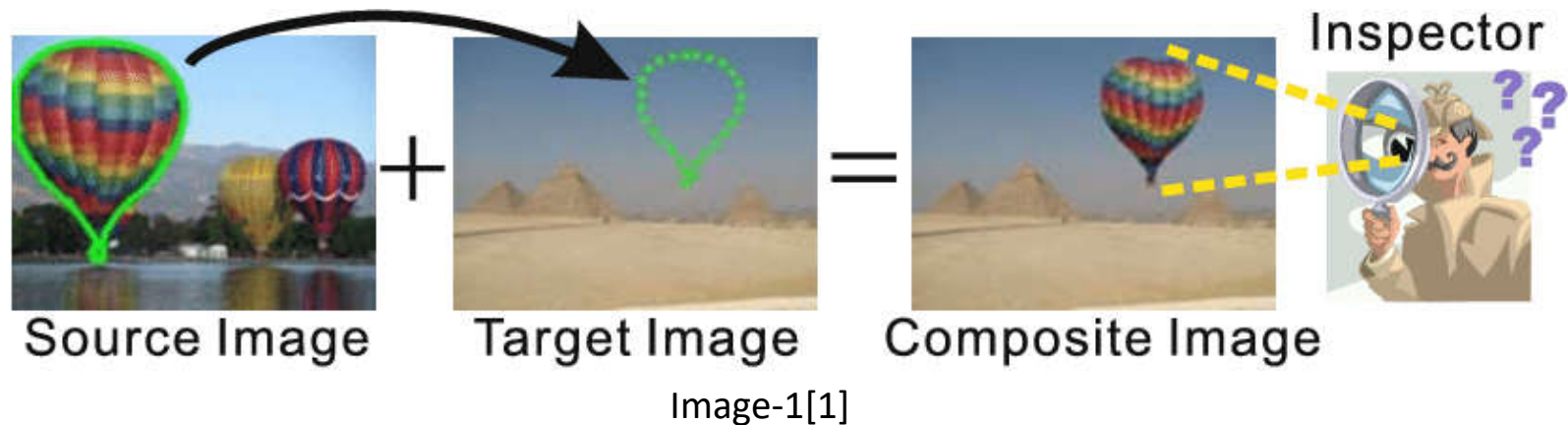


Image splicing forgery detection
combining coarse to refined
convolutional neural network and
adaptive clustering.

Shubh Mehta

Introduction

- What is Image Splicing Forgery ?



- Detection of forgery regions in the host image
(lighting, shadows, sensor noise, and camera reflections)

Introduction

- CNN architecture
- A two-stage hierarchical feature learning approach
 - a coarse CNN
 - a refined CNN
- An image-level CNN is further utilized to replace the patch-level CNN in C2RNet to reduce computational complexity
- An adaptive clustering is then applied to obtain the final detected splicing forgery regions

