Quantitative and Binary Steganalysis in JPEG: A Comparative Study

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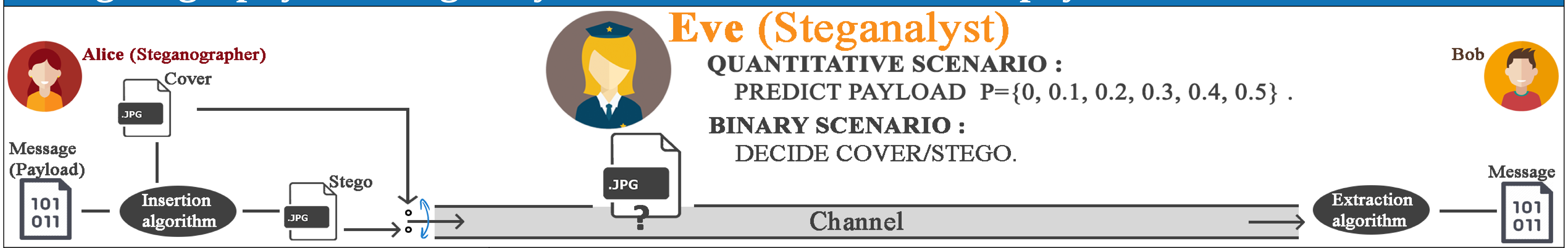
➢Steganography and Steganalysis in JPEG with unknown payload



- **Steganography:**
  - J-UNIWARD algorithm [1].
- **Steganalysis:**
  - Extraction of Gabor Filter Residual features [2].
  - Supervised Machine Learning approach.
  - Note that there is no assumption on the payload.

❑ Quantitative algorithm

- **QS algorithm [3]:** Machine Learning regression framework.
  - It assembles, via the process of *gradient boosting*, a large number of simpler *base learners* built on random subspaces of the original *high dimensional feature space*.
  - Each *base learner* is a Regression Tree adapted to reflect the specific nature of high dimensional feature spaces in Steganalysis.

❑ Binary algorithm

- **GLRT algorithm [4]:** it leverages the advantages of *Optimal Detectors* and *Steganalysis machine learning* approaches to employ an accurate statistical model for the base learners' projections in an Ensemble classifier.
  - Each base learner is a *Fisher Linear Discriminant* (FLD) classifier:
    - Each FLD is trained on a uniformly randomly selected subset of features,
    - Its projection is cast within *hypothesis testing theory*.

How to compare algorithms?

The results of the two algorithms are in **different forms**: cover/stego (binary), payload (float)

→ **Post-process them in order to compare QS and GLRT algorithms in Quantitative or Binary scenarios.**

➢Quantitative Scenario

- Construct two quantitative algorithms, the **GLRT-multiclass** and the **GLRT-regression** from the **GLRT** algorithm and compare with the **QS** algorithm.

➢Binary Scenario

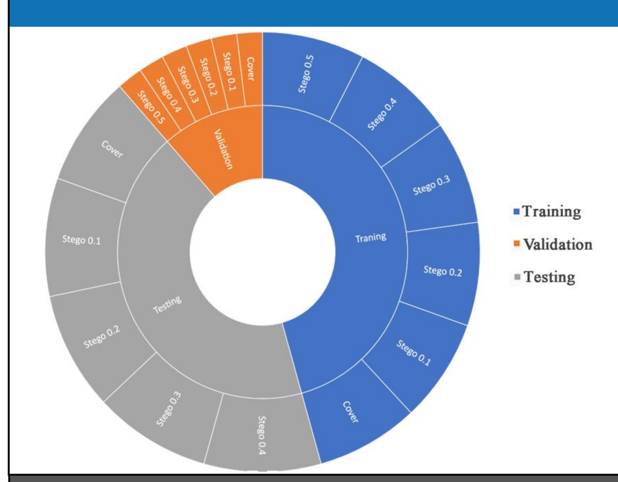
- Construct a *Binary Steganalysis algorithm* (called **QS-binary**) from the **QS** algorithm and compare with the **GLRT** algorithms.

