Median Filtering Forensics Based on Discriminative Multi-Scale Sparse Coding

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- The Proposed Method: DSC
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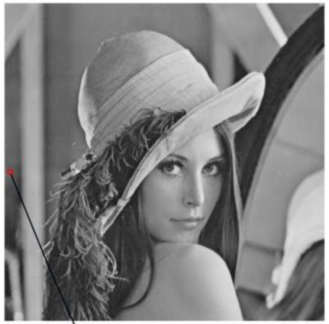
Background: Median Filtering Forensics

Non-median Filtered

Median Filtered

Background: Median Filtering Forensics

Non-median Filtered



96	98	95	99	101
98	99	101	97	95
100	95	99	101	98
98	98	98	98	99
99	96	99	101	97

Median Filtered

98	98	98	98	98
98	98	99	99	99
98	98	98	98	98
98	98	98	99	99
98	98	98	98	98

Background: Median Filtering Forensics

Non-median Filtered

Median Filtered

Median filtering tampering/forgery:

Use median filter to smooth the splicing boundaries

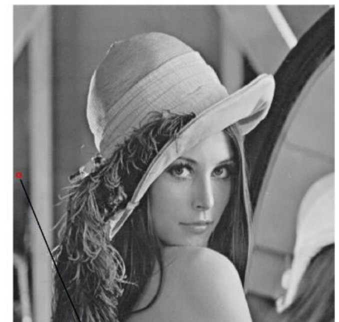
Cover tampering traces in many other image forgeries

Background: Median Filtering Forensics

Non-median Filtered

96	98	95	99	101
98	99	101	97	95
100	95	99	101	98
98	98	98	98	99
99	96	99	101	97

Median Filtered



98	98	98	98	98
98	98	99	99	99
98	98	98	98	98
98	98	98	99	99
98	98	98	98	98

Background: Median Filtering Forensics

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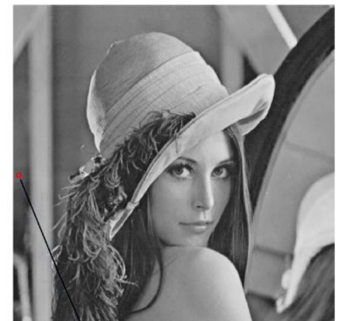
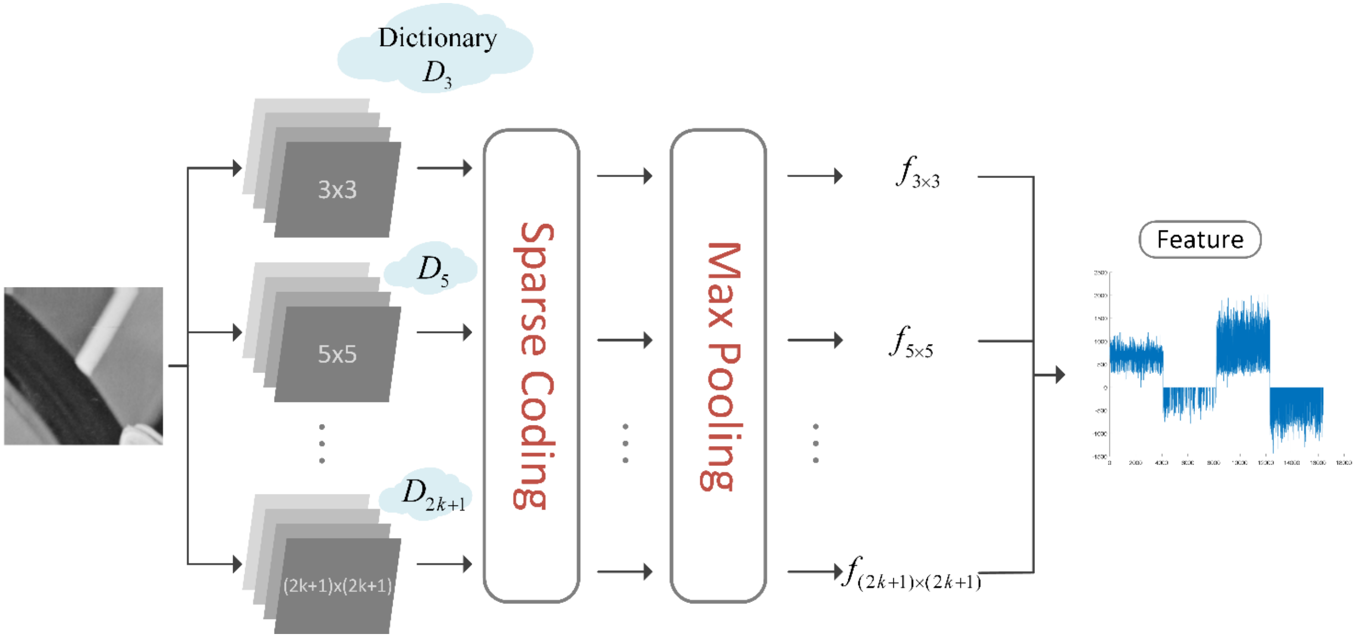
Median Filtered



