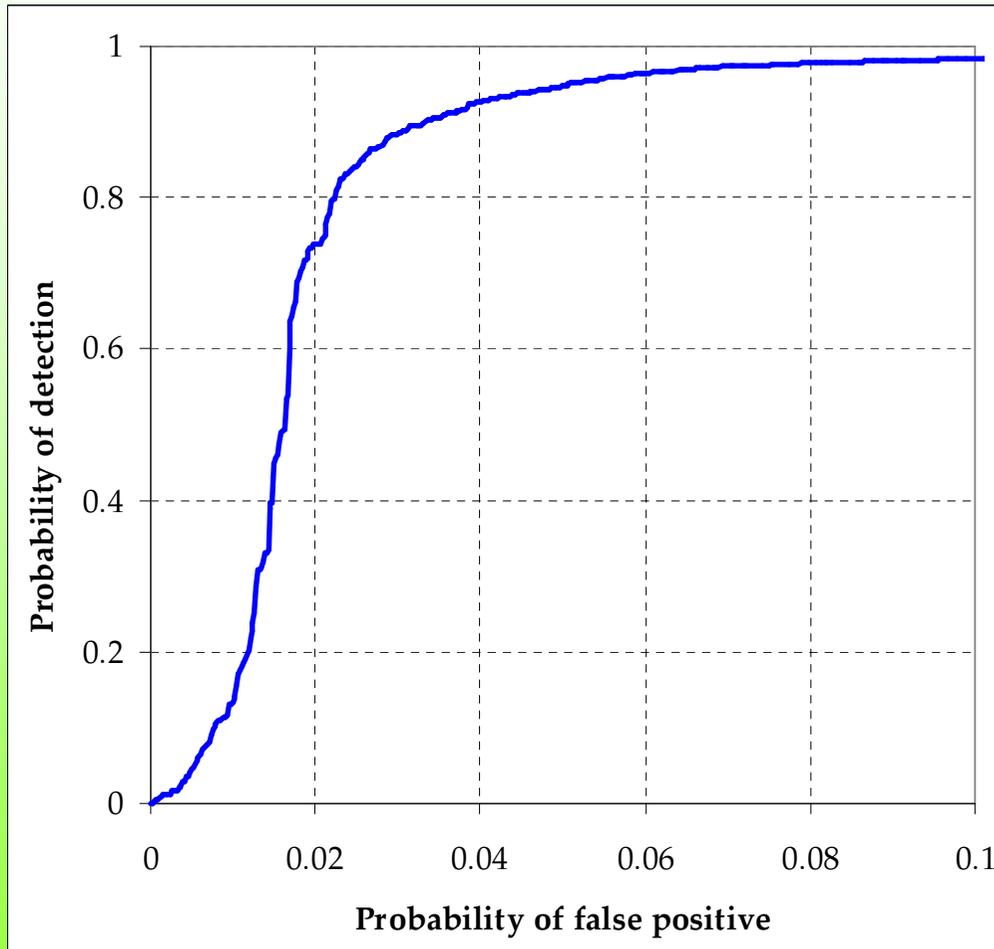
```
perl -n0777e '$_=unpack"b*",$_;split/(\s+)/,<STDIN>,5;  
@_[8]=~s{.}{$&&v254|chop()}&v1}ge;print@_'  
  
<input.pgm >output.pgm stegotext
```

# Sample Output: Histograms



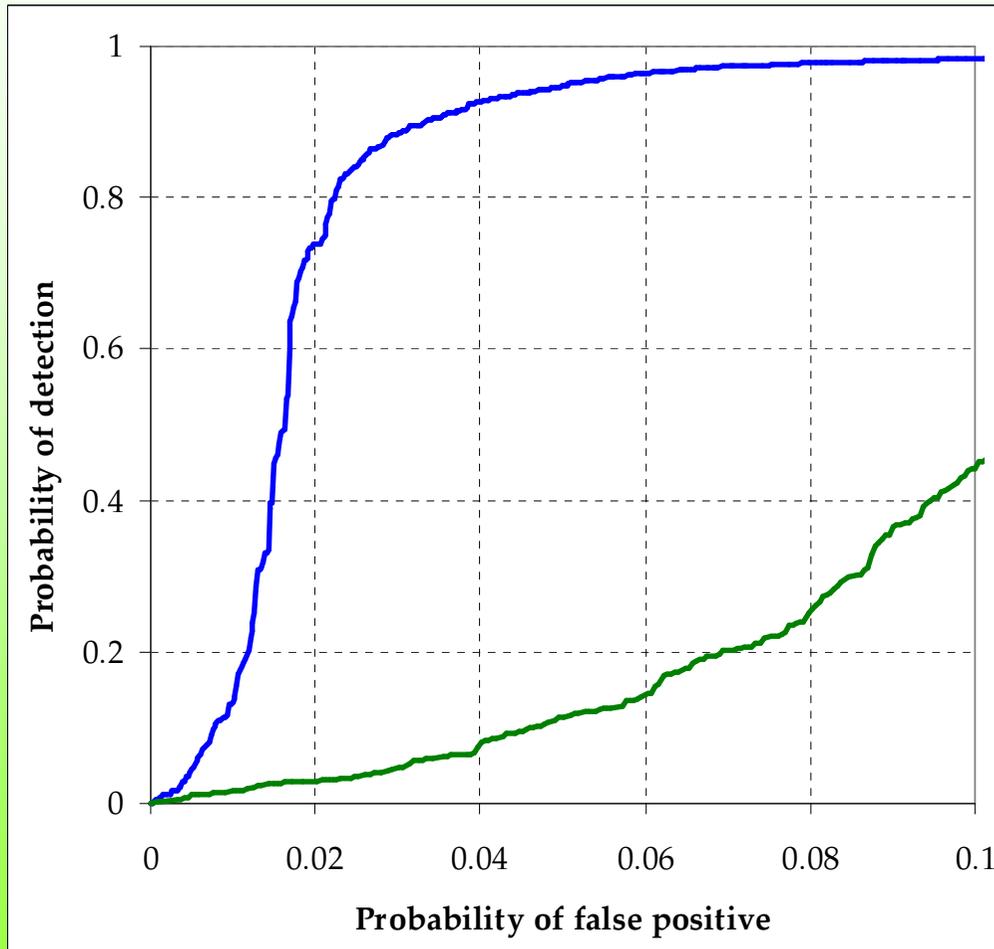
*Histograms of the standard "Couples" statistic, generated from 5000 JPEG images*

