

Optimally Weighted Least-Squares Steganalysis



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Outline

- Least-squares steganalysis
- Derivation of error distribution for least-squares detectors
- Optimally weighted least-squares detectors
- Experimental results

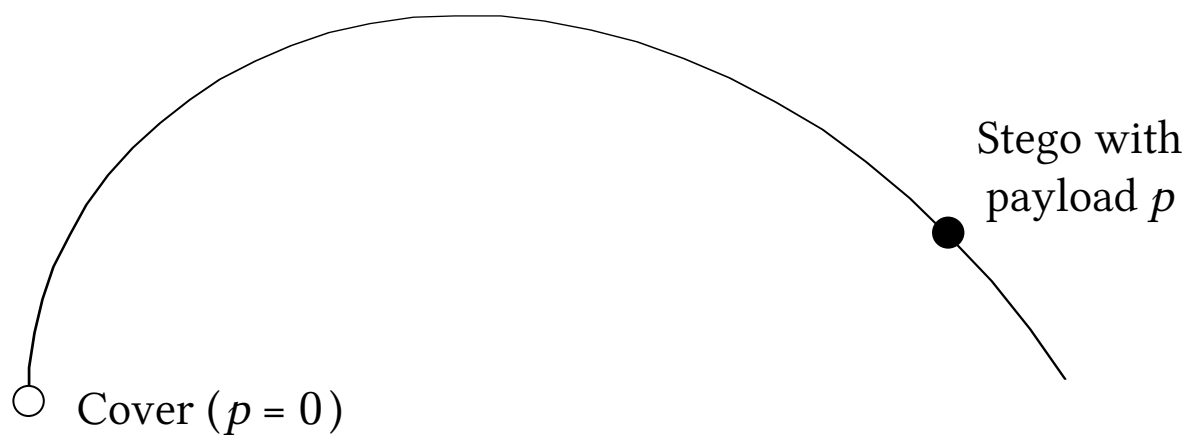
Least-Squares Structural Steganalysis

P. Lu *et al*, *An Improved Sample Pairs Method for Detection of LSB Embedding*, Proc. 6th Information Hiding Workshop, Springer LNCS, 2004.

A. Ker, *A General Framework for Structural Steganalysis of LSB Replacement*, Proc. 7th Information Hiding Workshop, Springer LNCS, 2005.

