

Multi-spectral Class Center Network for Face Manipulation Detection and Localization

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Abstract

As Deepfake contents continue to proliferate on the internet, advancing face manipulation forensics has become a pressing issue. To combat this emerging threat, previous methods mainly focus on studying how to distinguish authentic and manipulated face images. Despite impressive, image-level classification lacks explainability and is limited to some specific application scenarios. Existing forgery localization methods suffer from imprecise and inconsistent pixel-level annotations. To alleviate these problems, this paper first re-constructs the FaceForensics++ dataset by introducing pixel-level annotations, then builds an extensive benchmark for localizing tampered regions. Next, a novel **Multi-Spectral Class Center Network (MSCCNet)** is proposed for face manipulation detection and localization. Specifically, inspired by the power of frequency-related forgery traces, we design **Multi-Spectral Class Center (MSCC)** module to learn more generalizable and semantic-agnostic features. Based on the features of different frequency bands, the MSCC module collects multi-spectral class centers and computes pixel-to-class relations. Applying multi-spectral class-level representations suppresses the semantic information of the visual concepts, which is insensitive to manipulations. Furthermore, we propose a **Multi-level Features Aggregation (MFA)** module to employ more low-level forgery artifacts and structure textures. Experimental results quantitatively and qualitatively indicate the effectiveness and superiority of the proposed MSCCNet on comprehensive localization benchmarks. We expect this work to inspire more studies on pixel-level face manipulation localization. The annotations and code will be available.

1. Introduction

Advances in Deepfake technologies [11, 13, 29, 54, 55] lead to increasingly realistic Deepfake images/videos with

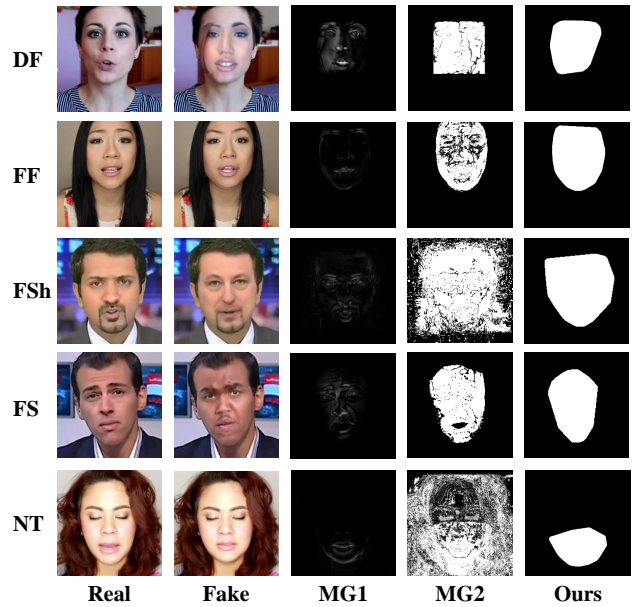


Figure 1. The different pixel-level annotation methods for FaceForensics++ (FF++) [47]. DF [11], FF [55], FSh [29], FS [13], and NT [54] rows are five different Deepfake technologies. The Real and Fake columns depict authentic and corresponding manipulated faces, respectively. In contrast, the MG1 column exhibits dispersed points, whereas the MG2 column contains numerous background regions. This paper proposes an annotation method (Ours column) that yields more precise and comprehensive masks of the tampered regions.

more imperceptible tampering artifacts. Despite their usefulness in the film and entertainment industries, these Deepfake tools have also been exploited for malicious purposes such as creating political propaganda or pornographic content. To address public concerns regarding misinformation, face manipulation detectors [4, 7, 15, 30–32, 32, 36, 44, 49, 57, 63, 64, 69, 70] that aim to provide coarse-grained binary classification results (real or fake) at the image-level or video-level have received extensive attention. However, the

pixel-level localization of manipulated regions in Deepfake images has been neglected, which is crucial for analyzing and explaining the Deepfake detection results. Therefore, it is imperative to develop face manipulation localization technology at the pixel level.

Several works [10, 20, 21, 41, 52, 60] have noticed this issue and attempted to identify manipulated regions at the pixel level. For example, Multi-task [41] designs an additional segmentation branch for localizing manipulated regions. FFD [10] directly applies the low-resolution attention map of the network to detect the tampered regions in face manipulation images. Due to the absence of a publicly available dataset with pixel-level annotation currently, these methods adopt diverse strategies to obtain pixel-level annotations from existing face manipulation datasets (e.g., FaceForensics++ [47]), which poses challenges for direct comparison of their localization performance. Besides, the quality of their annotation is unsatisfactory. There are two prevalent approaches for acquiring pixel-level annotations, denoted as *MG1* and *MG2* in Figure 1. *MG1* is used in some studies [7, 20, 30], which computes the pixel-wise difference between fake image and corresponding real image in RGB channels, converts it into grayscale, and divides by 255 to produce a map within the range of [0, 1]. Some other works [10, 21, 57] adopt *MG2* that binarizes the output of *MG1* using a pre-defined threshold to obtain a binary mask for manipulation regions. As shown in Figure 1, the annotations from *MG1* are incomplete while those from *MG2* contain authentic background regions. For example, the NeuralTextures (NT) [54] only manipulates local areas of expression (e.g., mouth, nose, etc.) as shown in the last row, but both two annotations contain errors. Such imprecise and inconsistent annotations greatly hinder the advancement of face manipulation localization.