# Sample Output: ROC Curves



*ROC curves for the "Couples" statistic. 5% embedding (0.05bpp).*

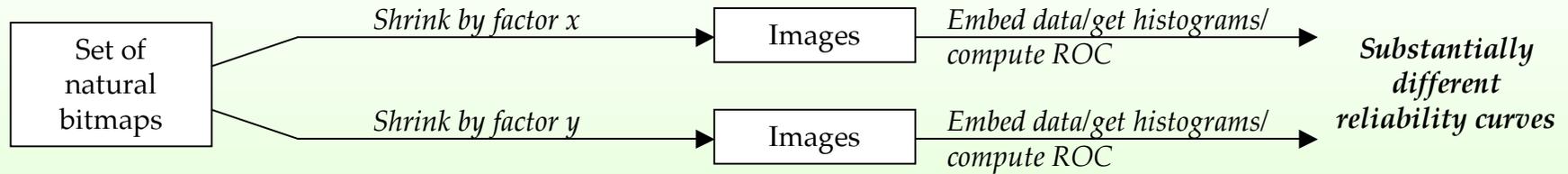
# Sample Output: ROC Curves



— Generated from 5000 high-quality JPEGs  
— Generated from 2200 uncompressed bitmaps

*ROC curves for the "Couples" statistic. 5% embedding (0.05bpp).*

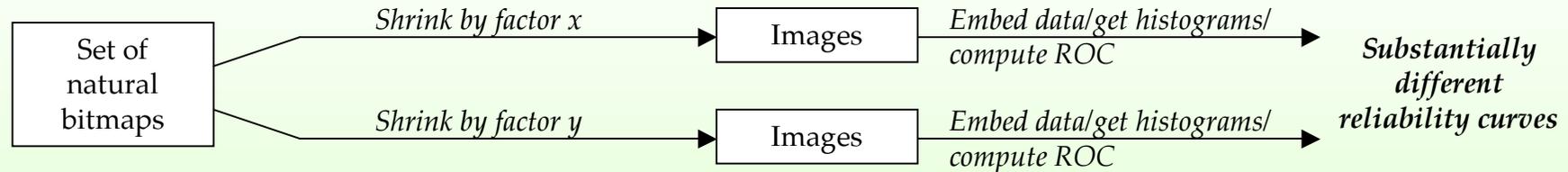
# Some Warning Examples



## Conclusion

- The size of the cover images affects the reliability of the detector, even for a fixed embedding rate

# Some Warning Examples



## Conclusion

- The size of the cover images affects the reliability of the detector, even for a fixed embedding rate.

## In [Ker, SPIE EI'04] we also showed that

- Whether and how much covers had been previously JPEG compressed affects reliability, sometimes a great deal.
- This effect persists even when the images are quite substantially shrunk after compression.
- Different resampling algorithms in the shrinking process can themselves affect reliability.

# Good Methodology for Evaluation

- We have to concede that there is no single “reliability” for a particular detector.
- One should test reliability with more than one large set of cover images.
- It is important to report:
  - a. How much data was hidden;
  - b. The size of the covers;
  - c. Whether they have ever been JPEG compressed, or undergone any other manipulation.
- Take great care in “simulating” uncompressed images.

# How does “Couples Analysis” work?

Simulate LSB replacement in proportion  $2p$  of pixels by flipping the LSBs of  $p$  at random.

Example cover image:

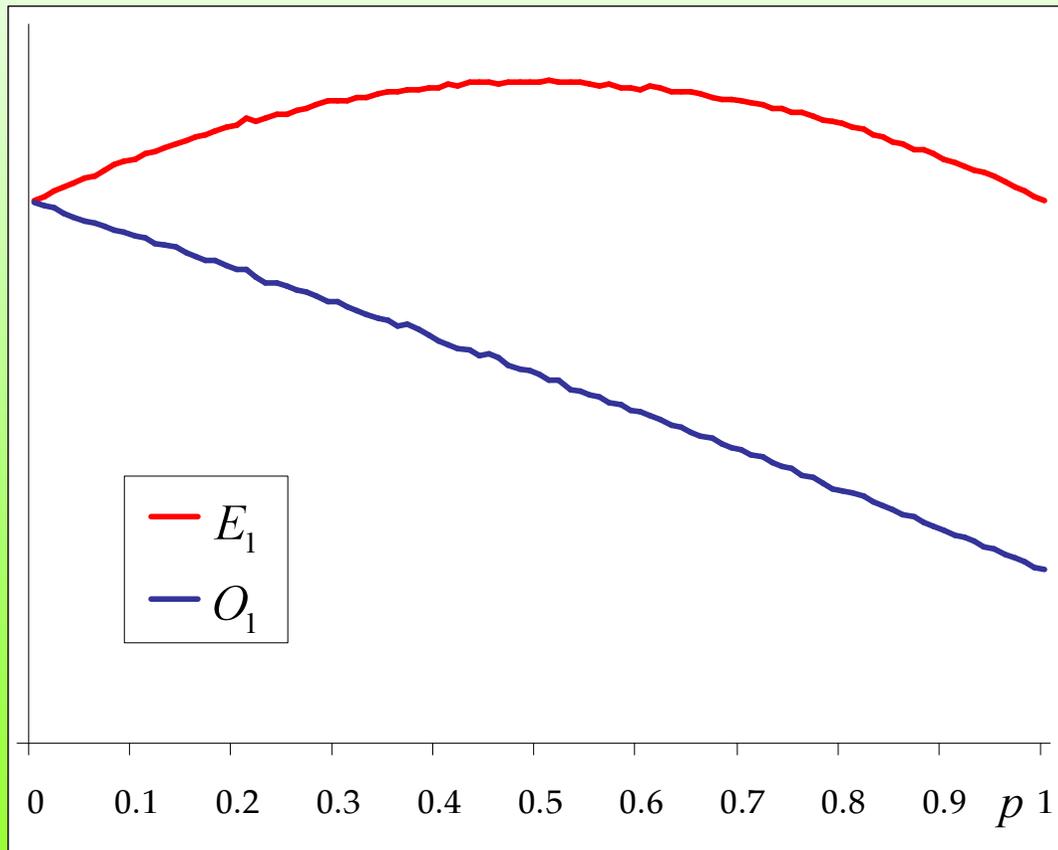


# How does “Couples Analysis” work?

As  $p$  varies, compute:

$E_i$  = number of adjacent pixels whose value differs by  $i$ , and the lower value is even

$O_i$  = number of adjacent pixels whose value differs by  $i$ , and the lower value is odd