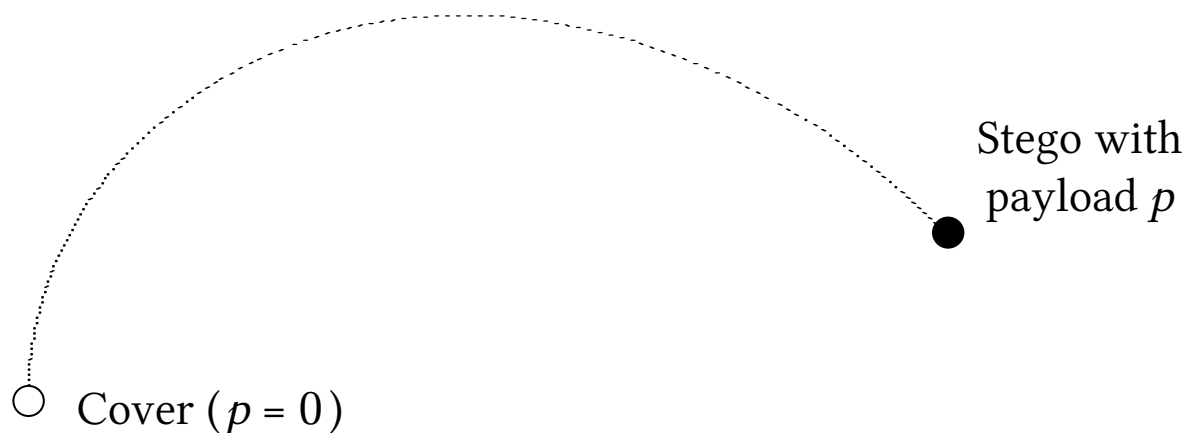
Least-Squares Structural Steganalysis

1. Consider some feature space;
2. Given cover, compute how features vary with payload size;



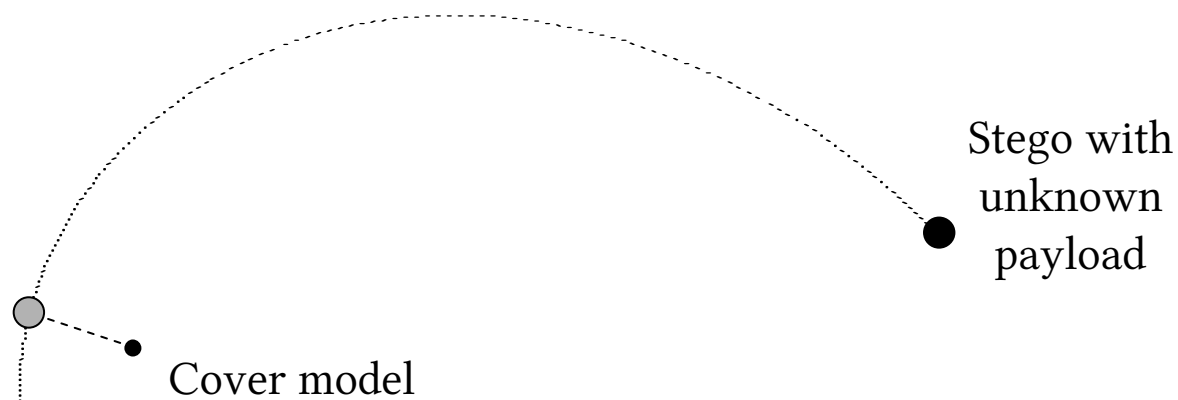
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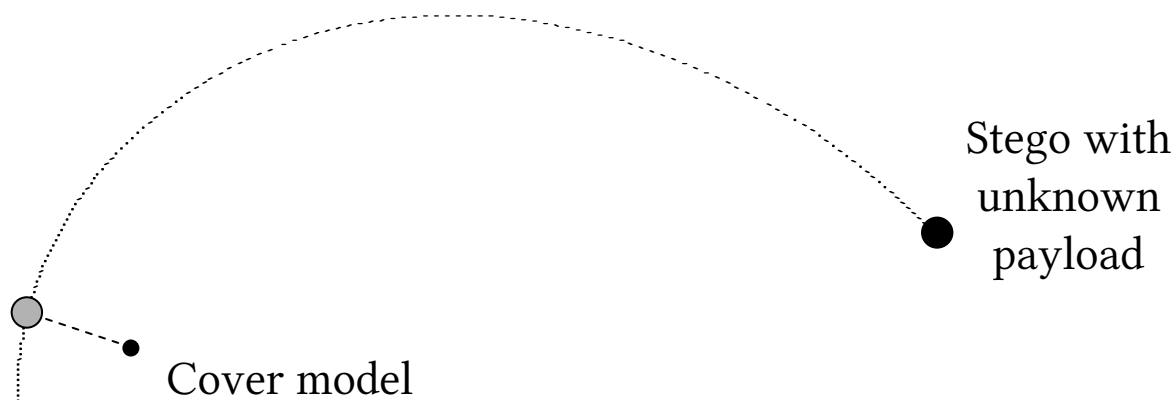
Least-Squares Structural Steganalysis

1. *Consider some feature space;*
2. *Given cover, compute how features vary with payload size;*
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4. *Formulate a model for features of covers;*



Least-Squares Structural Steganalysis

1. Consider some feature space;
2. Given cover, compute how features vary with payload size;
3. Invert: given stego object and payload size, determine the features of the implied cover;
4. Formulate a model for features of covers;
5. Payload estimator is value which minimizes **sum-square deviation** from ideal cover.



“Couples” Feature Vector

The detector *Couples/LSM* is based on the following observations of a series of samples:

$e_m = \#$ adjacent samples with second m larger than first, and first sample even

$o_m = \#$ adjacent samples with second m larger than first, and first sample odd

Feature vector z :

$$z_m = e_{2m+1} - o_{2m+1}$$

Cover model:

$$\forall m. z_m = 0$$

“Couples” Feature Vector

The detector *Couples/LSM* is based on the following observations of a series of samples:

$e_m = \#$ adjacent samples with second m larger than first, and first sample even

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$d_m = \#$ adjacent samples with second m larger than first

Feature vector \mathbf{z} :

$$z_m = e_{2m+1} - o_{2m+1}$$

Cover model:

~~$\forall m. z_m = 0$~~ $z_m \sim N(0, d_{2m+1})$

Derivation of Error Distribution

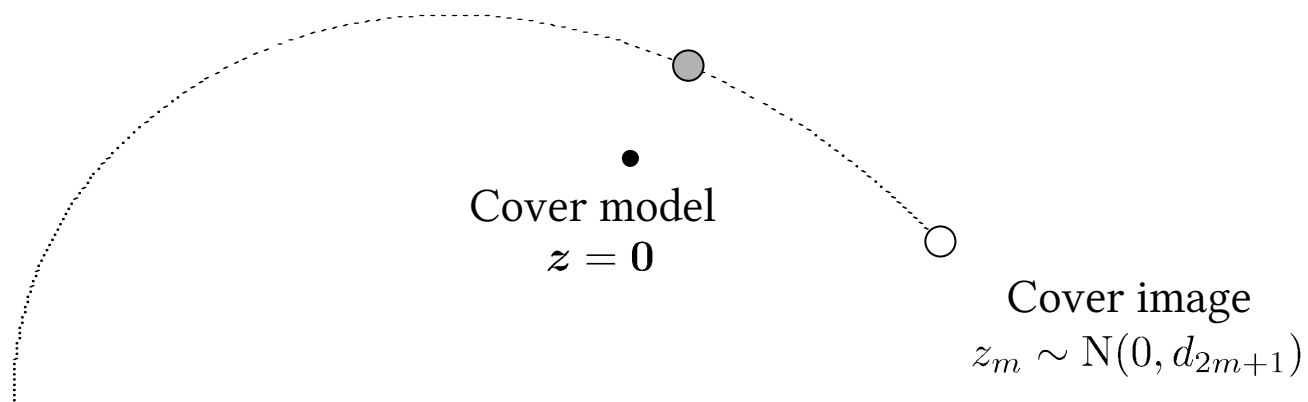
Suppose that NO payload is embedded.

•
Cover model
 $z = 0$

○
Cover image
 $z_m \sim N(0, d_{2m+1})$

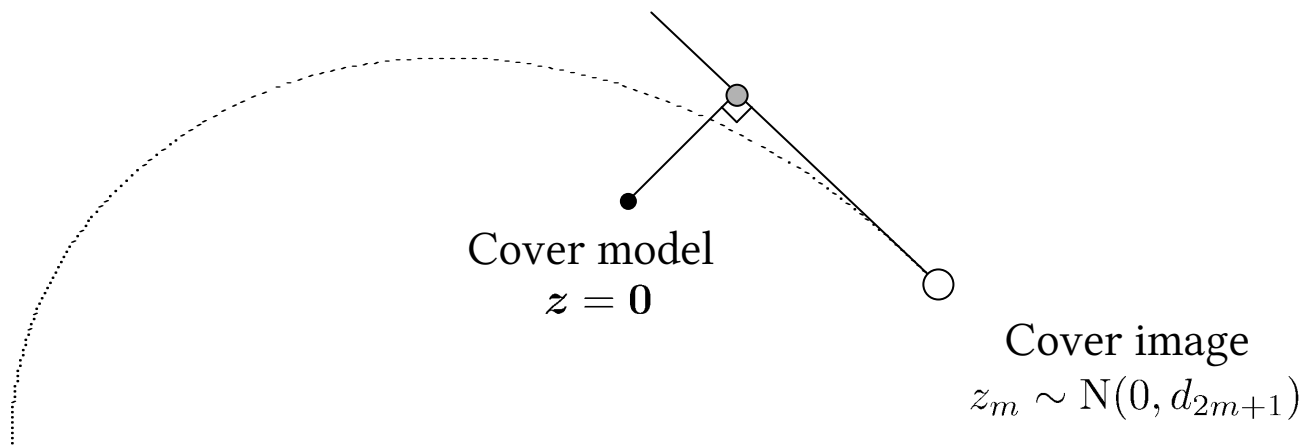
Derivation of Error Distribution

Suppose that NO payload is embedded.



Derivation of Error Distribution

Suppose that NO payload is embedded.



Error Distribution

Suppose that NO payload is embedded.

Then the distribution of the *Couples/LSM* estimator \hat{p} is (approximately)

$$\hat{p} \approx N(\mu(\mathbf{d}), v(\mathbf{d}))$$

where

$$v(\mathbf{d}) = \frac{4 \sum_m (d_{2m+2} - d_{2m})^2 d_{2m+1}}{(\sum_m (d_{2m+2} - d_{2m})^2)^2}$$
$$\mu(\mathbf{d}) = 2v(\mathbf{d}) - \frac{4 \sum_m d_{2m+1}}{\sum_m (d_{2m+2} - d_{2m})^2}.$$

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Improvement 1: subtract bias $\mu(\mathbf{d})$.

Improvement 2: downplay images with high $v(\mathbf{d})$.

