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Search Optimization for JPEG Quantization Tables

using a Decision Tree Learning Approach

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| Motivation | | | | |



- Growing popularity for taking pictures
- Digital images often recovered in forensic investigations
- Identify origin of images to a specific camera or common source
- Large sets of images are retrieved

Camera Identification:

- Intrinsic features of camera hardware give more reliable results[2]
- Sensor Imperfections, CFA Interpolation, Image Features

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| Motivation | | | | |

JPEG quantization tables

JPEG compression:

- RGB to Luminance-Chrominance colour space
- Splitting into two 8×8 blocks
- ▶ Discrete Cosine Transform (spatial domain → frequency domain)
- Compression ratio
- Correlated to camera make/model

'..is reasonably effective at narrowing the source of an image to a single camera make and model or to a small set of possible cameras.'[1]

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Decision tree learning algorithm

Camera identification problem \rightarrow pattern recognition problem:

map feature set to corresponding label

Decision tree learning algorithm:

- Rule based, generates best splits
- Simple to interpret / human readable

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| Research Question | | | | |

Research Question

Can searching through JPEG quantization tables be optimized with the use of decision tree learning?

Subquestions:

- 1. Can identifiable parameters be found in JPEG quantization tables?
- 2. What is the performance of decision tree learning with JPEG quantization tables?

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| Overview | | | | |



- 1. Extract quantization tables from images
- 2. Generate feature set
- 3. Train decision tree classifier (make/model)
- 4. Evaluate classifications
- 5. Compare against method using hash database

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| Data Preprocessing and Training | | | | |

Data Preprocessing and Training

1. Extract quantization tables from images

Unix command: djpeg

2. Generate feature set

- > Add features: sum, min, max, mean, median, var, std
- Run feature selection

3. Train decision tree classifier

CART: combines classification and regression trees

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| Evaluation | | | | |

Evaluation

- 4. Evaluate with weighted F_{β} -score
 - ▶ Recall is more important: $\beta = 2$

$$egin{aligned} \mathcal{F}_eta &= 1 + eta^2 * rac{ extsf{precision} * extsf{recall}}{(eta^2 * extsf{precision}) + extsf{recall}} \end{aligned}$$

5. Compare against method using hash database

- Database of hashed quantization tables
 - ► 1→1 mapping
 - ► 1→n mapping
- Use same training and validation data

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Results

Dataset:

- 45,666 images (NFI & Dresden Image Database)
- 41 camera models
- 19 camera makes
- 1,016 unique quantization tables

Identifiable parameters: 50 out of 128 603 nodes, depth of 26



Figure: Partial Decision Tree

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Zoom in: F2-score for camera make

| Make | F2 | Make | F2 |
|-----------|-------|------------|-------|
| Kodak | 99 % | Praktica | 43 % |
| Ricoh | 94 % | Nikon | 86 % |
| Panasonic | 79 % | Casio | 99 % |
| PS | 100 % | Canon | 98 % |
| Olympus | 64 % | Logitech | 100 % |
| Sony | 58 % | Motorola | 100 % |
| Agfa | 78 % | Epson | 100 % |
| Rollei | 84 % | BlackBerry | 100 % |
| Samsung | 67 % | Pentax | 80 % |
| FujiFilm | 96 % | | |

Table: F2-score for camera make

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Decision tree vs Hash databases

- 5-Fold Stratified Cross Validation
- 80 % Train set, 20 % Validation set

| Algorithm | Precision | Recall | F2-score |
|---------------|-----------|--------|----------|
| Hash (1-1) | 79 % | 68 % | 68 % |
| Hash (1-n) | 50 % | 99 % | 83 % |
| Decision tree | 90 % | 89 % | 89 % |

Table: Camera Make Identification

| Algorithm | Precision | Recall | F2-score |
|---------------|-----------|--------|----------|
| Hash (1-1) | 54 % | 39 % | 37 % |
| Hash (1-n) | 50 % | 98 % | 83 % |
| Decision tree | 78 % | 82 % | 80 % |

Table: Camera Model Identification

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- Both methods are prone for overfitting
- Hash database holds larger search space
- Training hash database is quicker

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Conclusions

- Parameters can be reduced to 50
- Decision tree classifier gains better F2-score of 89% (make)
- ▶ $1 \rightarrow N$ hash database gains better F2-score of 83% (model)
- \blacktriangleright Decision tree classifier is more flexible, reduces search space, but harder to train than 1 ${\rightarrow}N$ hash database

Future work:

- Compare to other learning algorithms
 - Naive Bayes
- Extend feature set

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Questions?

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