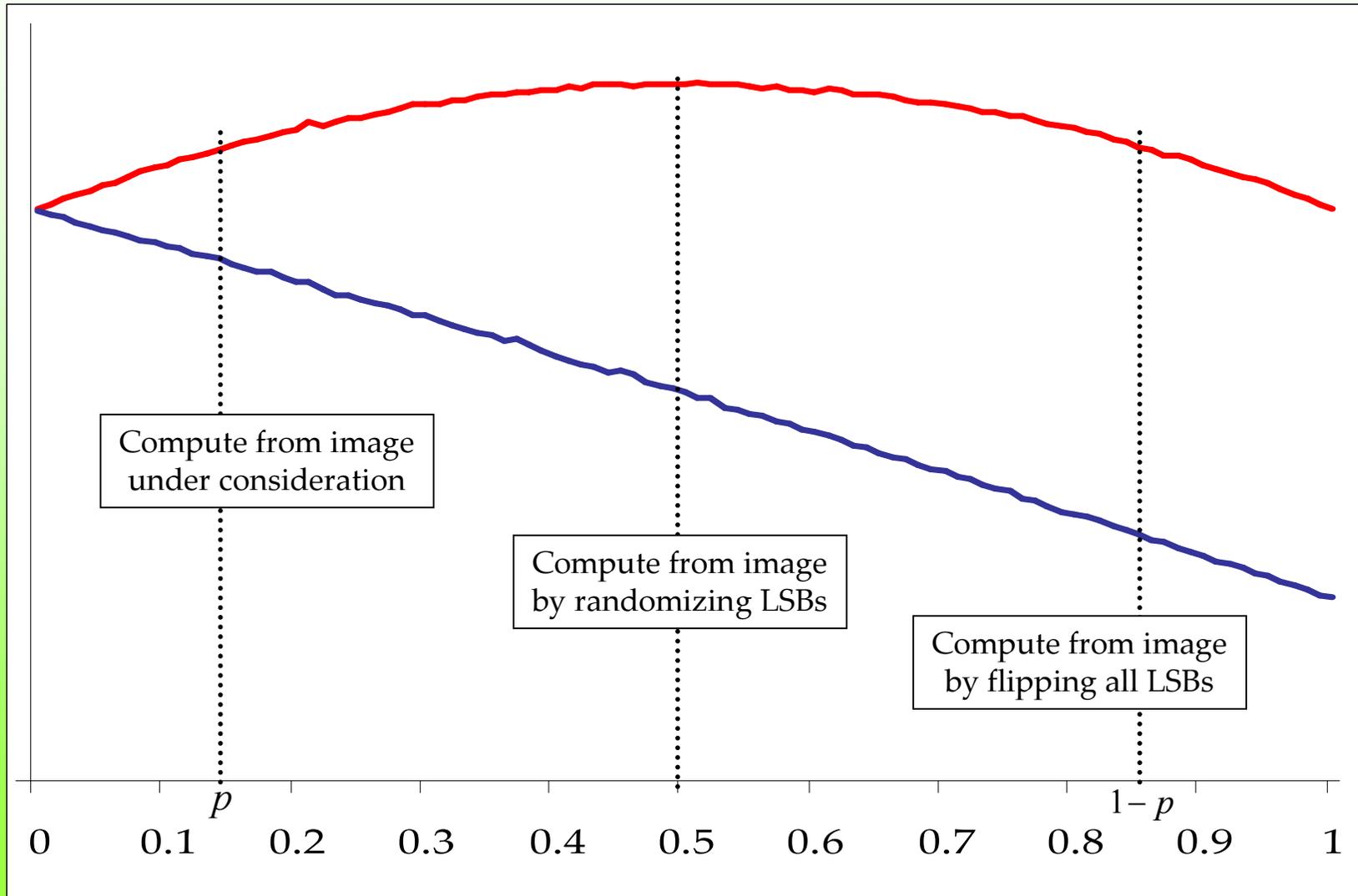
- Both curves quadratic in  $p$
- Meet at  $p=0$

The pairs of measures

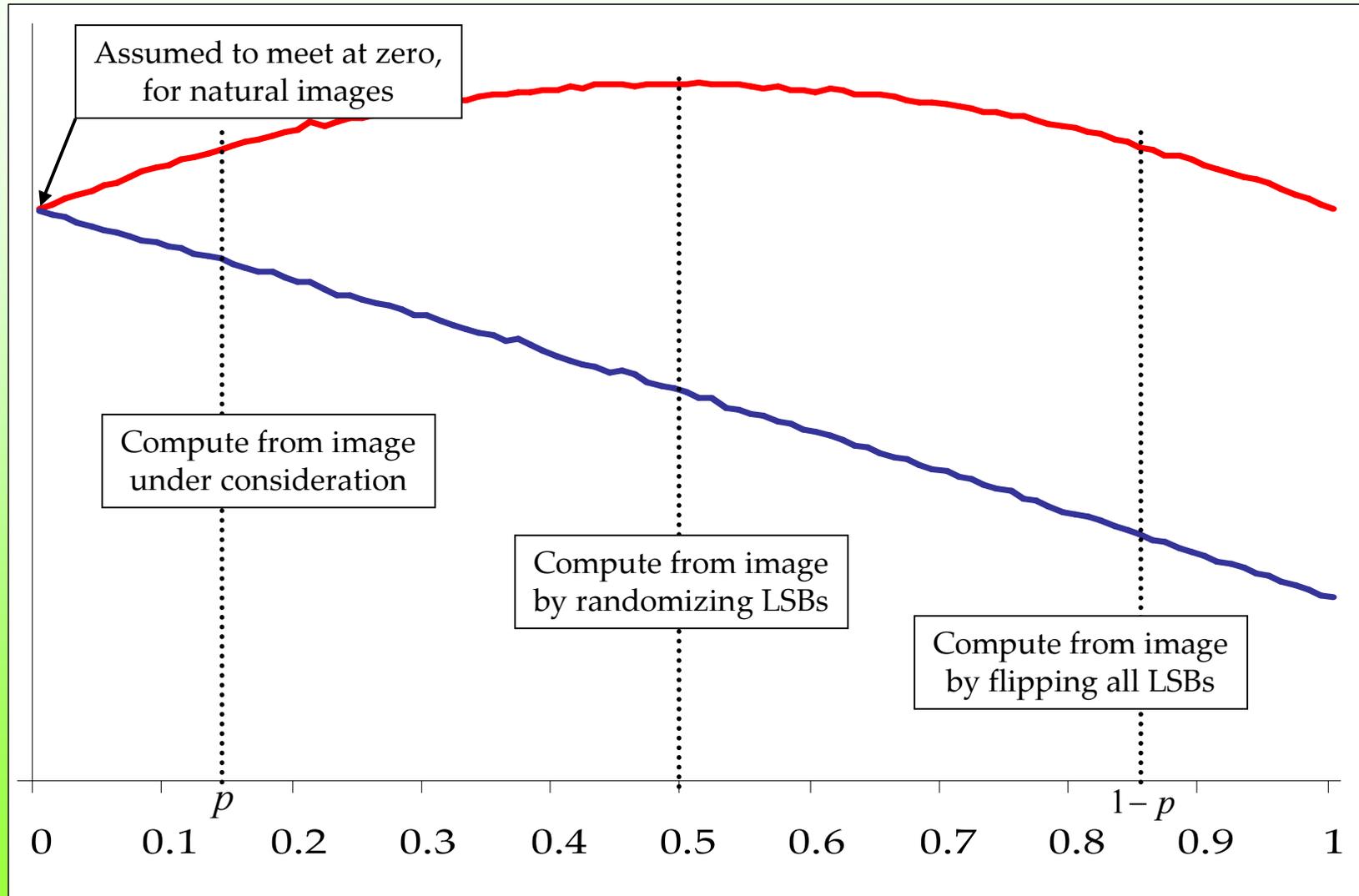
$$\begin{array}{c} E_3 \ \& \ O_3 \\ E_5 \ \& \ O_5 \\ \vdots \\ \sum_{\text{odd } i} E_i \ \& \ \sum_{\text{odd } i} O_i \end{array}$$

all have the same properties.

