

GLCF: A Global-Local Multimodal Coherence Analysis Framework for Talking Face Generation Detection

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Abstract

Talking face generation (TFG) allows for producing lifelike talking videos of any character using only facial images and accompanying text. Abuse of this technology could pose significant risks to society, creating the urgent need for research into corresponding detection methods. However, research in this field has been hindered by the lack of public datasets. In this paper, we construct the first large-scale multi-scenario talking face dataset (MSTF), which contains 22 audio and video forgery techniques, filling the gap of datasets in this field. The dataset covers 11 generation scenarios and more than 20 semantic scenarios, closer to the practical application scenario of TFG. Besides, we also propose a TFG detection framework, which leverages the analysis of both global and local coherence in the multimodal content of TFG videos. Therefore, a region-focused smoothness detection module (RSFDM) and a discrepancy capture-time frame aggregation module (DCTAM) are introduced to evaluate the global temporal coherence of TFG videos, aggregating multi-grained spatial information. Additionally, a visual-audio fusion module (V-AFM) is designed to evaluate audiovisual coherence within a localized temporal perspective. Comprehensive experiments demonstrate the reasonableness and challenges of our datasets, while also indicating the superiority of our proposed method compared to the state-of-the-art deepfake detection approaches.

Introduction

Recently, generative AI technology has achieved some significant advancements. Notably, digital human generation technology, a real-world application of AI generation technology, has been widely used in commercial live broadcasting and other fields, fostering societal and economic progress.

Talking face generation (TFG) represents a pivotal technology in creating digital humans, inherently differing from traditional deepfake approaches. While traditional deepfake methods rely on substituting facial regions within videos

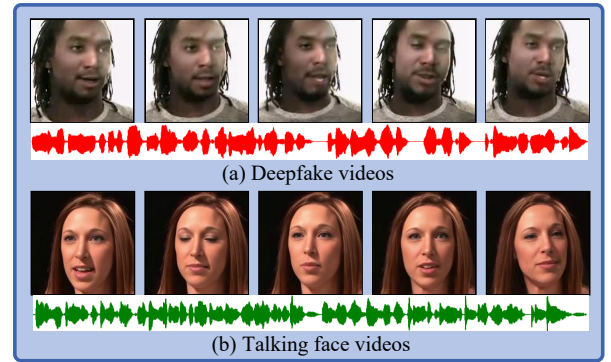


Figure 1: (a) Deepfake videos. (b) Talking face videos. Compared to deepfake videos, talking face videos demonstrate superior visual quality, exhibiting more realistic details, such as illumination uniformity, lip movements, teeth and so on.

to replace identities, the quality of the generated video is constrained by the existing video content. Through talking face generation technology, we can create a highly realistic speech video of a specific individual with just a single image of that person and a textual script, or alternatively, a video clip and an audio segment. The TFG videos demonstrate superior visual quality, exhibiting more realistic details, such as illumination uniformity, lip movements, and so on. Besides, this technology fundamentally advances the forgery process, transitioning from a reliance on strong references to mere weak ones, diminishing the difficulty of forgery. Thus, someone can effortlessly forge videos of renowned politicians making inappropriate statements through this technology, triggering public panic and a crisis of confidence.

For TFG detection, existing deepfake detection methods exhibit limited transferability. (Zhao et al. 2021) and (Peng et al. 2024) capture pixel-level forgery traces from the spatial domain. Since the superior visual quality of TFG videos, it is difficult to extract forgery traces solely from the spatial domain. As talking face generation relies solely on a sin-

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DataSet	Date	Modality	Real Video/Audio	Fake Video/Audio	Total Video/Audio	Manipulation Method	Audio Label
DF-TIMIT	2018	V	320	640	960	2	No
FF++	2019	V	1,000	4,000	5,000	4	No
DeeperForensics	2020	V	360	3,068	3,431	5	No
FFIW	2021	V	10,000	10,000	20,000	1	No
KoDF	2021	V	62,166	175,776	237,942	5	No
DF_Platter	2023	V	133,260	132,496	265,756	3	No
ASVspoof2019	2019	A	10,256	90,192	100,448	19	Yes
WaveFake	2021	A	0	5,160	5,160	7	Yes
CFAD	2023	A	38,600	77,200	115,800	12	Yes
DFDC	2020	A/V	23,654	104,500	128,154	8	No
FakeAVCeleb	2021	A/V	500	19,500	20,000	4	Yes
LAV-DF	2022	A/V	36,431	99,873	136,304	2	Yes
DefakeAVMiT	2023	A/V	540	6,480	7,020	5	Yes
MSTF(Ours)	2024	A/V	37,059	106,695	143,754	22	Yes

Table 1: Quantitative comparison of MSTF with existing publicly available deepfake datasets.

gle weak reference, the frequency domain characteristics of the videos do not exhibit the significant anomalies observed in deepfake videos. Thus, frequency-focused methods, such as (Mejri, Papadopoulos, and Aouada 2021) and (Tan et al. 2024), are difficult to attain robust performance. Since TFG offers more precise audio-visual synchronization, the existing detection techniques utilize multi-modal audiovisual interaction for deepfake video detection, such as (Zhou and Lim 2021) and (Feng, Chen, and Owens 2023), face significant limitations when applied to talking face videos. Works from other fields, such as (Yang et al. 2024) and (Pang et al. 2024), are insightful, but can’t be directly applied.

