# Score-Based Likelihood Ratios for Camera Device Identification

Stephanie Reinders, Yong Guan, Danica Ommen, and Jennifer Newman

Iowa State University

## Project Rational & Goals

**EVIDENCE.** An investigator has two pieces of evidence:

1. A digital image $I_u$ involved in a crime where $I_u$ is from an *unknown source (camera)*. The image $I_u$ is called the *questioned image*.
2. A digital *camera fingerprint* $F_k$ from a suspect's camera $\boldsymbol{C}_k$. The camera $\boldsymbol{C}_k$ is called the *specific known device*.

**KEY QUESTIONS.** How likely is it that the questioned image originated from the specific known source? How likely is it that the questioned image did not originate from the specific known source?

**HYPOTHESES.** The key questions are often expressed as two competing, *specific-source* hypotheses [1]:

$H_p$: image $I_u$ and camera fingerprint $F_k$ both originated from camera $C_k$

$H_d$: camera fingerprint $F_k$ originated from camera $C_k$ but image $I_u$ did not

**GOAL.** Implement three types of *score-base likelihood ratios* to evaluate the strength of the evidence with regard to the specific-source hypotheses and perform experiments on a wide range of camera models and devices.

## Materials & Methods

### TOOLS

- *Photo-response non-uniformity (PRNU)* [2] refers to slight variations in the pixels in a camera's sensor array caused during manufacturing. PRNU is an identifying characteristic, or *camera fingerprint*, and is estimated from *noise residuals*, images minus denoised versions.
- We measure the similarity between a noise residual $X_u$ from questioned image $I_u$ and a camera fingerprint $F_k$ with a *similarity score* $\Delta$, the *correlation distance* (1 minus the sample correlation):

$$\delta = \Delta(X_u, I_u F_k).$$

**SCORE-BASED LIKELIHOOD RATIOS (SLR).** Many forensic fields, including handwriting [3], glass fragments [4], and shoe impressions [4], have used SLRs, but SLRs have only been applied to small datasets for camera device identification and each research group focused on a single SLR type [5-7]. Building upon this previous work, we evaluate all three types of specific-source SLRs on a large dataset of 48 cameras representing 26 models.

**What is the probability of obtaining $\delta$ if $H_p$ is true? If $H_d$ is true? An SLR is the ratio between these two probabilities and quantifies the strength of the evidence.**

$$SLR_{source} = \frac{P(\delta \mid H_p)}{P(\delta \mid F_k, H_d)}, \qquad SLR_{trace} = \frac{P(\delta \mid H_p)}{P(\delta \mid I_u, H_d)}, \qquad SLR_{general} = \frac{P(\delta \mid H_p)}{P(\delta \mid H_d)}$$

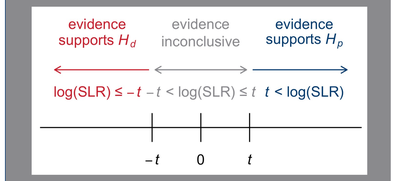
$P(\cdot)$ is a joint probability density function estimated from reference sets of *matching* (same specific source) or *non-matching scores* (different source) using kernel density estimation.

**DATASET.** We use 4,800 images (100 images from each camera) from 48 cameras, representing 26 camera models, from 4 image databases [8-11]. 80 images from each camera are used to estimate camera fingerprints and build reference sets of scores. 20 images from each camera are questioned images. For each questioned image, we set each of the 48 cameras as the specific known device (suspect's camera) in turn, and calculate the general match, source-anchored, and trace-anchored SLRs.

## Results

### Interpreting SLR values

**FIGURE 1.** An SLR value supports $H_p$ if $\log_{10}(SLR)$ is greater than an inconclusive threshold $t \geq 0$. If $\log_{10}(SLR)$ is less than or equal to -$t$ it supports $H_d$. Otherwise, the SLR is inconclusive.

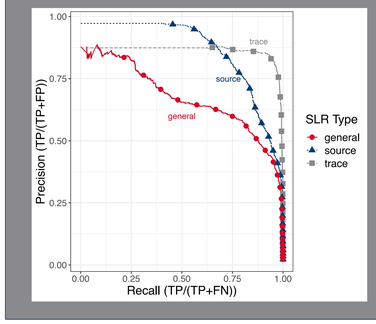



### Evaluation measures

- *True Positives (TP)* = the number of SLRs that correctly support $H_p$
- *True Negatives (TN)* = the number of SLRs that correctly supports $H_d$
- *False Positives (FP)* = the number of SLRs that incorrectly support $H_p$ when $H_d$ is true
- *False Negatives (FN)* = the number of SLRs that incorrectly support $H_d$ when $H_p$ is true

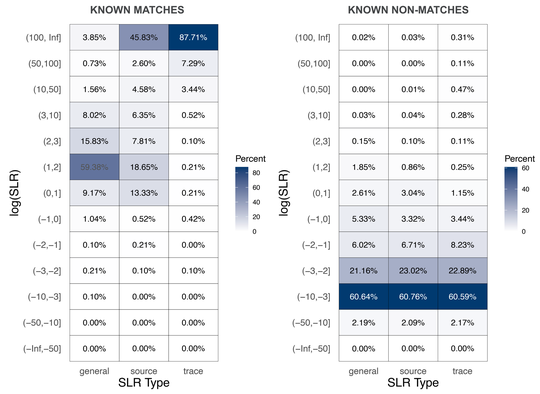
### Overall performance

**FIGURE 2.** The precision-recall (PR) curves compare overall performance of the general match, source-anchored, and trace-anchored SLRs. The closer a model gets to precision and recall equal to 1, the better it performs. (These PR curves were constructed with an inconclusive threshold of $t = 0$.)