Adaptation

- **GLRT-regression**: piecewise linear regression model, trained on a set of scores given from the GLRT classifier, to estimate the payloads.
- **GLRT-multiclass**: a multi-class classifier by calculating the maximum of votes given by applying the GLRT between each couple of payload classes.

QS-binary: thresholding to transform the estimated payloads given by the QS algorithm into a binary decision (cover/stego).

Dataset of images



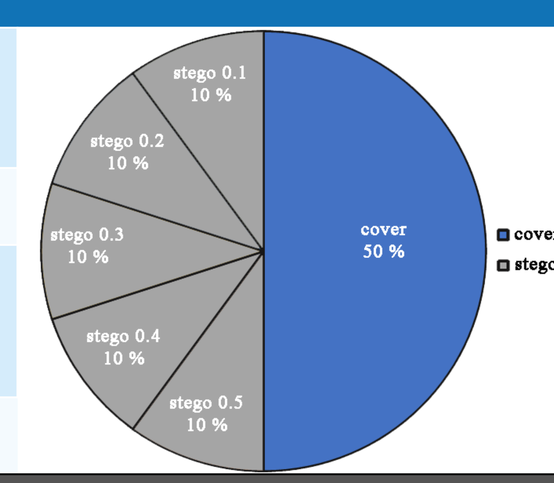
20,000 images, 50% cover and 50% stego.

J-UNIWARD steganographic algorithm.

- 6 payloads: 0, 0.1, 0.2, 0.3, 0.4, 0.5 (same ratio)
- ~50% training & ~50% testing
- Training: 8400,Validation: 2100, Testing: 9500.

- Stegos= {0.1, 0.2, 0.3, 0.4, 0.5} bpnzAC
- 50% training & 50% testing

17,000-dimensional feature vectors from the cover and stego images, using GFR.



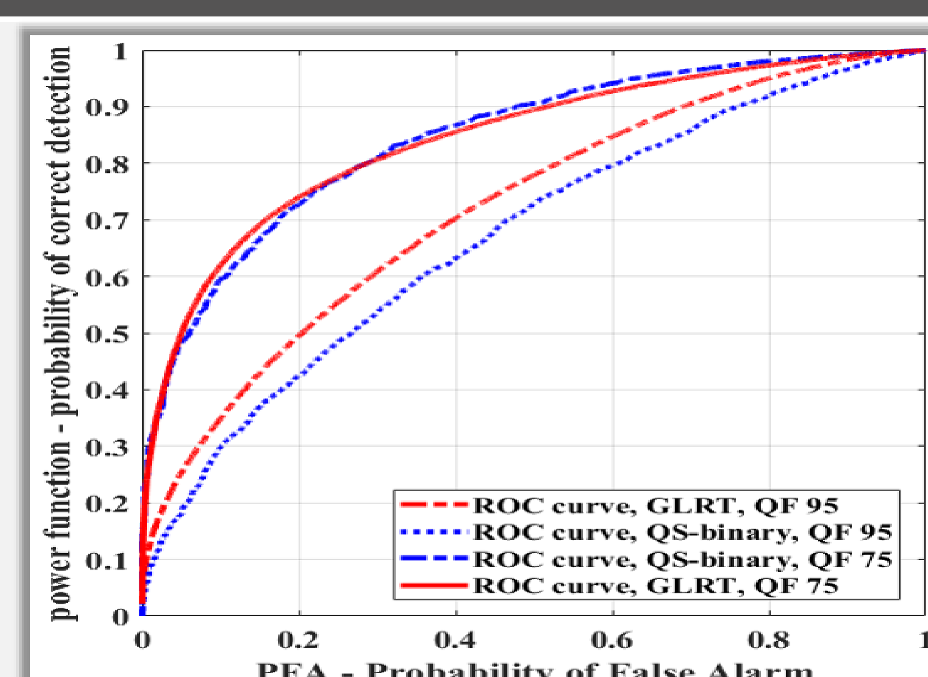
Results

Average predicted error (AVG), Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) for Quality Factor 75 and 95