Weighted Least-Squares

In our feature space, are all dimensions equal?

Consider minimising not the sum-square deviation from the cover model

$$\sum z_m^2$$

but a **weighted** sum-square deviation:

$$\sum w_m z_m^2$$

where w is a vector of weights.

Error Distribution

Suppose that NO payload is embedded.

Then the distribution of the *Couples/WLSM* estimator \hat{p} is (approximately)

$$\hat{p} \approx N(\mu(\mathbf{d}, \mathbf{w}), v(\mathbf{d}, \mathbf{w}))$$

where

$$v(\mathbf{d}, \mathbf{w}) = \frac{4 \sum_m w_m^2 (d_{2m+2} - d_{2m})^2 d_{2m+1}}{(\sum_m w_m (d_{2m+2} - d_{2m})^2)^2}$$
$$\mu(\mathbf{d}, \mathbf{w}) = 2v(\mathbf{d}, \mathbf{w}) - \frac{4 \sum_m w_m d_{2m+1}}{\sum_m w_m (d_{2m+2} - d_{2m})^2}.$$

Improvement 3: we can minimize the estimator variance $v(\mathbf{d}, \mathbf{w})$ if we choose

$$w_m = \frac{1}{d_{2m+1}}.$$

Extension to “Triples” Structure

The *Triples/LSM* features are rather similar:

$e_{m,n}$ = # triplets with successive differences of m , n , and first sample even

$o_{m,n}$ = # triplets with successive differences of m , n , and first sample odd

The cover model is $z_{m,n} = e_{2m+1,2n+1} - o_{2m+1,2n+1} = 0$

- The *Triples/LSM* estimator is better than *Couples/LSM*.
- *Triples/WLSM* is derived analogously to *Couples/WLSM*.

Caveats

Two reasons why the “optimal” weighting is not quite truly optimal:

1. Error distribution result only accurate for $p=0$, so weights for *stego images* will be suboptimal.

By continuity, expect that these weights will be “almost optimal” for “small payloads”.

2. Cover model is not very accurate for the particular cases $m=-1$ and 0

Weighting for these two components will be suboptimal.

Experimental Results

Used multiple cover sets including never-compressed and JPEG-compressed, colour and greyscale. Tested accuracy of:

1. Estimation of payload size.
2. Discrimination of innocent covers from payload-carrying objects.

Experimental Results

1. Estimation of payload size

Weighting decreases $v(\mathbf{d})$ by around 10-30%

...but increases $\mu(\mathbf{d})$ by as much as a factor of 100.

But

- *as long as the bias is subtracted, and*
- *as long as the true embedding rate is below $p=0.2$,*

overall weighted estimator errors are decreased correspondingly.

Experimental Results

2. Discrimination of covers and stego objects

There are many different metrics for this reliability. We use

Lowest payload for which, at worst, 5% false positives and 50% false negatives are observed.

Also in the paper:

Lowest payload for which, at worst, 0.1% false positives and 50% false negatives are observed.

Experimental Results

2. Discrimination of covers and stego objects

Lowest payload for which, at worst, 5% false positives and 50% false negatives are observed.

	Images scanned from film (0.3Mpixel)	
	Grayscale covers	Colour covers
<i>Couples/LSM</i> [Lu et al, IHW 2004]	4.5%	6.0%
<i>Couples/WLSM</i>	4.0%	5.6%
<i>Triples/LSM</i> [Ker, IHW 2005]	3.3%	4.1%
<i>Triples/WLSM</i>	2.8%	3.5%

Experimental Results

2. Discrimination of covers and stego objects

Lowest payload for which, at worst, 5% false positives and 50% false negatives are observed.

	RAW images direct from digital cameras (1.5Mpixel)	
	Grayscale covers	Colour covers
<i>Couples/LSM</i> [Lu et al, IHW 2004]	1.87%	0.87%
<i>Couples/WLSM</i>	0.79%	0.76%
<i>Triples/LSM</i> [Ker, IHW 2005]	0.51%	0.34%
<i>Triples/WLSM</i>	0.40%	0.24%

Conclusions

- The error derivation theory has an immediate application in finding optimal weights for least-squares structural steganalysis.

A number of other improvements are outlined in the paper.

- Weighting improves estimator accuracy by 10-30% (for small payloads only!) and allows for discrimination of payloads 10-50% smaller.

It seems surprising that “unweighted” methods were not further from optimal weights.

- It would be valuable to extend the error distribution result to nonzero payloads, or otherwise derive optimal weighting for this case.

End