To address this problem, we first adopt a sequence of image processing operations to compensate for the deficiency of pixel-level manipulation mask annotations in the FF++ [47] dataset. As illustrated in the last column of Figure 1, the proposed annotation strategy yields a more rational manipulated region mask that conforms to the technical characteristics of different face manipulation technologies (e.g., NT [54]). Based on the FF++ dataset with these pixel-level annotations, we further establish a comprehensive benchmark for face manipulation localization. We reproduce several existing forgery localization methods [10, 41, 61] using their publicly available source codes in our benchmark. Additionally, we also include some widely used semantic segmentation methods [6, 27, 62, 68] since they can naturally support the face manipulation localization task. Extensive experimental results show that existing forgery localization methods exhibit inadequate performance, while the semantic segmentation methods present substantial advantages due to their powerful global context modeling ca-

pability. Nevertheless, directly applying semantic segmentation models to the face manipulation localization task may not be optimal, as these models focus on the semantic information while the face manipulation localization model needs to predict tampering locations exclusively [3, 61, 71]. Previous studies [8, 18] also show that the deep semantic objective information would impact the learning of tampered features.

To handle this issue, we propose a novel **Multi-Spectral Class Center Network** (MSCCNet) for face manipulation detection and localization, which exploits class-level representations of different frequency component features to enhance the tamper localization capability. The MSCCNet consists of two key components: **Multi-level Features Aggregation** (MFA) and **Multi-Spectral Class Center** (MSCC) modules. The proposed MFA module effectively aggregates the low-level texture information and forgery artifacts, as these cues are predominantly present in shallow features [34, 36]. The MSCC module is designed to extract the semantic-agnostic forgery features by suppressing the semantic objective representation capability of the network. Specifically, we first decompose the semantic features using a frequency transformation and calculate pixel-class relations within each spectral feature. Then, the weighted attention of different frequency bands is acquired by computing similarity maps between different spectral class centers and the corresponding partial semantic features. Finally, we employ weighted attention to alleviate the impact of semantic objective information and refine the original global context.

In a nutshell, our main contributions could be summarized as:

- To facilitate the localization tasks, we first re-construct the FaceForensics++ (FF++) datasets by introducing more rational pixel-level annotations. Then we conduct a comprehensive benchmark for face manipulation localization based on the annotated FF++ datasets.
- A novel Multi-spectral Class Center Network (MSCCNet) is designed for face manipulation localization, which consists of a Multi-level Features Aggregation (MFA) module and a Multi-spectral Class Center (MSCC) module for learning more generalizable and semantic-agnostic features.
- Extensive experiments on pixel-level FF++ datasets show that MSCCNet compares favorably against the benchmark methods.

2. Related Work

2.1. Face Manipulation Detection and Localization

Early face manipulation detection methods [5, 9, 14, 15, 42, 43] utilize intrinsic statistics or hand-crafted features to

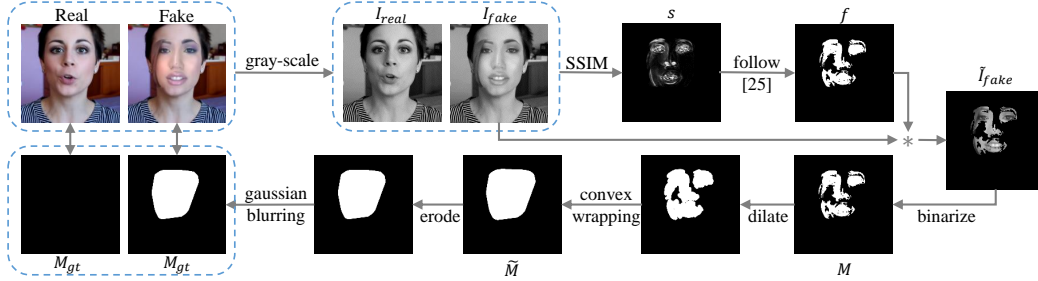


Figure 2. Pixel-level annotation procedure of FF++ [47]. The symbol $*$ is a multiplication operation.

model spatial manipulation patterns. Recently, data-derived detection models utilize spatial artifacts [1, 38, 50, 51, 53, 56, 58, 69, 72, 73] or forgery clues [12, 17, 34, 36, 37, 39, 40, 44] to learn discriminative forgery features and achieve remarkable detection performance. However, these methods ignore the importance of the manipulated regions for face manipulation detection. Some other studies [7, 30, 49, 57, 64, 70] explore the spatially tampered regions as additional supervised signals to improve the performance of real-fake binary classification, while they do not make prediction and evaluation for manipulated regions. Recently, a few methods [10, 20, 21, 41, 52, 60] have superficially examined the positioning problem and there are still many deficiencies. For example, [21] propose that one branch of the framework is used for segmenting the manipulated regions, and yet its performance leaves much to be desired. [60] employs the temporal motion feature to locate the forged regions in Deepfake videos. Both [20] and [52] present a localization method for GAN-synthesized fake images, but they cannot be accommodated to face manipulation data. Moreover, these methods all absent fine-grained tampered regions annotation datasets and comprehensive benchmark assessments.

2.2. Image Forgery Detection and Localization

Image forgery technologies (*e.g.*, splicing, copy-move, removal) have been around for a long time in contrast to the recent rise of face manipulation methods. Image forensics tasks also aim to detect images as spoof or bona fide and locate the tampering regions, but most image forgery localization methods only focus on fake image datasets rather than real-fake mixed datasets. One type of localization method is to segment the entire input image [8, 18, 61], and the other type is to perform binary classification repeatedly using a sliding window [46]. Our proposed framework takes the cropped facial areas as the input, which reduces the computational expenses compared to the full-image input and sliding window approaches. In addition, image forgery localization methods have only been studied for traditional image tampering techniques and cannot be tailored to the latest face manipulation algorithms. In this paper, we mainly

focus on localizing the manipulated regions created by advanced face forgery techniques [11, 13, 29, 54, 55].