Payload	GLRT-regression			GLRT-multiclass			QS		
	QF 75								
	AVG	RMSE	MAE	AVG	RMSE	MAE	AVG	RMSE	MAE
0	0.0541	0.096	0.0541	0.0692	0.1298	0.0692	0.1312	0.1568	0.1312
0.1	0.1334	0.1229	0.0989	0.1197	0.1309	0.1017	0.1645	0.1094	0.0812
0.2	0.1614	0.1355	0.1141	0.1876	0.1359	0.107	0.2182	0.0919	0.0749
0.3	0.2292	0.1544	0.129	0.2868	0.1331	0.098	0.2883	0.0909	0.0745
0.4	0.2826	0.1858	0.1495	0.3797	0.1148	0.0809	0.3623	0.0919	0.0704
0.5	0.3524	0.2103	0.1477	0.4548	0.0949	0.0452	0.4251	0.1021	0.0759
All		0.1508			0.1232			0.1071	
	QF 95								
	AVG	RMSE	MAE	AVG	RMSE	MAE	AVG	RMSE	MAE
0	0.0908	0.1498	0.0908	0.1494	0.2362	0.1494	0.2413	0.2506	0.2413
0.1	0.1431	0.1566	0.1224	0.1627	0.1925	0.1527	0.2478	0.1625	0.1478
0.2	0.1393	0.1466	0.1266	0.2084	0.1886	0.1646	0.2613	0.0916	0.0736
0.3	0.1826	0.1967	0.1703	0.2619	0.1896	0.1589	0.2816	0.0731	0.0599
0.4	0.27	0.22	0.1796	0.342	0.1838	0.1368	0.3096	0.1166	0.0986
0.5	0.2821	0.2795	0.218	0.3993	0.1874	0.1007	0.3422	0.1747	0.158
All		0.1915			0.1963			0.1448	

Probability of error P_e for Quality Factor 75 and 95

	QS-binary	GLRT
QF 75	0.2479	0.2275
QF 95	0.3795	0.3438



Empirical ROC curves for Quality Factor 75 and 95

Conclusion

- **For high payloads:** the QS approach provides better results than the GLRT-regression and the GLRT-multiclass.
- **For low payloads:** the GLRT approach gives better results.

- **For high and low payloads:** the detection power is better for GLRT approach whatever the training scenario (clairvoyant, payload mixture or fixed payload) compared to the QS-binary approach.

In our future work on pooled steganalysis, we will use the GLRT approach, since it is better for small payloads.

This comparison could also include a recent Deep Learning-based quantitative steganalysis algorithm [5].

➢ References

[1] V. Holub, J. Fridrich, and T. Denemark, "Universal distortion function for steganography in an arbitrary domain," EURASIP Journal on Information Security, vol. 2014, no. 1, p. 1, 2014.
[2] X. Song, F. Liu, C. Yang, X. Luo, and Y. Zhang, "Steganalysis of adaptive JPEG steganography using 2D Gabor filters," in 3rd ACM Workshop on Information Hiding and Multimedia Security. pp. 15–23, ACM, 2015.
[3] J. Kodovsky and J. Fridrich, "Quantitative steganalysis using rich models," in Media Watermarking, Security, and Forensics 2013, vol. 8665. International Society for Optics and Photonics, p. 0O 1-11, 2013.
[4] R. Cogranne and J. Fridrich, "Modeling and extending the ensemble classifier for steganalysis of digital images using hypothesis testing theory," IEEE Trans. on Information Forensics and Security, vol. 10, no. 12, 2015.
[5] M. Chen, M. Boroumand, and J. Fridrich, "Deep Learning Regressors for Quantitative Steganalysis," Proc. IS&T, Electronic Imaging, Media Watermarking, Security, and Forensics 2018, February, 2018.

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