98	98	98	98	98
98	98	99	99	99
98	98	98	98	98
98	98	98	99	99
98	98	98	98	98

Streak Artifact

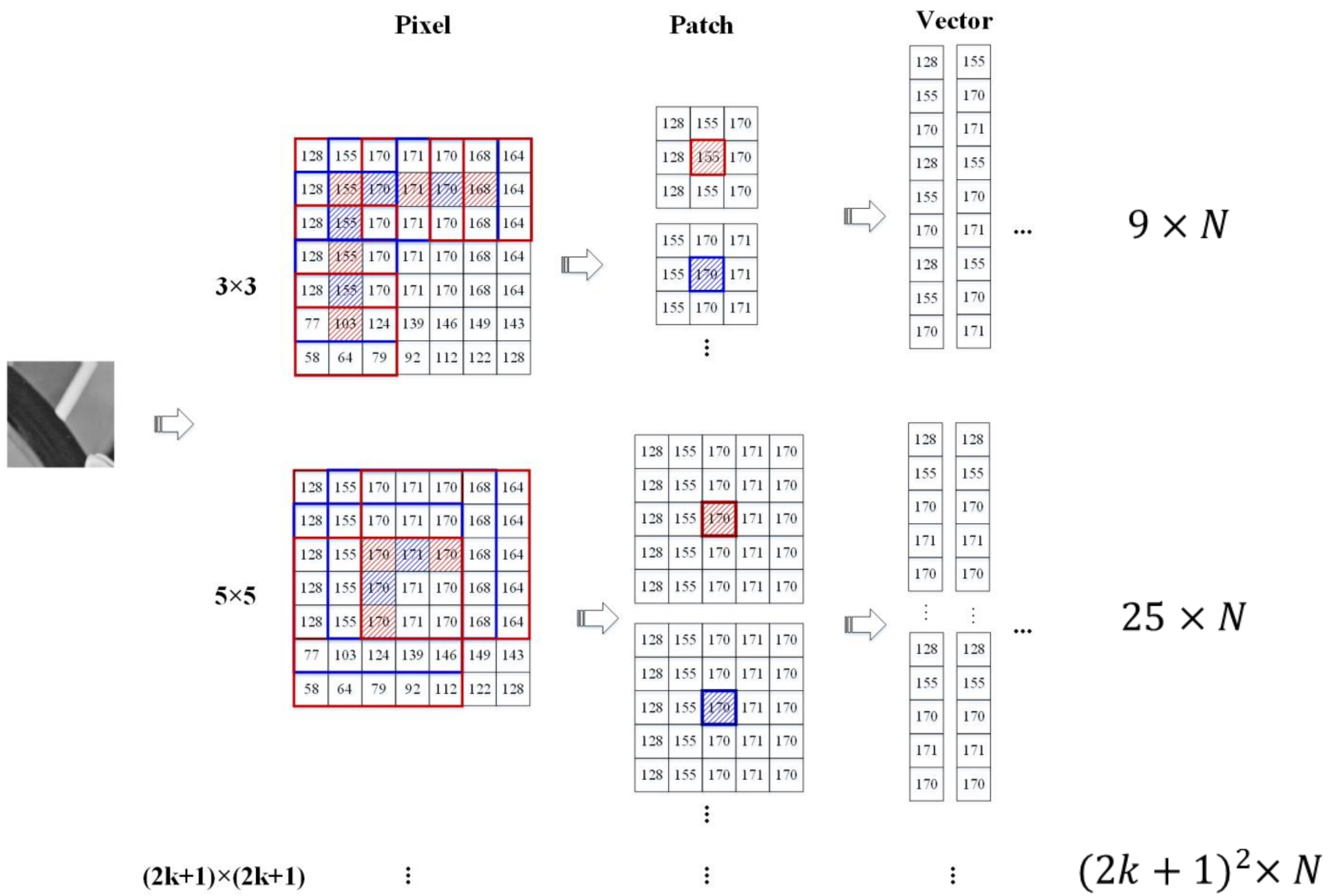
The Proposed Method: DSC



The Flowchart of DSC method:
model image local texture at different level

- Transform the image into different overlapping patches
- Train different discriminative dictionaries for different patches
- Max-pooing to reduce the feature dimension

Feature Extraction



Multi-scale Patch Domain Modeling

Feature Extraction