2.3. Semantic Segmentation

Semantic segmentation tasks aim to generate pixel-wise semantic object predictions (segmentation masks) for a given image [6, 22–27, 35, 48, 62, 65, 66, 68]. The face manipulation localization and semantic segmentation are very similar, differing only in the object type and class (*i.e.*, manipulated and authentic). Hence, the earliest image forgery localization [18, 61] and current face manipulation localization methods [20, 21, 41, 52] employ a semantic segmentation pipeline to segment the fake regions. But semantic segmentation networks are adept at learning semantic dependent objects, in other words, they cannot adapt well to tampering target localization [3, 71]. Because the manipulated regions (or objects) are semantic-agnostic features [8, 18], compressing image content information is the key to developing face manipulation locators within the image semantic segmentation network. In this paper, we proposed a multi-spectral class center module to enhance the forgery region localization ability of the localization branch and suppress the semantic objective information in images.

3. Dataset and Benchmark

To facilitate the study of face manipulation localization, we define this task as the recognition of pixel-level manipulated regions as possible from a given face image. Since there is no single-face image dataset annotated with manipulation at pixel-level, we first construct a pixel-level single-face manipulation dataset by further preprocessing and annotating the existing FF++ [47] dataset. The FF++ [47] dataset is the most widely used dataset and it provides the authentic source image corresponding to the forgery image, which establishes the theoretical support for pixel-level annotation [7, 10, 30, 57, 70]. Most previous single face forgery datasets [16, 28, 33, 63] cannot have the advantages of FF++ [47].

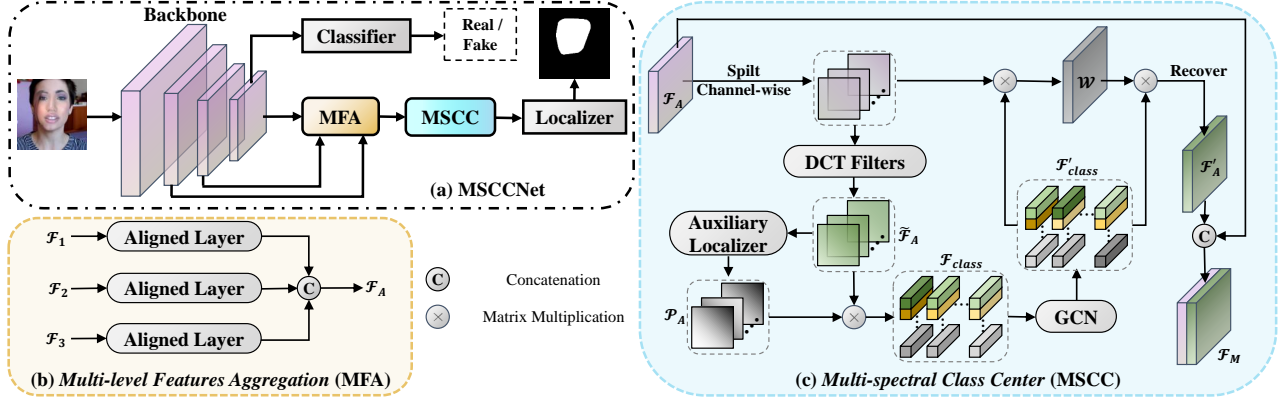


Figure 3. Detailed architecture of the proposed MSCCNet. The overall network structure is shown in (a), which consists of a backbone network, a classification branch, and a localization branch. (b) shows the scheme of the forgery-related low-level texture features aggregation. (c) illustrates the process of multi-spectral class centers and different frequency attention calculations. They are solely dedicated to enhancing the capabilities of the localization branch.

3.1. Pixel-level Annotation for FaceForensics++

The FF++ [47] is a challenging face forgery video dataset and consists of 1,000 original (youtube) videos and 5,000 corresponding fake videos that are generated through five typical manipulation methods, including Deep-fakes (DF) [11], Face2Face (FF) [55], FaceSwap (FS) [13], FaceShifter (FSh) [29], and NeuralTextures (NT) [54]. Meanwhile, it is adopted with three quality levels, *i.e.*, Raw Quality (C0), High Quality (C23), and Low Quality (C40). For each video, we interval select 20 frames to form the single-face manipulation image datasets. Then, we follow FF++ [47] to divide the training, validation, and testing sets.

In this paper, we further preprocess the FF++ [47] with annotations to facilitate forged region localization tasks. As shown in Figure 2, we apply the real-fake image pairs of Raw Quality to generate the pixel-level annotation, because forgery images and their corresponding authentic images have pixel-level differences in the manipulated regions and are identical in the untampered regions [7, 10, 30, 57, 70]. To be specific, for the real face image and the fake face image of the RGB image pairs, we convert them into gray-scale (*i.e.*, I_{real} and I_{fake}) and compute the structural dissimilarity (SSIM) [59] between them to produce an SSIM map S in the range of $[0, 1]$, following [70]. To accurately portray the pixel-level discrepancy S on the forged images, we first employ the S to compute the coarse manipulated regions factor f , following [30]. Second, f and the I_{fake} are multiplied to obtain \tilde{I}_{fake} , which is then binarized to produce M . But the M still is scattered and disjointed for practical manipulation region labels, as shown in Figure 2. Therefore, we dilate the M to fill the missing tampered area and then generate a more comprehensive tamper region mask \tilde{M} by convex wrapping twice. Finally, to eliminate the deviation

of the convex hull \tilde{M} edges, we apply an erosion operation to them, and then the binary manipulation mask M_{gt} is generated by Gaussian blurring followed by the threshold of 0. The above process produces the ground truth masks M_{gt} for the fake images, and for the corresponding real images, we apply zero-maps as its M_{gt} .