# How does “Couples Analysis” work?



# How does “Couples Analysis” work?



# Choice of Discriminators

Unlike Pairs and RS, Couples has a number of estimators for the proportion of hidden data:

$\hat{p}_0$  from  $E_1$  and  $O_1$

$\hat{p}_1$  from  $E_3$  and  $O_3$

$\hat{p}_2$  from  $E_5$  and  $O_5$

$\vdots$

$\hat{p}$  from  $\sum_{\text{odd } i} E_i$  and  $\sum_{\text{odd } i} O_i$

The last one is used in [Dumitrescu *et al*, IHW'02]

# Choice of Discriminators

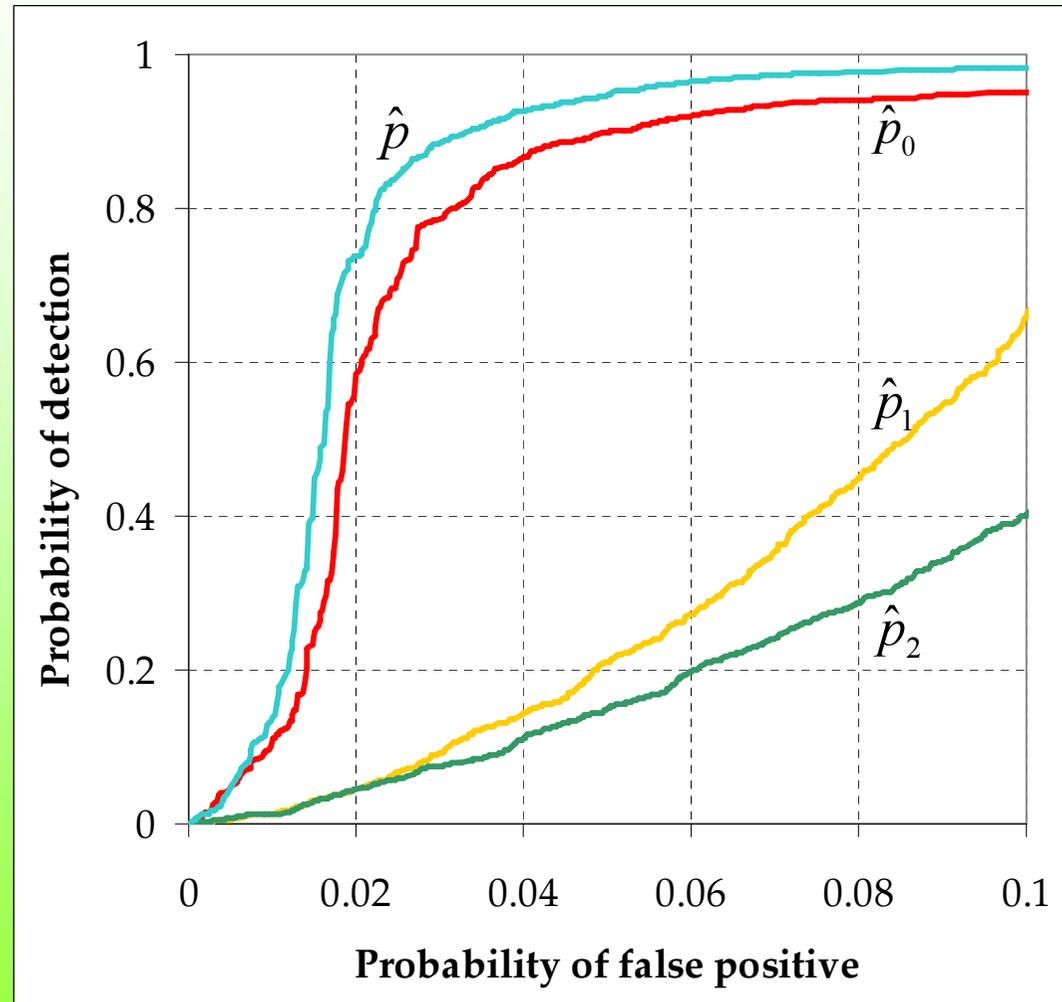
$\hat{p}_0$  from  $E_1$  and  $O_1$

$\hat{p}_1$  from  $E_3$  and  $O_3$

$\hat{p}_2$  from  $E_5$  and  $O_5$

⋮

$\hat{p}$  from  $\sum_{\text{odd } i} E_i$  and  $\sum_{\text{odd } i} O_i$



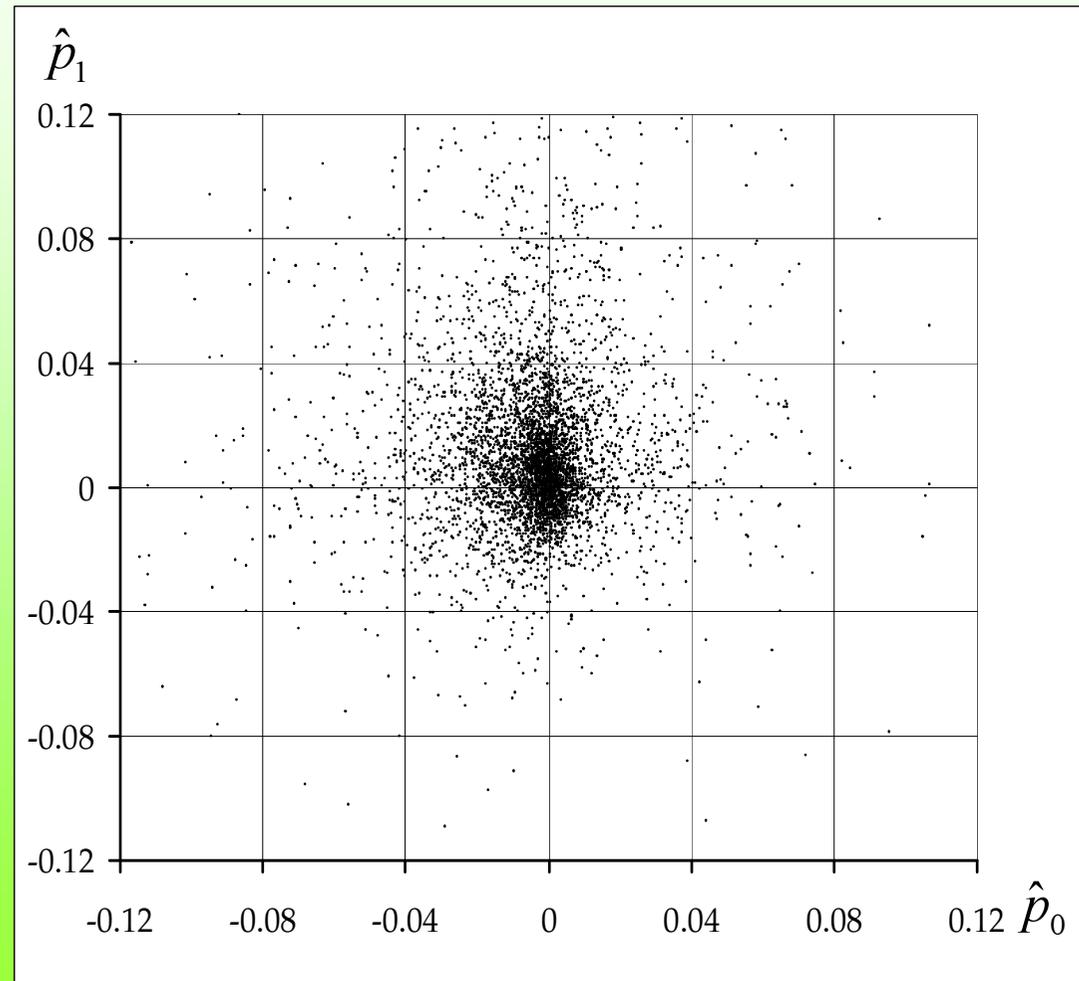
*ROC curves generated from 5000 JPEG images of high quality. 5% embedding (0.05bpp).*