Framework of proposed SFD Method

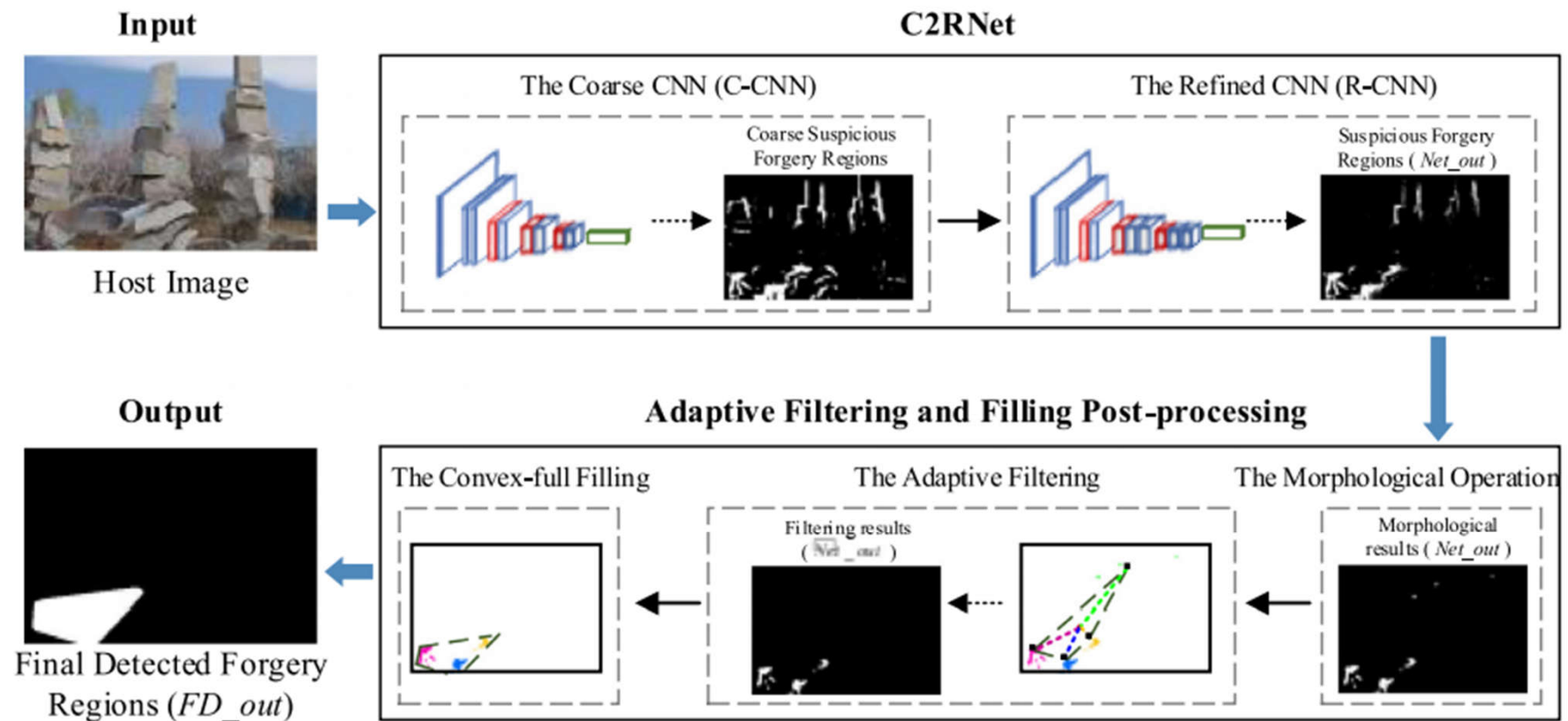


Fig. 2. Framework of the proposed splicing forgery detection method.

Proposed Method

- Coarse-to-refined network (C2RNet)
 - Coarse CNN (C-CNN) in C2RNet

13 convolutional layers, five max-pooling layers, and two fully connect layers
 - Refined CNN (R-CNN) in C2RNet

16 convolutional layers, five max-pooling layers, and three fully connected layers
 - Image-level CNN for fast computations
- Adaptive clustering approach