3.2. Benchmark Methods

We conduct a competitive benchmark for face manipulation localization, in which we train and evaluate existing localization-related methods across various scenarios, including quantitative and qualitative evaluations. For the purpose of a just and reproducible comparison, we broadly select methods associated with the task of localizing tampered faces for which source code is publicly available. 1) Face manipulation localization methods: FFD [10] and Multi-task [41]. 2) Image forgery localization method: ManTraNet [61]. 3) Semantic segmentation methods: FPN [27], DeepLabV3 [6], PSPNet [68], and UPerNet [62]. Among them, FFD [10] and Multi-task [41] are well-known face manipulation localization models that early propose to localize tampered regions. The ManTraNet [61] is a traditional image forensics architecture capable of performing various known types of image forgeries localization, which broadens the diversity of benchmarks. The remaining methods are widely used semantic segmentation models that can be transferred to the tampering localization task with simple modifications.

3.3. Metrics

The Accuracy (ACC) and Area Under the Receiver Operating Characteristic Curve (AUC) are reported for face manipulation detection comparison metrics, following [10, 41].

For the evaluation of localization results, we employ the

pixel-level F1-score and mIoU (mean of class-wise intersection over union), following image forgery localization tasks [61] and semantic segmentation tasks [6, 27, 62, 68]. The higher value indicates that the performance is better.

4. Methodology

4.1. Problem Formulation

As demonstrated in Figure 3 (a), our proposed face manipulation forensics architecture consists of a backbone network, a classification branch and a localization branch, where the backbone network is utilized to project each input image $\mathcal{I} \in \mathbb{R}^{3 \times H \times W}$ into multi-scale feature space $\mathcal{F} = \{\mathcal{F}_1, \mathcal{F}_2, \mathcal{F}_3\}$, where $H \times W$ is the shape of the input image. After that, a multi-level forgery patterns aggregation scheme is designed to aggregate \mathcal{F} and output $\mathcal{F}_A \in C \times h \times w$, where C denotes for the number of feature channels. Next, a multi-spectral class center (MSCC) module is proposed to calculate the contextual information tampered regions over different frequency bands.

To explore the global contextual representation of tampered regions over different frequency bands from aggregated \mathcal{F}_A , we propose the multi-spectral class center (MSCC) module as \mathcal{M} , and then we have:

$$\mathcal{F}_M = \mathcal{M}(\mathcal{F}_A), \quad (1)$$

where $\mathcal{F}_M \in \mathbb{R}^{C \times h \times w}$ is the enhanced features from different spectral class centers perspective. Finally, \mathcal{F}_M is leveraged to predict the label of each pixel in the input image:

$$\mathcal{P}_1 = \text{Upsample}_{8 \times}(\mathcal{C}_1(\mathcal{F}_M)), \quad (2)$$

where \mathcal{C}_1 is a pixel-level classification head and $\mathcal{P}_1 \in \mathbb{R}^{k \times H \times W}$ indicates the predicted pixel-level class probability distribution. Moreover, we apply the last layer output features \mathcal{F}_3 of the backbone network as image-level classification head \mathcal{C}_2 input, we have:

$$\mathcal{P}_2 = \mathcal{C}_2(\mathcal{F}_3), \quad (3)$$

in which, $\mathcal{P}_2 \in \mathbb{R}^k$ represents the image-level prediction probability distribution. Here, k is the number of classes and $k = 2$.

4.2. Multi-level Features Aggregation

The forgery artifacts (e.g., blending boundary, check-board, blur artifacts, etc.) and local structure are low-level texture features, which are mostly exiting shallow layers of the network [34, 36]. However, previous face manipulation localization methods [10, 41] primarily focused on deep semantic information and disregarded low-level texture features and location information, which would result in coarse and inaccurate output and disrupt some crucial low-level

details (see Figure 4). To leverage the forgery-related low-level texture features, we propose the Multi-level Features Aggregation (MFA) scheme, which exploits texture-related information from multi-level and enhances the texture details of high-level semantic features.

As shown in Figure 3 (b), we first gain multi-level features $\mathcal{F}_1, \mathcal{F}_2, \mathcal{F}_3$ from the backbone network and then employ three different aligned layers (i.e., $\mathcal{N}_1, \mathcal{N}_2$, and \mathcal{N}_3) for each of them:

$$\mathcal{F}'_1 = \mathcal{N}_1(\mathcal{F}_1), \mathcal{F}'_2 = \mathcal{N}_2(\mathcal{F}_2), \mathcal{F}'_3 = \mathcal{N}_3(\mathcal{F}_3), \quad (4)$$

where $\mathcal{F}'_1, \mathcal{F}'_2, \mathcal{F}'_3 \in \mathbb{R}^{C \times h \times w}$. Each aligned layer consists of a *Conv* and a *Downsample*, which aligns the different level features to assure the effectiveness of the lower-level texture information. Then, we aggregate the aligned multi-level features $\mathcal{F}'_1, \mathcal{F}'_2, \mathcal{F}'_3$ by channel-wise concatenation operation *Cat* as follows:

$$\mathcal{F}_A = \text{Conv}(\text{Cat}([\mathcal{F}'_1, \mathcal{F}'_2, \mathcal{F}'_3])). \quad (5)$$

where $\mathcal{F}_A \in \mathbb{R}^{C \times h \times w}$ and the *Conv* layer to make the channel size of $3C$ to C .