# Estimators are Uncorrelated

We observe that the estimators  $\hat{p}_i$  are very loosely correlated.

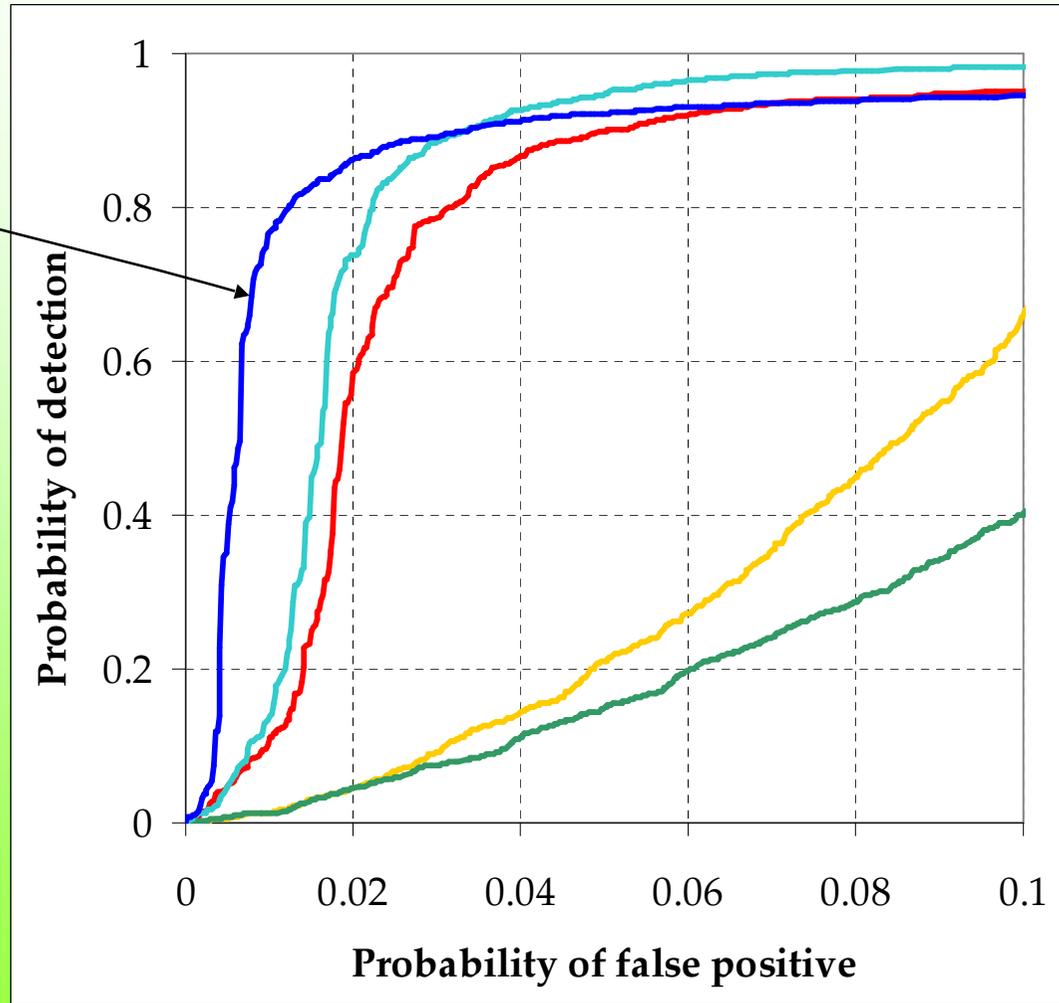
Scattergram shows  $\hat{p}_0$  &  $\hat{p}_1$  when no data embedded in 5000 high-quality JPEG images; the correlation coefficient is **-0.036**

$\hat{p}_0$  &  $\hat{p}_1$  form independent discriminators



# Improved Couples Discriminator

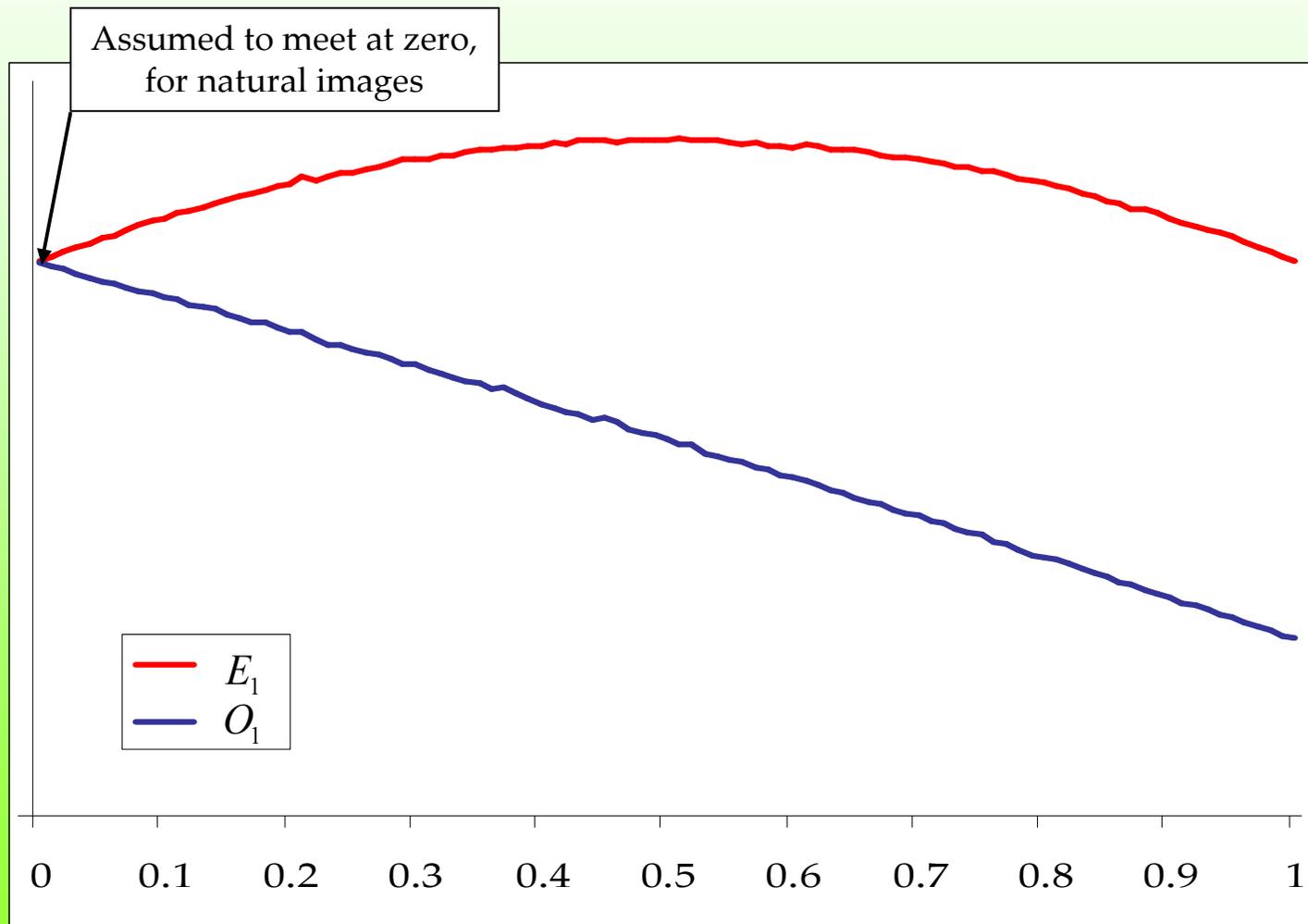
$$\min(\hat{p}_0, \hat{p}_1, \hat{p}_2)$$