Patch-level and Image-level CNNs comparison

- convolutional filter

$\begin{bmatrix} 0.0779, 0.0150 \\ 0.0318, 0.1077 \end{bmatrix}$

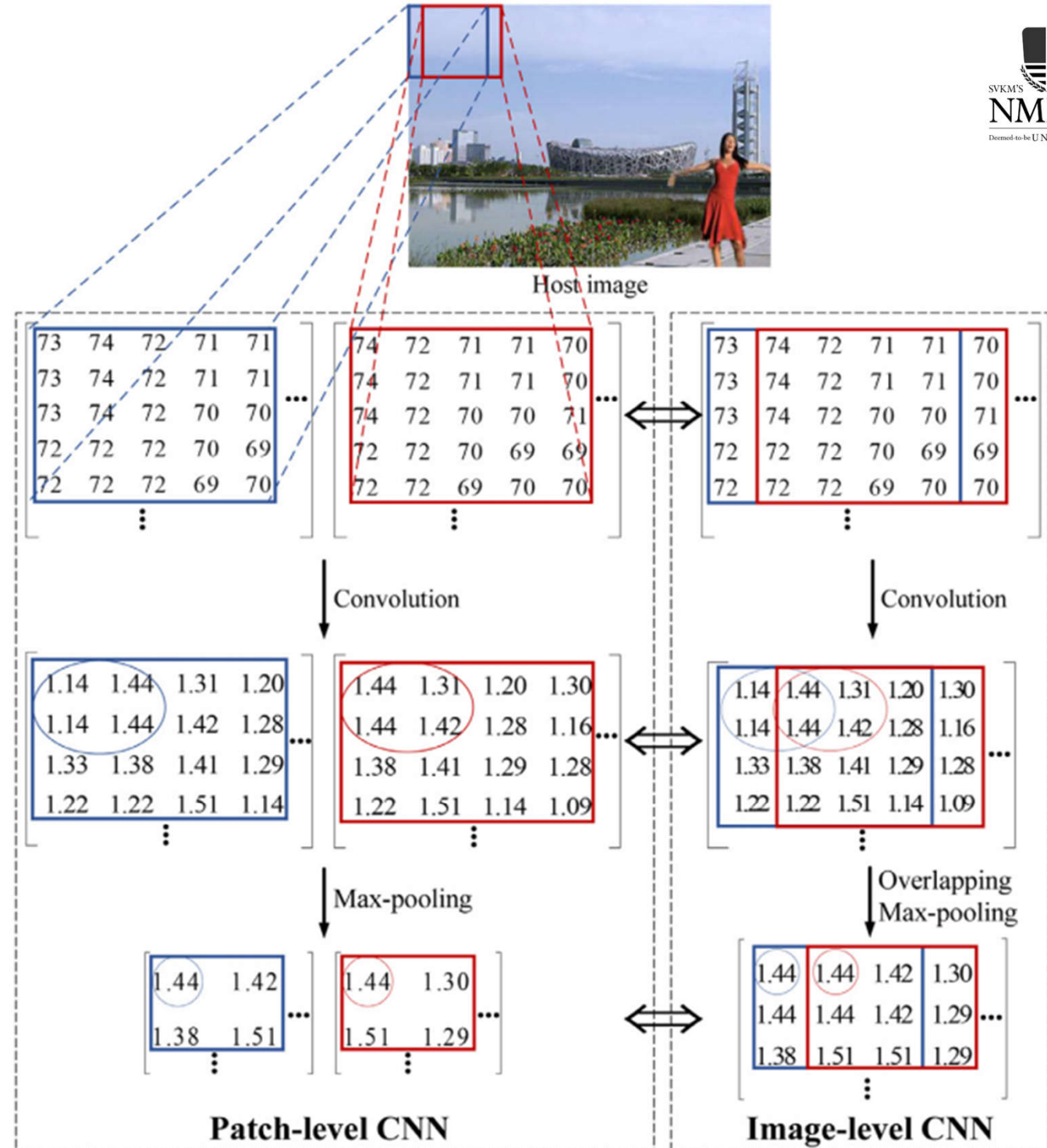


Fig. 5. Relationship between patch-level and image-level CNNs.

Architecture of C-CNN and R-CNN

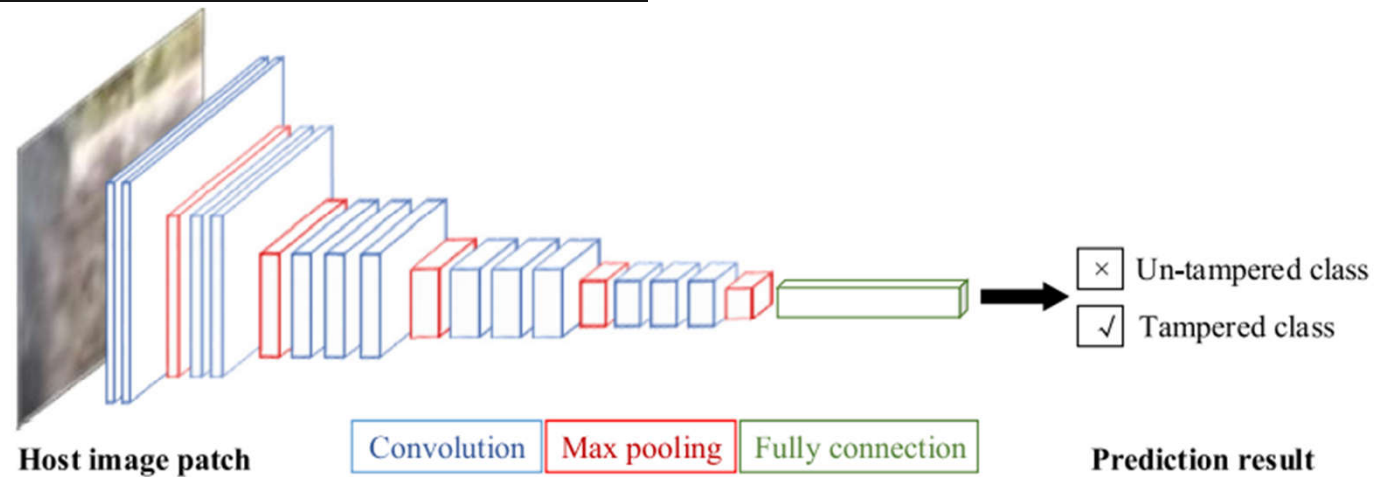


Fig. 3. Architecture of coarse CNN (C-CNN).