4.3. Multi-spectral Class Center

Previous face manipulation localization approaches [10, 21, 41] have primarily focused on feature learning within the backbone network while neglecting to fully exploit the effectiveness of a rich global context at the localization branch. The discriminative contextual features play a crucial role in predicting meaningful object regions, yet research on them has been limited to the semantic segmentation community. However, these off-the-shelf semantic segmentation networks [6, 27, 35, 48, 62, 65, 66, 68] do not be suitable for face manipulation localization tasks [3, 71]. As face manipulation localization models solely require the localization of tampered regions rather than all meaningful regions, further analysis indicates that semantic objective features interfere with the forgery cue [8, 18]. Therefore, the primary concern is how to develop and train a face manipulation localization model that can acquire semantic-agnostic features with sensitivity towards manipulations. The manipulated elements have discrepancies in the frequency domain compared to the authentic part, and extracting frequency information in the contextual features helps to suppress the semantic objective features [7, 34, 36, 44]. Inspired by these motivations, we propose a novel Multi-spectral Class Center (MSCC) module to learn semantic-agnostic forgery features from the different-frequency bands perspective, as shown in Figure 3 (c).

Discrete Cosine Transform (DCT) Filters Following [2, 45], the 2D DCT basis functions as follows:

$$D_{u,v} = \sum_{i=0}^{H-1} \sum_{j=0}^{W-1} d_{i,j} \cos\left(\frac{\pi u}{U}\left(i + \frac{1}{2}\right)\right) \cos\left(\frac{\pi v}{V}\left(j + \frac{1}{2}\right)\right)$$

s.t. $u \in \{0, 1, \dots, U-1\}, v \in \{0, 1, \dots, V-1\}$,

(6)

where $d \in \mathbb{R}^{H \times W}$ is a two-dimensional data and $D_{u,v} \in \mathbb{R}^{H \times W}$ is the 2D DCT frequency spectrum with the transformation basis of (u, v) . For simplicity, we define the above DCT operation as $\mathcal{D}_n(\cdot)$, in which $n \in \{0, 1, \dots, N\}$ and N is the number of frequency transformation basis of (u, v) . In this paper, we first split the features $\mathcal{F}_A \in \mathbb{R}^{C \times h \times w}$ into N parts along the channel dimension, where each channel of the n -th part feature $\mathcal{F}_A^n \in \mathbb{R}^{c \times h \times w}$ is defined $f_i^n \in \mathbb{R}^{h \times w}$, $i \in \{0, 1, \dots, c\}$ and $c = \frac{C}{N}$. Then, every f_i^n is transformed through $\mathcal{D}_n(\cdot)$ with n -th transformation basis (u, v) , as follows:

$$\tilde{\mathcal{F}}_A^n = \text{Cat}([\mathcal{D}_n(f_1^n), \mathcal{D}_n(f_2^n), \dots, \mathcal{D}_n(f_c^n)]), \quad (7)$$

where $\tilde{\mathcal{F}}_A^n \in \mathbb{R}^{c \times h \times w}$ is the frequency features for specific spectral component. Similarly, we can obtain the frequency information of the \mathcal{F}_A for all spectral components and concatenate them together channel-wise:

$$\tilde{\mathcal{F}}_A = \text{Cat}([\tilde{\mathcal{F}}_A^1, \tilde{\mathcal{F}}_A^2, \dots, \tilde{\mathcal{F}}_A^N]), \quad (8)$$

in which, $\tilde{\mathcal{F}}_A \in \mathbb{R}^{N \times c \times h \times w}$ is multi-spectral feature maps with N different frequency bands (*i.e.*, N transformation basis).

Multi-spectral Class Center After getting the multi-spectral feature maps $\tilde{\mathcal{F}}_A \in \mathbb{R}^{N \times c \times h \times w}$, we calculate the coarse segmentation predictions of different frequency components through a pixel-level classification head \mathcal{C}_3 , then we have:

$$\mathcal{P}_A = \mathcal{C}_3(\tilde{\mathcal{F}}_A), \quad (9)$$

where $\mathcal{P}_A \in \mathbb{R}^{N \times k \times h \times w}$ indicates the probability of a pixel belonging to a specific class in N different frequency bands. After that, we perform a matrix multiplication \otimes between the \mathcal{P}_A and the transpose of $\tilde{\mathcal{F}}_A$ to calculate the multi-spectral class centers $\mathcal{F}_{class} \in \mathbb{R}^{N \times k \times c}$ as follows:

$$\mathcal{F}_{class} = \mathcal{P}_A \otimes \tilde{\mathcal{F}}_A^\top. \quad (10)$$

Multi-spectral class centers are expected to learn a global representation of each class from a different frequency perspective. Since the class centers of the different spectra are calculated independently, there are missing interactions between them. To address this, we first treat the multi-spectral class centers as distinct nodes, then message across each

node, and finally update the features for each node. The graph node modeling process can be formulated as follows:

$$\mathcal{F}'_{class} = \mathcal{G}(\mathcal{F}_{class}), \quad (11)$$

where \mathcal{G} is a GCN layer that enhances the relationships between different spectral class centers.

Feature Refinement. We employ the multi-spectral class centers \mathcal{F}'_{class} to refine the aggregated multi-level features \mathcal{F}_A through an attentional calculation mechanism. We first compute a multi-spectral weight matrix to represent pixel similarity maps between each class center and the corresponding partial feature in \mathcal{F}_A , as follows:

$$\mathcal{W} = \text{Softmax}(\mathcal{F}_A \otimes (\mathcal{F}'_{class})^\top), \quad (12)$$

where $\mathcal{W} \in \mathbb{R}^{N \times h \times w \times k}$ and \mathcal{F}_A is split by channel-wise and reshaped as $N \times h \times w \times c$. Then, the weighted features $\mathcal{F}'_A \in \mathbb{R}^{N \times h \times w \times c}$ are calculated as follows:

$$\mathcal{F}'_A = \mathcal{W} \otimes \mathcal{F}'_{class}. \quad (13)$$

Finally, the multi-spectral class centers refined features $\mathcal{F}_M \in \mathbb{R}^{C \times h \times w}$ is obtained by fusing the original features \mathcal{F}_A and weighted features \mathcal{F}'_A via a *Conv* layer, we have:

$$\mathcal{F}_M = \text{Conv}(\text{Cat}([\mathcal{F}_A, \mathcal{F}'_A])). \quad (14)$$

Note that \mathcal{F}'_A is recovered and permuted to have a size of $C \times h \times w$ and the *Conv* layer to make the channel size of $2C$ to C .