*ROC curves generated from 5000 JPEG images of high quality. 5% embedding (0.05bpp).*

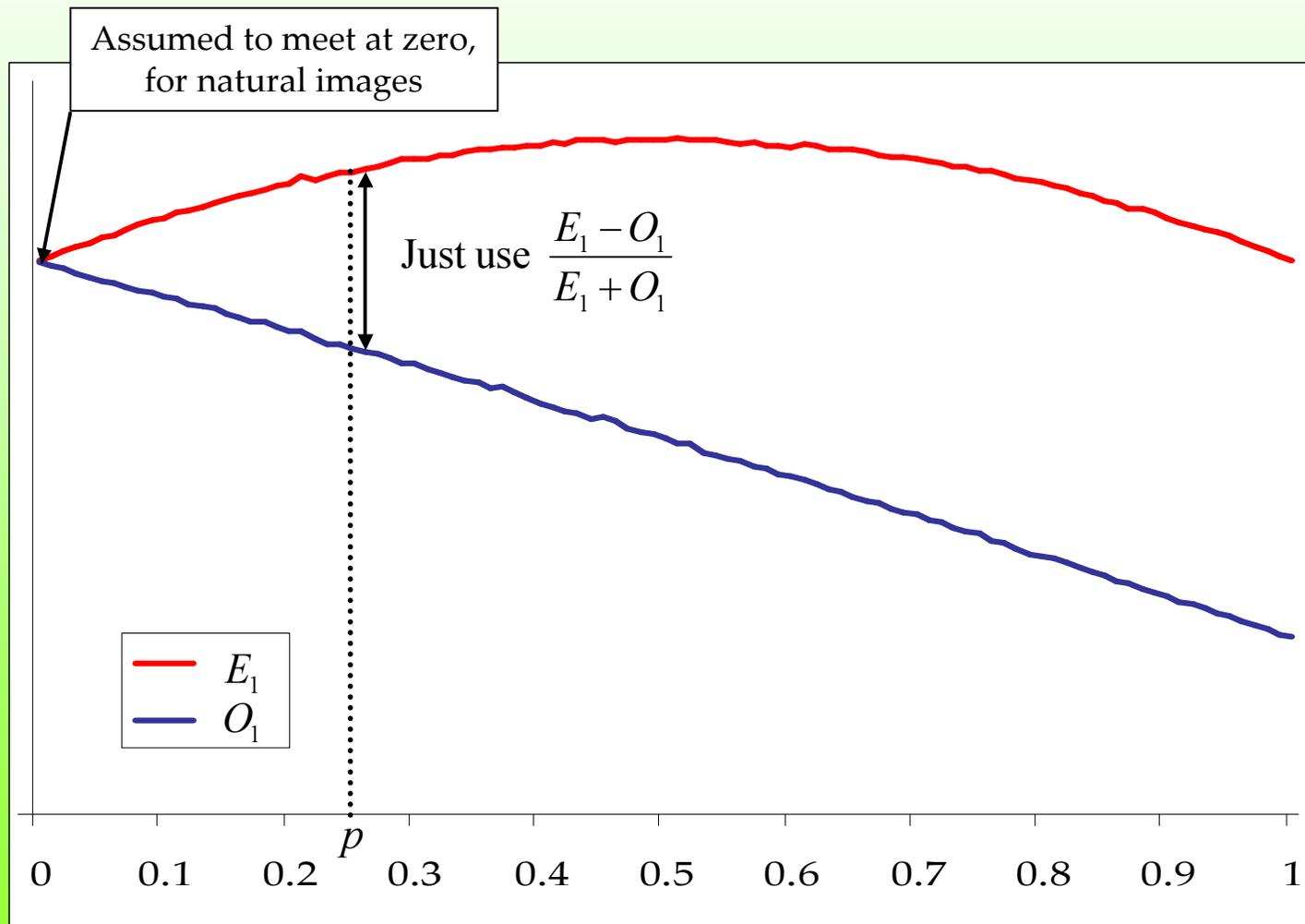
# Dropping the Message-Length Estimate

There is a much simpler sign that data has been embedded, which does not involve solving a quadratic equation:

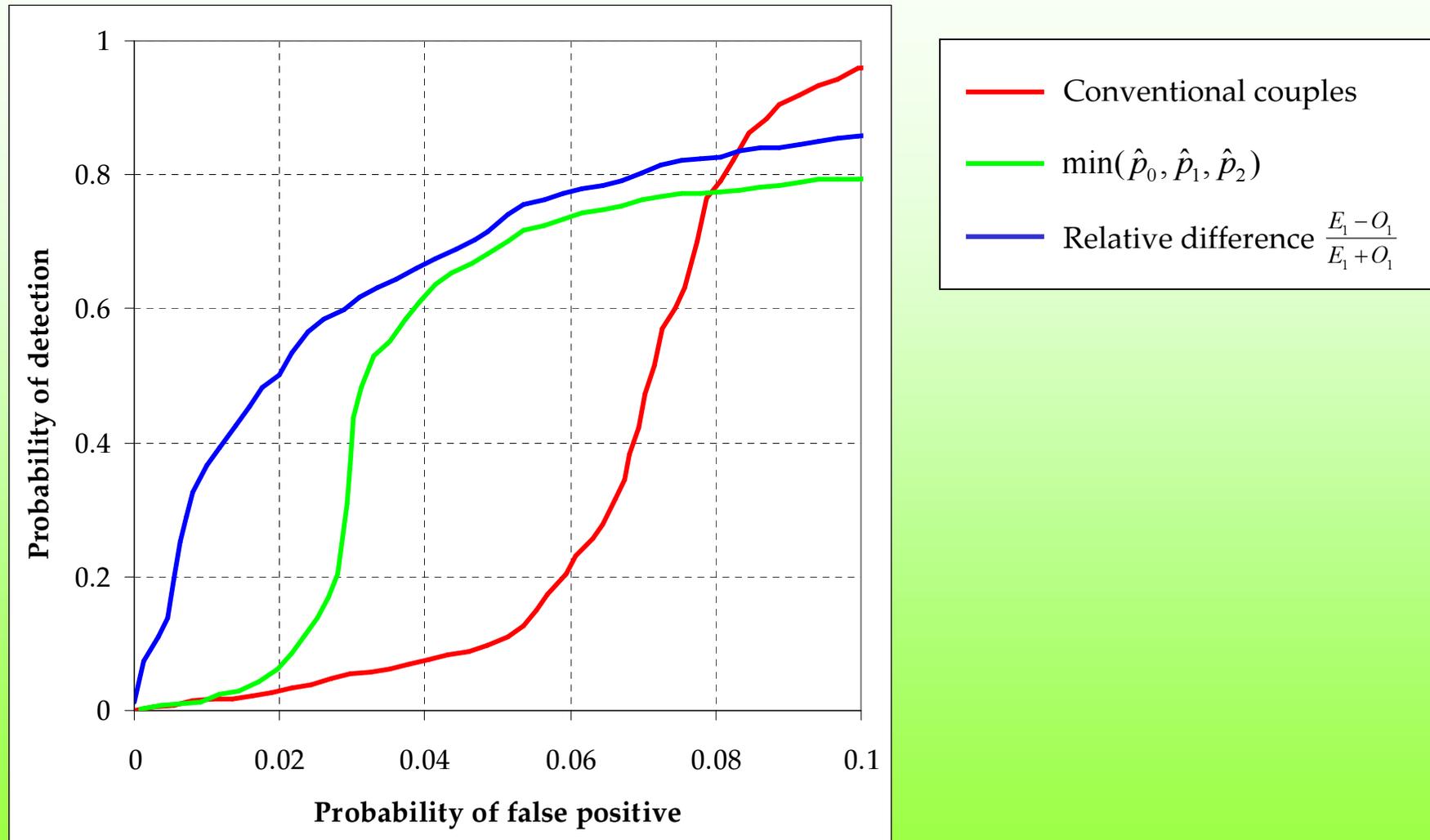


# Dropping the Message-Length Estimate

There is a much simpler sign that data has been embedded, which does not involve solving a quadratic equation:



# Dropping the Message-Length Estimate



ROC curves generated from 15000 mixed JPEG images, 3% embedding.

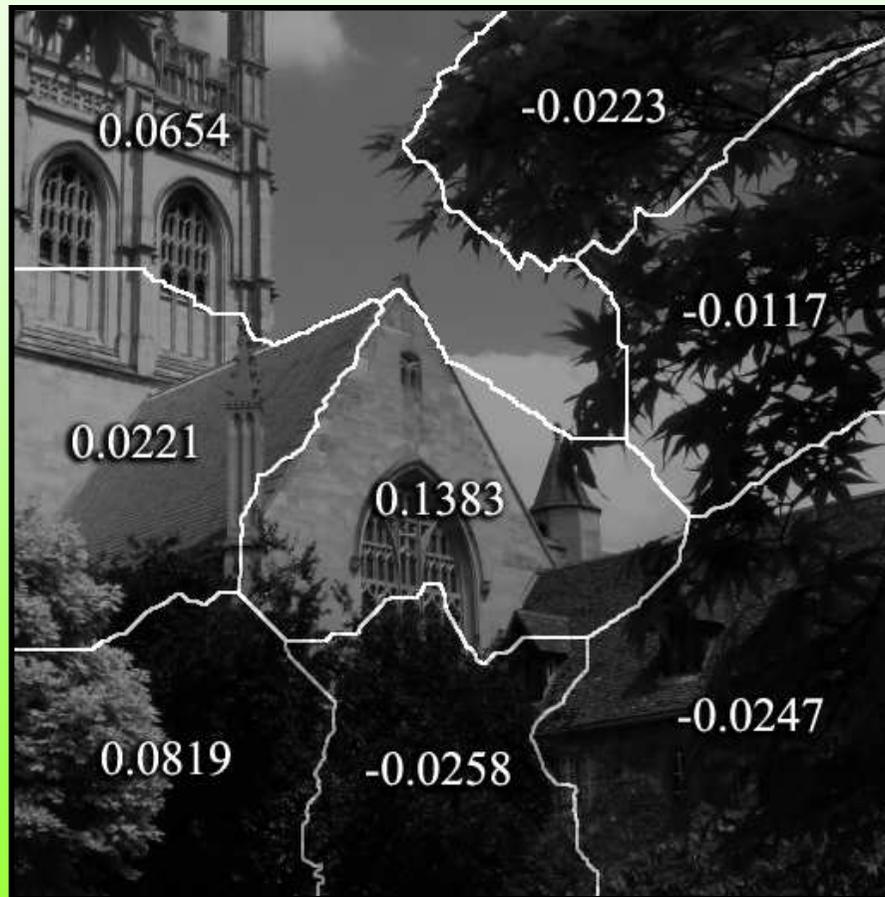
# Splitting into Segments

Using the standard RS method this image, which has no hidden data, estimates an embedding rate of 6.5%.