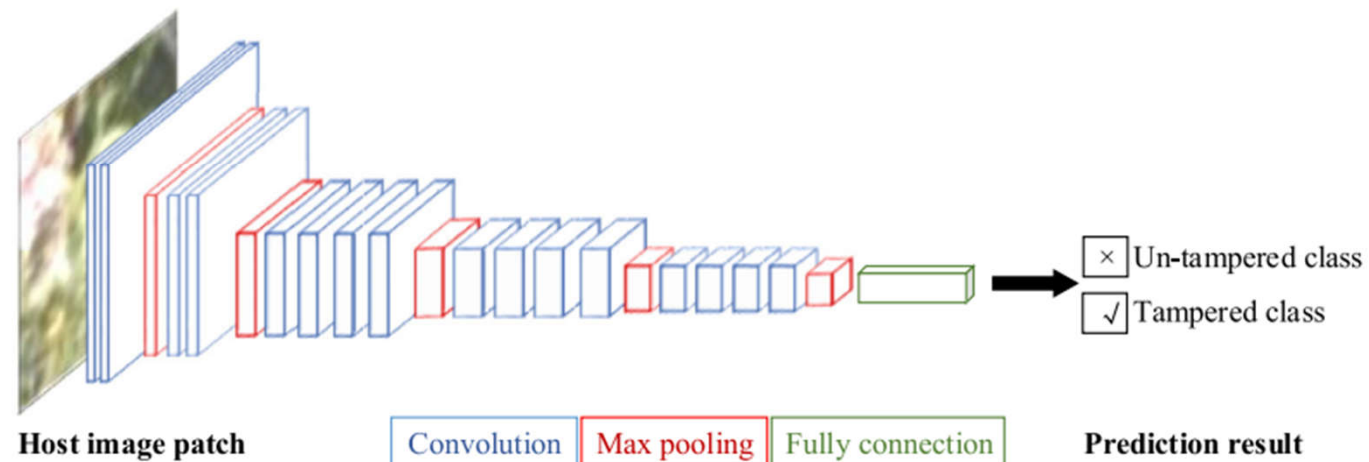


Fig. 4. Architecture of a refined CNN (R-CNN).

Adaptive clustering approach

Algorithm 1 Adaptive Clustering Approach.

Input: Suspicious Forgery Regions Net_out

Output: Detected Forgery Regions FD_out

STEP-1: Divide Net_out into clusters $\{C_1, C_2, \dots, C_{n-1}, C_n\}$, and then calculate their distribution.

STEP-2: If the clusters $\{C_1, C_2, \dots, C_{n-1}, C_n\}$ have a centralized distribution, the output of the adaptive outlier filtering $\widetilde{Net_out}$ is Net_out .

STEP-3: If the clusters $\{C_1, C_2, \dots, C_{n-1}, C_n\}$ do not have a centralized distribution, the benchmark cluster C_k is selected to filter out those clusters that are far away by applying an adaptive threshold t_h , whereas the remaining clusters are the output of the adaptive outlier filtering $\widetilde{Net_out}$.

STEP-4: Apply a convex hull filling operation on $\widetilde{Net_out}$ to generate FD_out .

adaptive threshold

$$t_h = \log_2 \left(2n \times \prod_{i=1}^n d_{i,k} \right)$$

Standard Deviation

$$sd = \sqrt{\frac{1}{n} \sum_{i=1}^n (d_{1,gc} - \overline{d_{gc}})^2},$$

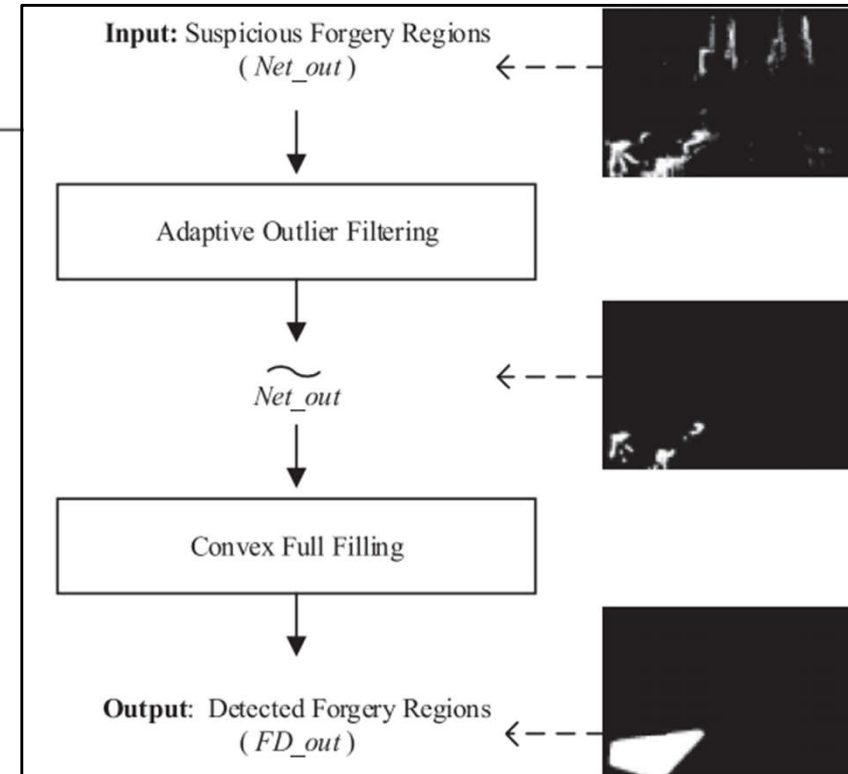


Fig. 6. Process of the proposed adaptive clustering approach.