Our MSCC module represents pixel-class relationships over different spectra features. The decomposed class centers are employed to calculate the attention of different frequency bands for suppressing semantic contextual information. This is because the original semantic-aware features are frequency aliasing states, with particularly low-frequency information dominating and high-frequency forgery cues easily discounted [67]. Hence, our MSCC module enhances the capacity of the model to learn semantic-agnostic features that are sensitive to face manipulation traces.

4.4. Loss Function

We first apply two cross-entropy loss functions for the predictions \mathcal{P}_1 and \mathcal{P}_2 of the MSCCNet, *i.e.*, a pixel-level loss \mathcal{L}_{seg} for localizing the manipulated regions and an image-level loss \mathcal{L}_{cls} for classifying the authentic or manipulated face. Then, for coarse segmentation predictions $\mathcal{P}_A \in \mathbb{R}^{N \times k \times h \times w}$ in Eq.(9), we employ a 1×1 *Conv* to fuse the multi-spectral results as follow:

$$\mathcal{P}'_A = \text{Conv}(\mathcal{P}_A), \quad (15)$$

Table 1. Quantitative results for face manipulation localization and detection on the test set of FF++ [47] datasets. The C40, C23, and Raw indicate different compression levels.

Methods	Image-level						Pixel-level					
	C40		C23		Raw		C40		C23		Raw	
	ACC	AUC	ACC	AUC	ACC	AUC	F1	mIoU	F1	mIoU	F1	mIoU
FFD [10]	70.71	80.35	86.76	94.51	99.51	99.95	70.35	58.32	73.68	61.94	78.93	67.82
ManTraNet [61]	-	-	-	-	-	-	53.88	46.35	64.45	53.53	82.28	71.74
Multi-task [41]	67.98	74.60	86.18	93.38	99.60	99.90	73.25	61.26	80.65	69.66	89.04	81.01
FPN [27]	87.47	87.22	96.90	98.96	99.73	99.99	85.16	74.78	90.06	82.25	92.00	85.42
DeepLabV3 [6]	87.61	87.93	96.85	98.92	99.74	99.99	85.70	75.55	90.48	82.93	92.00	85.41
PSPNet [68]	87.86	87.76	96.63	98.86	99.73	99.99	85.94	75.94	90.45	82.87	92.02	85.45
UPerNet [62]	87.56	87.29	96.82	98.95	99.73	99.98	85.95	75.94	90.37	82.74	91.75	85.01
MSSCNet (ours)	88.07	87.61	97.21	98.94	99.74	99.99	86.82	77.22	90.71	83.29	92.02	85.45

where $\mathcal{P}'_A \in \mathbb{R}^{k \times h \times w}$ is global representations. Similarly, the cross-entropy loss function is employed to calculate its loss \mathcal{L}_{mscc} . Finally, the multi-task loss function \mathcal{L} is used to jointly optimize the model parameters, we have:

$$\mathcal{L} = \mathcal{L}_{cls} + \mathcal{L}_{seg} + \mathcal{L}_{mscc}. \quad (16)$$

5. Experiments

In this section, we first compare the results of various methods on FF++ [47] datasets in Sec. 5.2. Then, we analyze different modules of proposed MSSCNet on the FF++ [47] C40 dataset in Sec. 5.3.

5.1. Experimental Setup

Model Architecture As previously defined, the backbone of our MSSCNet is the dilated ResNet-50 network [19], the classification branch is a simple fully connected layer, and the localization branch consists of the proposed MFA and MSSC modules. Specifically, the ResNet-50 [19] backbone is initialized by the weights pre-trained on ImageNet datasets, while the remaining layers and modules are randomly initialized. The output stride of the dilated ResNet-50 [19] is set to 8, so $h = \frac{H}{8}$ and $w = \frac{W}{8}$ in the MSSCNet. For fair comparison, the semantic segmentation methods [6, 27, 62, 68] in the benchmark also are implemented with the same dilated ResNet-50 [19] backbone network. The remaining models follow the original papers unless stated otherwise.

Implementation Details We train the proposed MSSCNet with SGD setting the initial learning rate to 0.009, the momentum to 0.9, and the weight decay to $5e - 4$. The learning rate is decayed according to the ‘‘poly’’ learning rate policy with factor $(1 - \frac{iter}{total.iter})^{0.9}$. The size of the input images is 512×512 and the batch size is 64. We apply random horizontal flipping as the only data augmenta-

tion method for the training phase. Synchronized batch normalization implemented by Pytorch 1.8.1 is enabled during multi-GPU training. Note that the semantic segmentation networks [6, 27, 62, 68] are implemented in the same setting as our MSSCNet model for fair comparisons. The training protocols of the remaining methods follow the original papers unless stated otherwise.