- Characterizing image patches with sparse codes

$$w = \arg\min_{c \in R^d} ||p - Dc||_2 \; s.t. ||c||_0 \leq T$$

- Discriminative dictionary learning

$$D_{opt} = \arg\min_{D} ||P - DW||_2^2 + \alpha ||L - AW||_2^2 + \beta ||S - BW||_2^2 \quad s.t. \forall i, ||w_i||_0 \leq T$$

- Feature Generation by Max-pooling

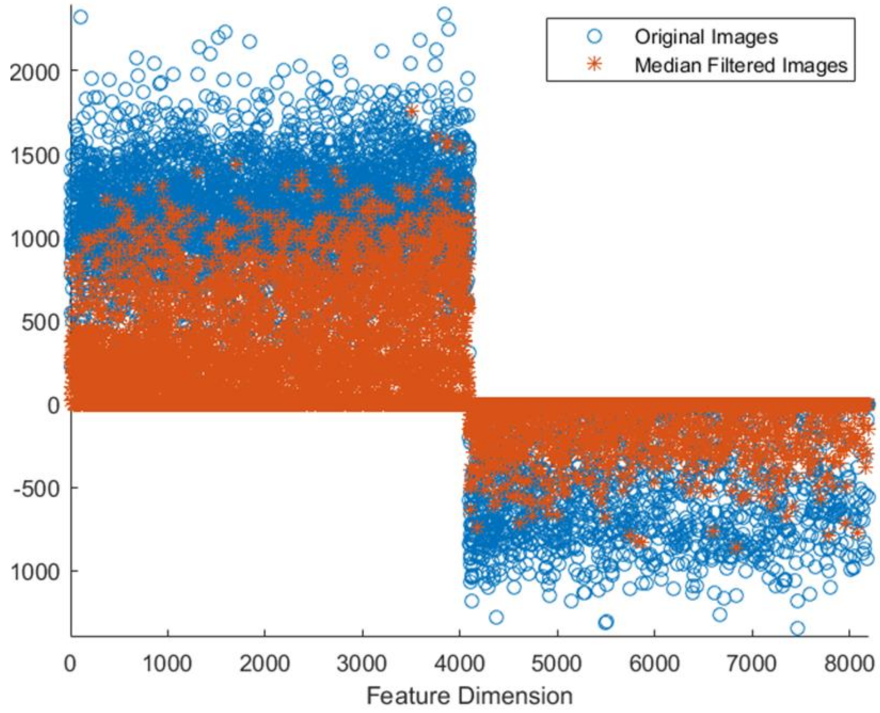
$$f_{b \times b}(j) = \begin{cases} (w_{1,j}, \ldots, w_{N,j})_{max}, & 1 \leq j \leq d \\ (-w_{1,(j-d)}, \ldots, -w_{N,(j-d)})_{max}, & d \leq j \leq 2d \end{cases}$$