Adaptive clustering approach

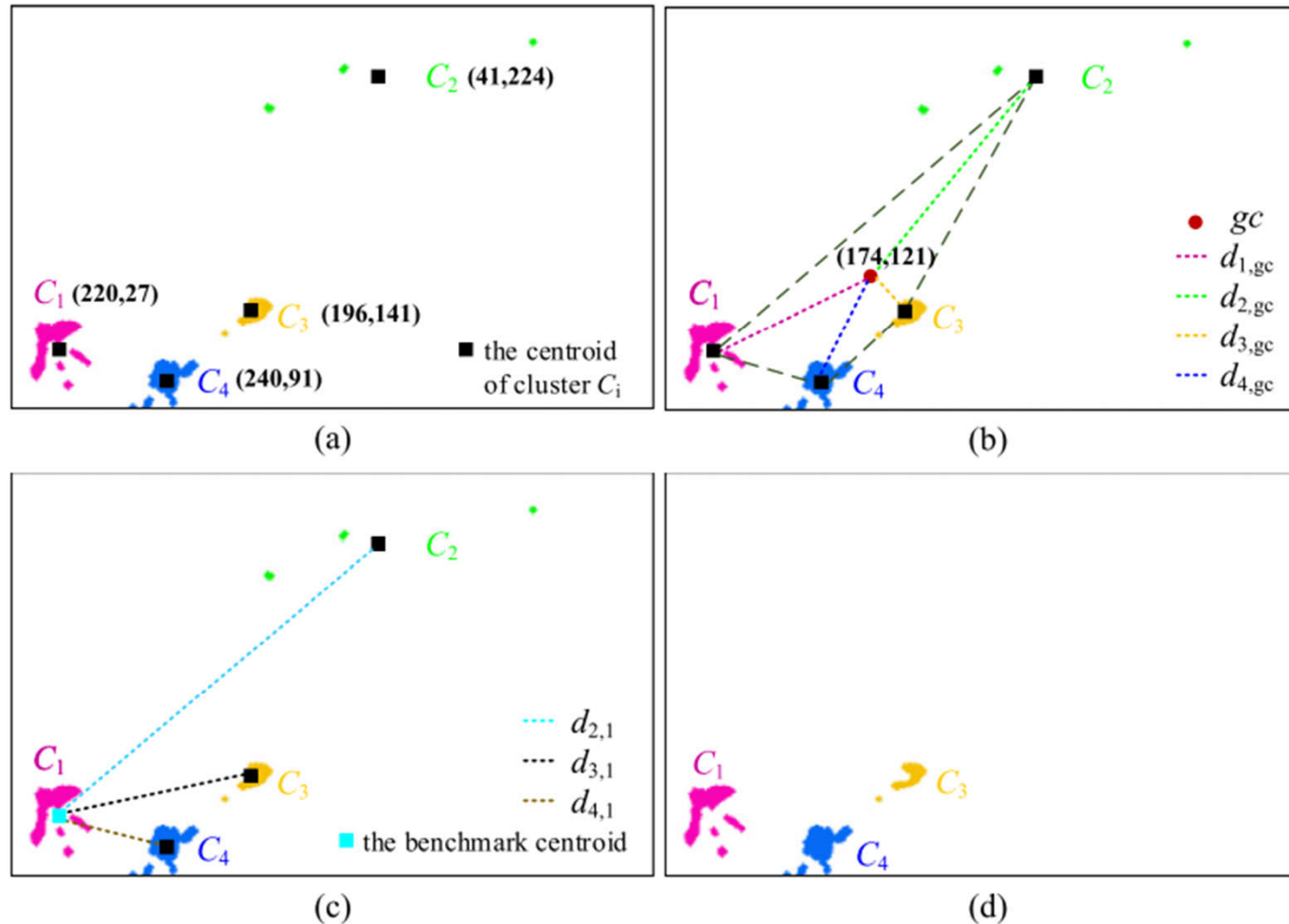
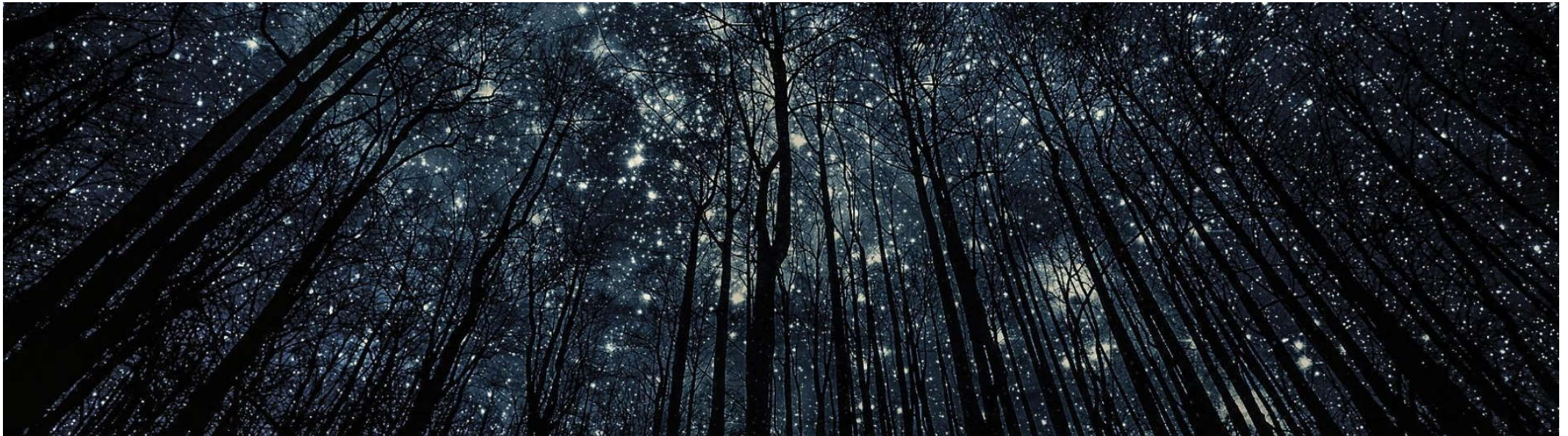