5.2. Benchmark for Pixel-level FF++

Quantitative Evaluation We first investigate the localization performance of benchmark approaches on the C40, C23, and Raw sets [47]. This task is more practical and challenging, yet is rarely explored in the previous literature. As shown in Table 1, the existing forgery localization methods (*i.e.*, FFD [10], ManTraNet [61], and Multi-task [41]) still suffer from poor results, which demonstrates a deficiency in the global contextual representation of their localization branch. Conversely, owing to their robust global context modeling capability, semantic segmentation models [6, 27, 62, 68] present substantial performance advantage over alternative benchmark methods. However, the off-the-shelf image semantic segmentation networks exhibit sub-optimal performance when dealing with low-quality C40 datasets. This inherently caused by the diminished discrepancy between tampered and real areas in low-quality forged images, leading to a reduction in distinctive semantic objective features and consequent localization failures. In comparison to alternative models, our MSSCNet model exhibits superior performance, especially on the C40 dataset. This outcome suggests that the proposed MFA and MSSC modules enhance global contextual representations that are semantic-agnostic features while enabling the suppression of objective semantic-related information.

We next analyze the image-level classification performance of the face forgery localization approaches on the FF++ [47]. While face manipulation detection methodologies have already extensively studied classification tasks,

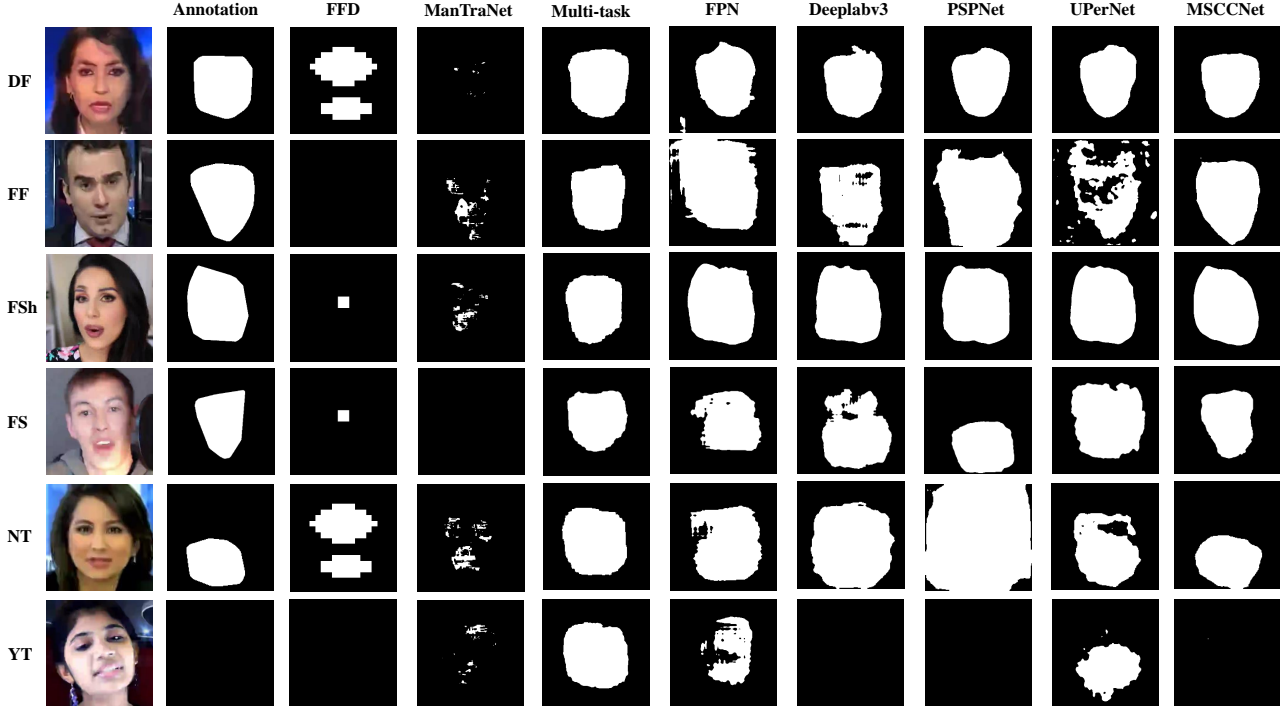


Figure 4. Visualization mask predictions of benchmark methods and our MSCCNet. The examples are randomly selected from the C40 test set of FF++ [47]. DF [11], FF [55], FSh [29], FS [13], and NT [54] rows are five different face manipulation technologies. YT (youtube) row is the original face image. Column Annotation indicates the proposed pixel-level manipulation region mask in this paper.

our findings from Table 1 illustrate that preceding localization methods [10, 41] have yielded inadequate classification outcomes on the C40 and C23 datasets. These localization and classification results of C40 and C23 sets show that FFD [10] and Multi-task [41] are not suitable for low-quality datasets. On the high-quality (Raw) set, all methods achieve remarkable performance. Our MSCCNet and semantic segmentation models [6, 27, 62, 68] yield comparable classification outcomes, primarily due to the application of the same backbone network (*i.e.*, ResNet-50) for feature extraction. It is worth noting that our proposed MFA and MSCC modules are specifically designed to enhance the localization branch’s function, without directly augmenting image-level classification abilities.

Qualitative Comparisons After training, our model can generate high-quality mask predictions that depict tampering locations on the test set. Here, we provide some qualitative samples in Figure 4. The predictions of FFD [10] are small and coarse due to the limited low-resolution of the attention map. Multi-task [41] predictions are almost always the same, suggesting that it is incapable of adapting to different forgery techniques. ManTraNet [61] can not be suitable for advanced face manipulation images, so it is impossible to predict all areas of tampering. The detrimental im-

Table 2. Analysis of different modules of the proposed MSCCNet.