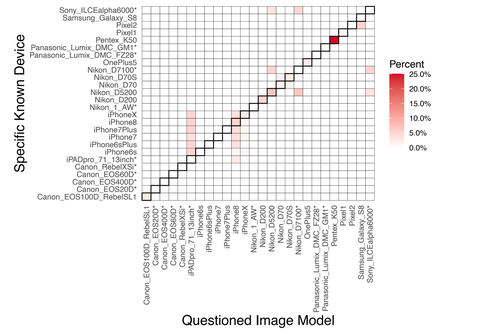

### What is the strength of the evidence in favor of $H_p$ or $H_d$?

**FIGURE 3.** The plots display the percentages of $\log_{10}(SLR)$ values for each SLR type that belong to each interval. [Left] The $\log_{10}(SLR)$ values from known matches ($H_p$ is true). [Right] The $\log_{10}(SLR)$ values from known non-matches ($H_d$ is true).




### Are false positive rates high among cameras of the same model?

**FIGURE 5.** The plot displays percentages of false positives by camera model for source-anchored SLRs and inconclusive threshold $t = 2$. Models that only have a single camera are denoted with an asterisk at the end of their name. All other models have 2, 3, or 4 cameras. Single camera models are included in this plot because they may produce false positives with devices of different models.




### Can we decrease the false positive rate by increasing the inconclusive threshold $t$? What is the trade-off?

**FIGURE 4.** Each column of plots shows results for a different inconclusive threshold $t = 0, 1, 2, 3, 4$. The plots on the top display the percentages of known matches ($H_p$ is true) whose $\log_{10}(SLR)$ values are true positives, inconclusive, and false negatives. The plots on the bottom display the percentages of known non-matches ($H_d$ is true) whose $\log_{10}(SLR)$ values are false positives, inconclusive, and true negatives.


## Discussion & Future Work

- In cases where the questioned document originated from the specific known device ($H_p$ is true), 87.71% of the trace-anchored SLRs provide *extremely strong* [12] support for $H_p$ rather than $H_d$ while only 45.83% of the source-anchored and 3.85% of the general match SLRs provide the same level of support. [See Figure 3]
- In cases where the questioned document did not originate from the specific known device ($H_d$ is true), around 80% of all three types of SLRs provide *strong*, *very strong*, or *extremely strong* [12] support for $H_d$ rather than $H_p$. [See Figure 3]
- Incorporating an inconclusive threshold $t$ lowers the false positive rates for all three SLR types, but as a trade-off the true positive and true negative rates also decrease. [See Figure 4]
- The false positive rates are low between cameras of the same model, expect the Pentex K50, for the source-anchored SLRs and inconclusive threshold $t = 2$. [See Figure 5]
- In future work, we plan to further investigate *close non-matches*, where cameras belong to the same model, with a minimum of 10 cameras per model.

## References

[1] Ommen, Danica and Christopher P. Saunders. "A problem in forensic science highlighting the differences between the Bayes factor and likelihood ratio." *Statistical Science*, 2021 preprint.

[2] Lukas, Jan, Jessica Fridrich, and Miroslav Goljan. "Determining digital image origin using sensor imperfections." In *Image and Video Communications and Processing 2005*, vol. 5685, pp. 249-260. International Society for Optics and Photonics, 2005.

[3] Hepler, Amanda B., Christopher P. Saunders, Linda J. Davis, and JoAnn Buscaglia. "Score-based likelihood ratios for handwriting evidence." *Forensic Science International* 219, no. 1-3 (2012): 129-140.

[4] Park, Soyoung. "Learning algorithms for forensic science applications." Ph.D. dissertation, Iowa State University, 2018.

[5] Nordgaard, Anders and Tobias Höglund. "Assessment of approximate likelihood ratios from continuous distributions: a case study of digital camera identification," *Journal of Forensic Sciences*, vol. 56, no. 2, pp. 390-402, 2011.

[6] van Houten, Wiger, Ivo Alberink, and Zeno Geradts, "Implementation of the likelihood ratio framework for camera identification based on sensor noise patterns," *Law, Probability and Risk*, vol. 10, no. 2, pp. 149-159, 2011.

[7] Reinders, Stephanie, Li Lin, Wenhao Chen, Yong Guan, and Jennifer Newman. "Score-based likelihood ratios for camera device identification." In *Electronic Imaging 2020*, no. 4 (2020): 215-1.

[8] "Alaska version 1," 2019, https://alaska.utt.fr (visited on 12/01/2019).

[9] "Bossbase database," 2010, http://agents.fel.cvut.cz/stegodata/ (visited on 01/04/2019).

[10] "Dresden image database," 2010, http://forensics.inf.tu- dresden.de/ddimgdb/ (visited on 12/01/2019).

[11] "StegoAppDB," 2018, https://forensicstats.org/stegoappdb/ (visited on 12/01/2019).

[12] "ENFSI guideline for evaluative reporting in forensic science: Strengthening the evaluation of forensic results across Europe (STEOFRAE)." *European Network of Forensic Science Institutes*, 2015.

*This work was funded (or partially funded) by the Center for Statistics and Applications in Forensic Evidence (CSAFE) through Cooperative Agreements 70NANB15H176 and 70NANB20H019 between NIST and Iowa State University, which includes activities carried out at Carnegie Mellon University, Duke University, University of California Irvine, University of Virginia, West Virginia University, University of Pennsylvania, Swarthmore College and University of Nebraska, Lincoln.*