Fig. 7. Procedure of the adaptive outlier filtering: (a) divided clusters $\{C_1, C_2, C_3, C_4\}$ and their corresponding centroids $\{b_1, b_2, b_3, b_4\}$, (b) geometrical center gc and corresponding Euclidean distances $\{d_{1,gc}, d_{2,gc}, d_{3,gc}, d_{4,gc}\}$, (c) Euclidean distances $\{d_{1,1}, d_{2,1}, d_{3,1}, d_{4,1}\}$, and (d) the remaining clusters $\{C_1, C_4\}$ as \widetilde{Net}_{out} .

Experiment and Analysis



Experiment datasets

- CASIA Data Set - 1275 sets of images (1275 forgery images and 1275 original images) in TIFF format - 384×256
- COLUMB Data Set - 179 sets of images in TIFF format - 757×568
- FORENSICS Data Set - 144 sets of images in PNG format - 2018×1536

Experiment datasets

Table 1

Experiment dataset based on CASIA [35], COLUMB [14], and FORENSICS [10].

Set	Cases	Parameter	Range	Step	CASIA [35]	COLUMB [14]	FORENSICS [10]
Training Set	Plain Splicing	—	—	—	1226	139	94
	Original Image	—	—	—	1226	139	94
Testing Set	Plain Splicing	—	—	—	49	40	50
	JPEG Compression	Quality Factor	50 ~ 90	10	245	200	250
	Noise Addition	Variance	0.002 ~ 0.01	0.002	245	200	250
	Combined attacks	JPEG 80 & Noise Addition		0.002	245	200	250
		0.002 ~ 0.01					
		JPEG 60 & Noise Addition		0.002	245	200	250
		0.002 ~ 0.01					
	Scaling	Scale Factor	0.5 ~ 2	0.5	196	160	200
	Rotation	Rotation Angle	60 ~ 240	60	196	160	200

- Total images for experiments used is 6949

Evaluation metrics

- Number of correctly detected tampered pixels (TP)
- Number of incorrectly detected tampered pixels (FP)
- Number of incorrectly detected un-tampered pixels (FN)

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F - measure = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

comparative analysis

Table 2

Existing splicing forgery detection methods employed for comparison.

Method	Description
ADQ	Dual quantization forgery detection method using distribution alignment of DCT coefficients in the image.
DCT	An inconsistent detection method for a JPEG image using a DCT coefficient histogram.
ELA	Error level analysis aiming to detect parts of the image that have undergone less JPEG compression than the rest of the image.
NADQ	A non-aligned double quantization detection method from the DCT coefficients of the image.
CFA	Interference in the CFA interpolation pattern is modeled as a mixture of Gaussian distributions. Because the algorithm needs to know the CFA filter mode used by the camera, the CFA filter estimation algorithm in [41] is applied here.
NOI	Wavelet filtering for local image noise variance modeling.
NFC	The local image noise variance is modeled using the characteristics of frequency sub-band coefficient kurtosis in a natural image.
MPRNU	A detection method based on a non-uniformity analysis of the photo response.
C-Net	Detection using non-overlapping blocks followed by a post-processing based on the superpixel segmentation.
DF-Net	Utilizing a big image patch as input to obtain more feature information.
LSC-Net	The EXIF meta-data of an image are used as a supervisory signal to determine whether an image is self-consistent.