Feature Extraction

Final Feature:

$$F = \{f_{3\times3}, f_{5\times5}, \dots\}$$

Feature Distribution



Experimental Setup

- Database: UCID image database
  - Train set : Test set = 3:1
- Classifier: C-SVM with linear kernel
  - Five-fold cross-validation
- Twenty times repeating experiments

$$Accuracy = \frac{Correctly\ predicted\ samples}{Total\ testing\ samples}$$

Multiscale Patch Selection

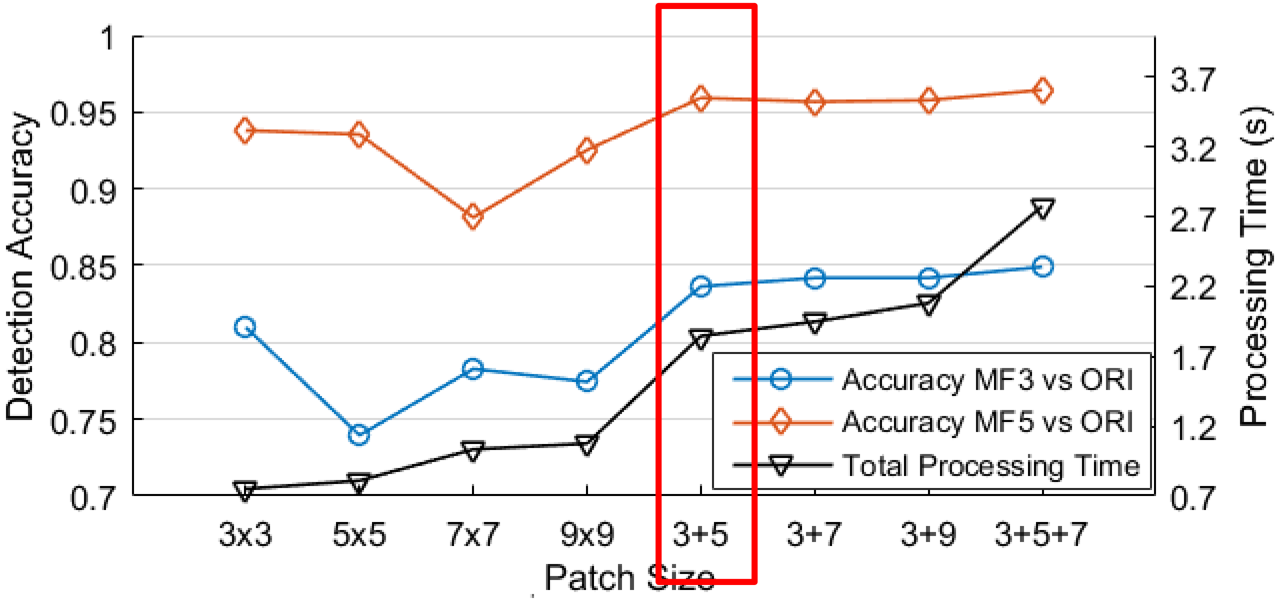


Fig. 5. Accuracy and total time cost for multiscale patch selection: a+b represents the scenario both $a \times a$ and $b \times b$ patch size are used for feature extraction

The combination of patch 3*3 and 5*5 is a better choice.