Base.	MFA	MSCC	\mathcal{L}_{mscc}	Image-level		Pixel-level	
				ACC	AUC	F1	mIoU
✓	-	-	-	87.49	86.67	83.79	72.84
✓	✓	-	-	87.29	86.68	83.98	73.11
✓	✓	✓	-	87.38	86.99	85.82	75.76
✓	✓	✓	✓	88.07	87.61	86.82	77.22

plications of semantic segmentation methods [6, 27, 62, 68] that excessively prioritize objective semantic features are evident in Figure 4. For example, NT [54] is local forgery technology, while PSPNet [68] predicts the whole face object regions. In the case of real face images (YT row), where the facial area is meaningless object, both FPN [27] and UPerNet [62] exhibit localization errors. The superior performance of our MSCCNet is evident from its ability to identify tampered regions in distinct types of forgeries, as well as real facial images. This capability highlights the strength of our method in effectively modeling semantic-agnostic features.

5.3. Ablation Study

Analysis on MSCCNet Architecture We set the baseline (*Base.*) model by removing the MFA and MSCC modules,

Table 3. Analysis of the proposed MSCC module.

GCN	DCT	Add	Concat	Image-level		Pixel-level	
				ACC	AUC	F1	mIoU
✓	✓	-	✓	88.07	87.61	86.82	77.22
-	✓	-	✓	87.60	87.17	86.41	76.62
✓	-	-	✓	87.61	87.43	85.94	75.92
✓	✓	✓	-	88.03	87.10	86.44	76.66

and remaining other convolutional blocks. As summarized in Table 2, applying the MFA module could bring 0.27% mIoU improvements, which demonstrates that low-level local textures are helpful for manipulated regions localization. MSCC module is the key component for modeling semantic-agnostic features, it achieves 75.76% in terms of mIoU. The multi-spectral features of the coarse segmentation supervision mechanism enable the assessment of the probability of pixel attribution to its specific class. These features subsequently drive the MSCC module’s ability to approximate a robust class center. From the last line in Table 2, we can observe that \mathcal{L}_{mscc} improves the localization performance from 75.76% to 77.22%. Our results show that the combination of semantic-agnostic features and low-level artifacts improves face manipulation localization. Moreover, the proposed MSCC module offers a viable solution to suppress semantic-related information through a multi-frequency perspective.

Influence of GCN The GCN layer in our MSCC module improves the consistency of multi-spectral class-level representations by enhancing interaction between class centers across various frequency bands. As can be seen in Table 3, if the GCN layer is removed, the localization performance drops from 77.22% to 76.62% mIoU. It helps with multi-frequency attention map calculation in feature refinement operations.

Influence of DCT Filters In Sec. 4.3, the DCT filters decompose semantic context features to different frequency bands, which relieves the aliasing among low-frequency and high-frequency components [67]. Given that forgery traces are more prominent in high-frequency rather than low-frequency components [7, 34, 36, 44, 57], the multi-spectral class centers have the potential to model frequency-dependent forgery traces, particularly in high-frequency regions. To show the effectiveness, we remove the DCT filters of the MSCC module, the performance drops to 75.92%. In comparison, applying DCT filters brings 1.3% mIoU improvements, as indicated in Table 3.

Influence of Fusion Type There are two feature fusion types: addition (Add) and concatenation (Concat) options

Table 4. Analysis of the number of transformation basis of the MSCC module.

Number of Transformation Basis	Image-level		Pixel-level	
	ACC	AUC	F1	mIoU
1	87.68	86.83	86.23	76.34
4	88.07	87.61	86.82	77.22
16	88.06	87.44	86.46	76.70

for Eq. (14). In Table 3, we try both addition and concatenation, and the experimental results demonstrate that the concatenation type is better performance.

Influence of the Number of Transformation Basis The number of transformation basis of 2D DCT can be denoted as N in Sec. 4.3. To investigate the performance of using different N , various experiments are conducted and the experimental results are shown in Table 4. When setting N to 1, the (u, v) only is $(0, 0)$, which indicates that the features are decomposed to low-frequency components and miss high-frequency forgery traces. Thus, its mIoU is 0.88% lower than $N = 4$. Note that $N = 4$ means the (u, v) is $(0, 0)$, $(0, 1)$, $(1, 0)$, and $(1, 1)$, which decomposes the more frequency components including low- and high-frequency. We also notice that performance drops to 76.70 if we use $N = 16$. This is primarily due to the increased difficulty of predicting accurate coarse segmentation outcomes for multi-frequency features, resulting in inadequate class-level representations when N is too large. Therefore, we adopt $N = 4$ for the other experiments.

6. Limitation

Although we have achieved satisfactory outcomes on face manipulation localization through benchmark experiments, we remain cognizant of certain limitations that exist in this paper.

First, it must be acknowledged that the pixel-level annotation method proposed in this work may not generate absolute and unequivocal tampering mask labels. Nevertheless, none of the current existing single-face manipulation datasets offer definitive and ground-truth tampering mask labels. This makes the masks generated based on pixel-level disparities between real-fake-image pairs the most suitable approximation of the ground-truth labels. Our approach and benchmark can be readily utilized in the event that more precisely-formed forged region mask labels come to fruition.

Besides, the proposed MSCCNet makes no attempt to improve classification performance, since recent methodologies for single-face classification have been extensively studied. Moving forward, we plan to investigate and op-

timize both the classification and location branches of our approach in a unified fashion.

7. Conclusion

This paper proposes a novel Multi-spectral Class Centers Network (MSCCNet) to facilitate the acquisition of more generalizable and semantic-agnostic features for improved face manipulation localization outcomes. To avoid reliance on semantic objective information, we employ the multi-spectral class centers (MSCC) module to compute different frequency class-level contexts and weighted attention, which enables the refinement of deep semantic features. The Multi-level Feature Aggregation (MFA) module is integrated to fuse low-level forgery-specific textures. Our extensive experiments demonstrate the superior localization ability of MSCCNet on comprehensive benchmarks introduced in this paper. It is our hope that the benchmarks and methodologies presented here will encourage further investigations into pixel-level face manipulation localization tasks.

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