# Splitting into Segments

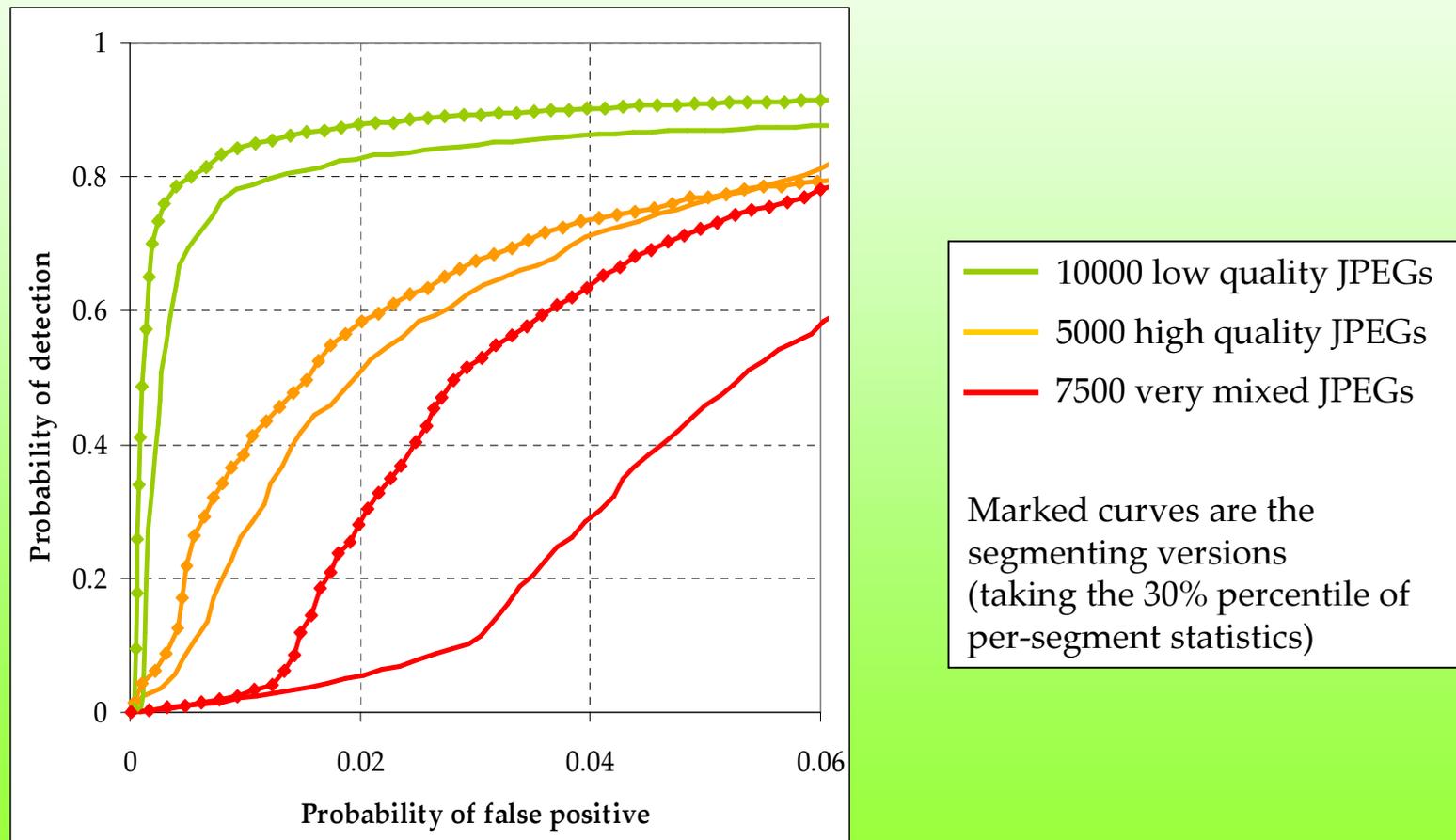
Segment the image using the technique in [Felzenszwalb & Huttenlocher, IEEE CVPR '98] and compute the RS statistic for each segment.



Taking the median gives a more robust estimate, in this case of 0.5%.

# Result of Segmenting

Segmenting is a “bolt on” which can be added to any other estimator. Here, to the modified RS method which computes the relative difference between  $R$  and  $R'$  (analogous to  $E_1$  and  $O_1$ ).



ROC curves from three image sets. 3% embedding.

# Experimental Evidence of Improvements

We have computed very many ROC curves which depend on:

- which cover image set was used;
- (if not JPEG compressed already) how much JPEG pre-compression applied;
- how much data was hidden;
- which detection statistic is used as a discriminator.

There are too many curves. The database of statistic computations is 4.3Gb!

... How to display all this data?

*We make an arbitrary decision that a “reliable” statistic is one which makes false positive errors at less than 5% when false negatives are 50%.*

For each statistic and image set display the lowest embedding rate at which this reliability is achieved.

*Lowest embedding rate for which 50% false negatives achieved with no more than 5% false positives:*

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Conventional Pairs

[Fridrich *et al*, SPIE EI'03]

Conventional RS

[Fridrich *et al*, ACM Workshop '01]

Conventional Couples

[Dumitrescu *et al*, IHW'02]

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RS w/ optimal mask

Improved Pairs

} [Ker, SPIE EI'04]

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Improved Couples  $\min(\hat{p}_0, \hat{p}_1, \hat{p}_2)$

Relative difference of  $E_1$  &  $O_1$   
(using non-overlapping pixel groups)

Relative difference of  $R, R'$   
(using optimal mask and non-overlapping pixel groups and segmenting the image into 6-12 groups, taking 30<sup>th</sup> percentile of the per-segment statistics)

} Presented here

*Lowest embedding rate for which 50% false negatives achieved with no more than 5% false positives:*

2200 bitmaps

Conventional Pairs	10%
Conventional RS	11%
Conventional Couples	9%
RS w/ optimal mask	10%
Improved Pairs	8%
Improved Couples $\min(\hat{p}_0, \hat{p}_1, \hat{p}_2)$	<b>3.2%</b>
Relative difference of $E_1$ & $O_1$ (using non-overlapping pixel groups)	8.5%
Relative difference of $R, R'$ (using optimal mask and non-overlapping pixel groups and segmenting the image into 6-12 groups, taking 30 <sup>th</sup> percentile of the per-segment statistics)	--

*Lowest embedding rate for which 50% false negatives achieved with no more than 5% false positives:*

	2200 bitmaps + JPEG compression	
	<i>none</i>	<i>q.f. 50</i>
Conventional Pairs	10%	6%
Conventional RS	11%	5.5%
Conventional Couples	9%	5%
RS w/ optimal mask	10%	5%
Improved Pairs	8%	2.8%
Improved Couples $\min(\hat{p}_0, \hat{p}_1, \hat{p}_2)$	<b>3.2%</b>	1.8%
Relative difference of $E_1$ & $O_1$ (using non-overlapping pixel groups)	8.5%	<b>0.8%</b>
Relative difference of $R, R'$ (using optimal mask and non-overlapping pixel groups and segmenting the image into 6-12 groups, taking 30 <sup>th</sup> percentile of the per-segment statistics)	--	--

*Lowest embedding rate for which 50% false negatives achieved with no more than 5% false positives:*

	2200 bitmaps + JPEG compression		5000 JPEGs (high quality)	10000 JPEGs (low quality)	7500 JPEGs (very mixed)
	none	q.f. 50			
Conventional Pairs	10%	6%	4%	1.8%	7%
Conventional RS	11%	5.5%	2.8%	1.6%	7%
Conventional Couples	9%	5%	3%	1.4%	6.5%
RS w/ optimal mask	10%	5%	2.2%	1.2%	5.5%
Improved Pairs	8%	2.8%	3%	1.2%	5%
Improved Couples $\min(\hat{p}_0, \hat{p}_1, \hat{p}_2)$	<b>3.2%</b>	1.8%	2%	3.8%	3.6%
Relative difference of $E_1$ & $O_1$ (using non-overlapping pixel groups)	8.5%	<b>0.8%</b>	2.4%	0.6%	2.8%
Relative difference of $R, R'$ (using optimal mask and non-overlapping pixel groups and segmenting the image into 6-12 groups, taking 30 <sup>th</sup> percentile of the per-segment statistics)	--	--	<b>1.4%</b>	<b>0.5%</b>	<b>2.0%</b>

The End