Detecting median filtering manipulation in JPEG images

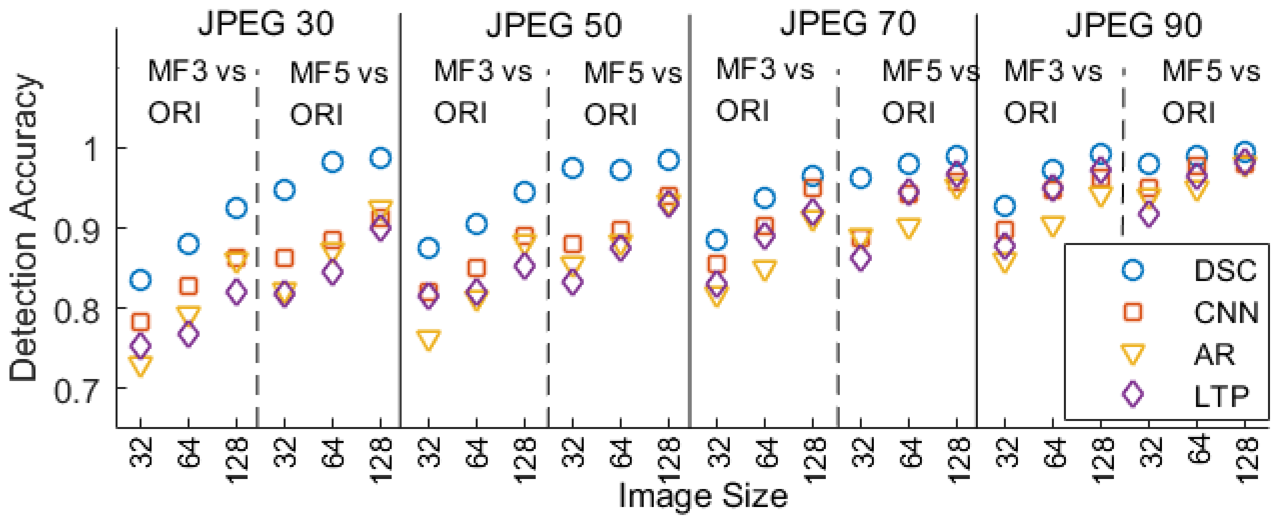


Fig. 6. Detection accuracy of DSC, LTP and AR for JPEG compressed images

The performance improvement is more apparent for images with smaller size and with stronger compression

Blind Median Filtering Detection

MF35: 3*3 and 5*5 median filtered images
ALL : original, Gaussian filtering, average filtering and rescaled images

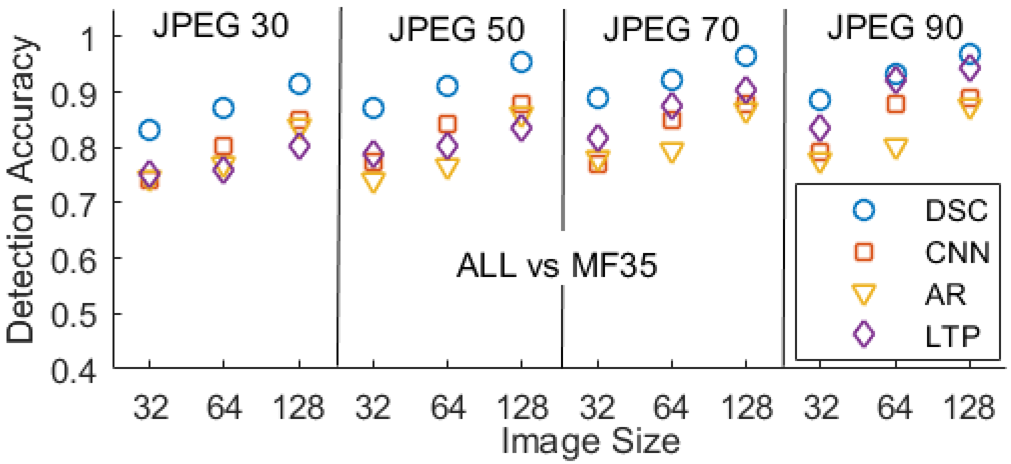


Fig. 7. Detection accuracy of DSC, CNN, LTP and AR detector in a more complex scenario

The proposed method is robust against various kinds of image manipulations

Conclusion

Three distinguishing characteristics of the proposed feature lie in:

i) The proposed sparse coding based feature is directly learned from the training samples;

ii) An overcomplete, discriminative dictionary is trained to represent various distinguishing patterns caused by median filtering;

iii) With the multi-scale patch analysis, the local image characteristics are analyzed with various resolutions, which makes the final feature more comprehensive.

THANK YOU!