comparative analysis

Table 3

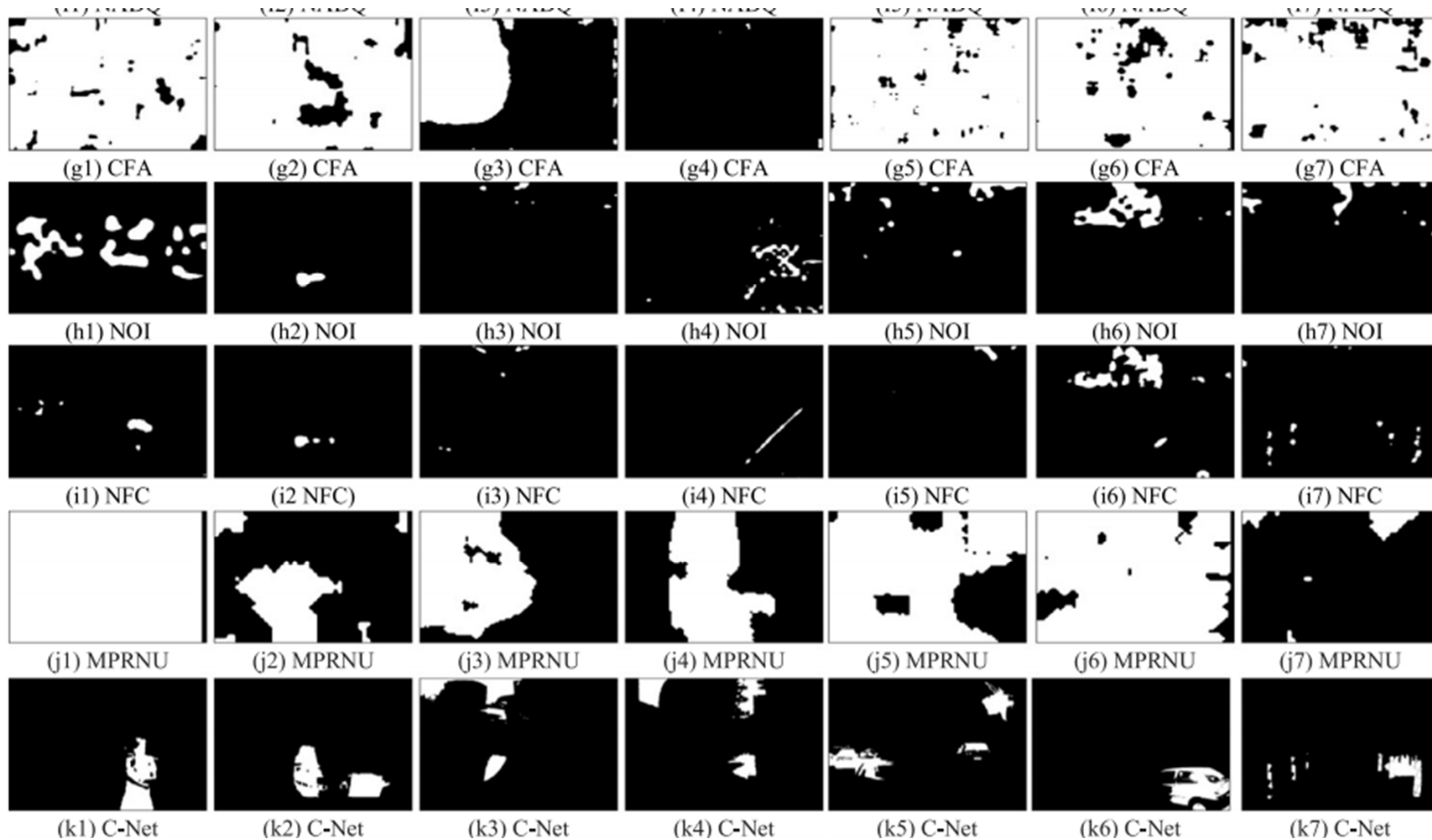
Detection results under plain splicing forgery.

Methods	CASIA [35]			COLUMB [14]			FORENSICS [10]		
	<i>P</i>	<i>R</i>	<i>F</i>	<i>P</i>	<i>R</i>	<i>F</i>	<i>P</i>	<i>R</i>	<i>F</i>
ADQ [21]	0.470	0.603	0.528	0.433	0.524	0.474	0.079	0.51	0.137
DCT [40]	0.392	0.828	0.533	0.333	0.683	0.448	0.0918	0.846	0.166
ELA [27]	0.521	0.213	0.303	0.584	0.013	0.026	0.201	0.005	0.0103
NADQ [4]	0.101	0.663	0.175	0.351	0.626	0.450	0.118	0.577	0.196
CFA [9]	0.078	0.824	0.142	0.544	0.423	0.476	0.083	0.833	0.151
NOI [26]	0.099	0.097	0.098	0.260	0.016	0.030	0.185	0.062	0.093
NFC [24]	0.282	0.060	0.099	0.306	0.007	0.014	0.213	0.032	0.056
MPRNU [18]	0.078	0.257	0.120	0.873	0.754	0.809	0.042	0.389	0.076
C-Net [38]	0.610	0.497	0.548	0.574	0.099	0.169	0.359	0.331	0.344
DF-Net [22]	—	—	—	0.511	0.441	0.473	0.087	0.759	0.155
LSC-Net [15]	0.119	0.580	0.197	0.728	0.843	0.781	0.114	0.448	0.182
Our Method	0.581	0.808	0.6758	0.804	0.612	0.695	0.367	0.747	0.492

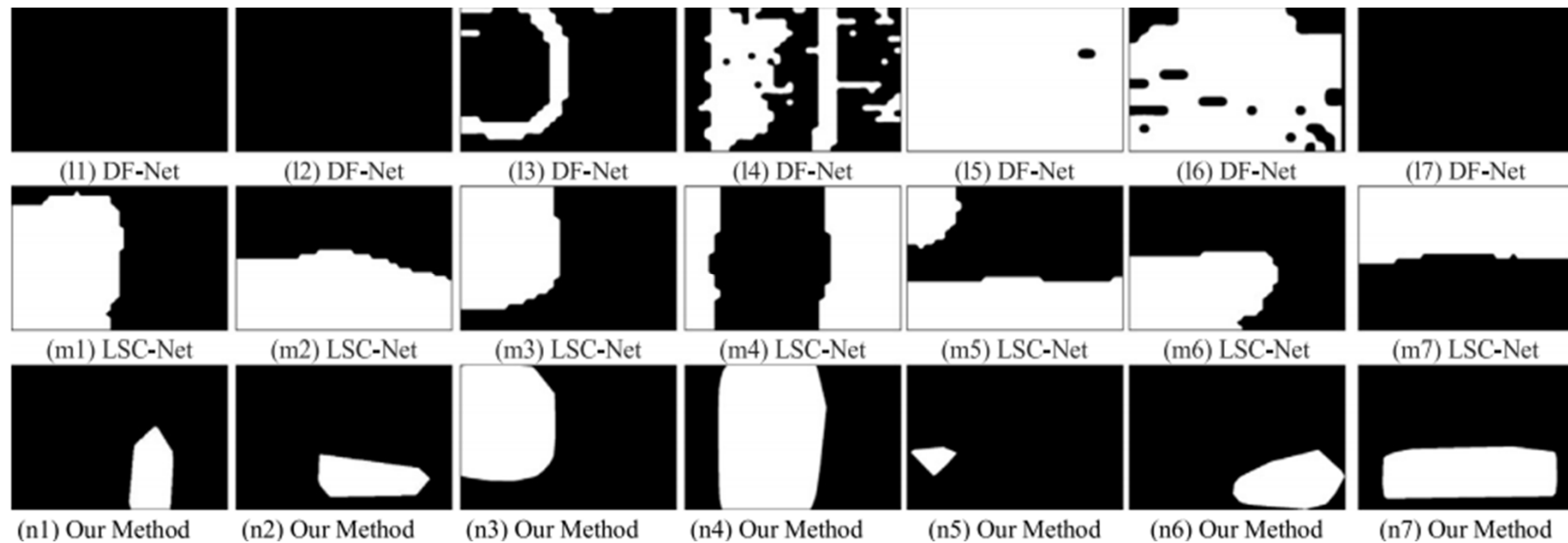
Visual Results



Visual Results



Visual Results



Run time of methods

Table 4

Comparison of run time of various methods.

Methods	Running time(s)		
	CASIA [35]	COLUMB [14]	FORENSICS [10]
ADQ [21]	0.471	0.552	1.372
DCT [40]	0.215	0.425	0.978
ELA [27]	0.179	0.361	0.912
NADQ [4]	2.193	2.925	3.631
CFA [9]	2.001	4.375	11.813
NOI [26]	0.167	0.591	1.306
NFC [24]	5.538	12.825	34.628
MPRNU [18]	12.732	15.926	39.815
C-Net [38]	12.32	18.45	43.358
DF-Net [22]	34.41	40.12	112.351
LSC-Net [15]	281.72	212.64	1408.364
Our method (patch-level CNN)	268.83	375.76	832.248
Our method (image-level CNN)	10.75	15.14	35.323

Conclusion

- C-CNN can generally predict suspicious coarse forgery regions
- C2RNet then utilizes an R-CNN to further obtain refined results based on the detection results from the C-CNN
- The proposed detection method was evaluated and compared with other state-of-the-art detection methods.
- Focuses on a single tampered region in an image

References

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1. https://www.researchgate.net/figure/The-process-of-image-splicing-forgery_fig1_220722135
 2. Image splicing forgery detection combining coarse to refined convolutional neural network and adaptive clustering Bin Xiaoa , Yang Wei , Xiuli Bi , Weisheng Li , Jianfeng Ma

Questions & Comments