Therefore, developing targeted detection methods for talking face generation is critical. Currently, the public datasets are mainly visual unimodality. Multi-modal datasets emphasize face replacement forgery, making it challenging to support research on talking face detection. To fill this gap, we propose the first challenging and multi-scenario talking face dataset (MSTF) with the following characteristics: (1) Large-scale, comprising over 100,000 entries. (2) Containing 22 forgery techniques, which is the largest number of forgery techniques among the current mainstream datasets. (3) 11 kinds of generation scenarios. (4) More than 20 kinds of semantic scenarios. Thus, MSTF could effectively support the research of the corresponding detection methods.

Besides, we also propose a framework to analyze both global and local coherence in the multimodal content of the videos, achieving high-precision TFG detection. Given the superior visual quality in TFG videos, we focus on the global temporal coherence across the frames to expose more elusive forgery artifacts. We design a region-focused smoothness detection module (RSFDM), utilizing an attention-like mechanism to target the motion areas and extract the motion information, capturing the incoherent forgery traces during frame transitions. From the local temporal perspective, a visual-audio fusion module (V-AFM) is designed to evaluate the modality coherence which is the primary strength of TFG compared to deepfake but also the aspect most sus-

ceptible to errors. Since frames in TFG videos are produced sequentially, they inevitably exhibit incoherence in the spatial domain, which may be regarded as motion areas in RSFDM. Given the highly precise audiovisual synchronization in TFG, it is difficult to comprehensively capture subtle audiovisual coherence solely through V-AFM. Thus, we design a discrepancy capture-time frame aggregation module (DCTAM) to capture subtle differences between frames, complementing the function of RSFDM. Additionally, it improves the precision of modality alignment, thereby enhancing the performance of V-AFM. Firstly it quantifies the magnitude of pixel differences, activating anomalous regions through discrepancy metrics, and then it adaptively integrates spatial information from adjacent frames at multiple granularities. This module serves as a link between RSFDM and V-AFM to make our framework more cohesive.

We conduct a series of experiments, demonstrating the challenges and advancement of our dataset. Compared to the current state-of-the-art deepfake detection methods, our framework achieves the best performance on the talking face dataset, while also exhibiting good performance on other deepfake datasets. The main contributions of this work are summarized as follows:

- We propose a large-scale multi-scenario talking face dataset, which contains 22 audio and video forgery methods and 11 generation scenarios.
- We also propose a TFG detection framework that analyzes multi-granularity global spatiotemporal coherence and multimodal local coherence.
- An RSFDM is proposed to target the motion areas, capturing the incoherent traces during global frame transitions. A V-AFM is introduced to evaluate the audiovisual modality incoherence from a local temporal perspective.
- A DCTAM is designed to quantify and activate anomalous pixel regions, and then adaptively aggregates spatial information from adjacent frames at multiple granularities, serving as a link between RSFDM and V-AFM.

Talking Face Dataset

Comparison with Existing Datasets

Constrained by the immaturity of forgery techniques and limited computational resources during that period, deepfake datasets such as DF-TIMIT (Korshunov and Marcel 2018), DF (Jiang et al. 2020) and FF++ (Rossler et al. 2019) are typically characterized by their small scale and noticeable visual artifacts.

With the advancement in computational power and the technical improvements, higher-quality and larger-scale deepfake datasets, such as FFIW (Zhou et al. 2021), KoDF (Kwon et al. 2021) and DF_Platter (Narayan et al. 2023) have emerged in succession. However, these datasets primarily focus on video-only unimodal forgery. Subsequently, with the maturation of audio forgery technology, datasets such as ASV2019 (Todisco et al. 2019), WaveFake (Frank and Schönherr 2021), and CFAD (Ma et al. 2022), which focus solely on the audio modality, have been proposed, further diversifying the forms of forgery data.

DFDC (Dolhansky et al. 2020), the first large-scale dataset with audio-video forgery, mostly uses GAN-based face swapping but lacks clear audio authenticity labels, limiting its application potential. FakeAVCeleb (Khalid et al. 2021), introduced in 2021, holds significant importance for multimodal deepfake detection. However, FakeAVCeleb and DefakeAVMiT (Yang et al. 2023) are constrained by limited talking face generation methods and video quantity, hindering their coverage of complex generated scenarios. LAV-DF (Cai et al. 2023) is proposed to support the novel research task of multi-modal forgery temporal localization.

Thus, these datasets could not meet the need for research on talking face detection methods. To fill this gap, we introduce a large-scale, multi-scenario talking face dataset (MSTF) that includes five generation methods and seventeen audio forgery techniques. Though combining various reference inputs, we simulate 11 generation scenarios. These generation scenarios ensure that the TFG videos exhibit multi-level coherence across different modalities, including facial expressions, eye movements, and so on. Additionally, images from different shooting scenes and audio on various topics are combined to make our dataset encompass nearly 40 semantic scenarios. The diverse scenarios make our dataset more relevant to real-world applications of TFG technique, providing a foundation for the research of robust detection methods.

Collection

To better cover a variety of talking face generation scenarios, we collected multiple image, audio, and video datasets.

Image and Video Collection We collect and utilize CelebA-HQ (Karras et al. 2018), Cream-D (Cao et al. 2014), VoxCeleb (Nagrani, Chung, and Zisserman 2017), VoxCeleb2 (Chung, Nagrani, and Zisserman 2018), Mead (Wang et al. 2020), DFDC and LSR2 (Son Chung et al. 2017) as source data. We also collect speech videos from YouTube with some high-quality videos, including scenes from news broadcasts and interviews.

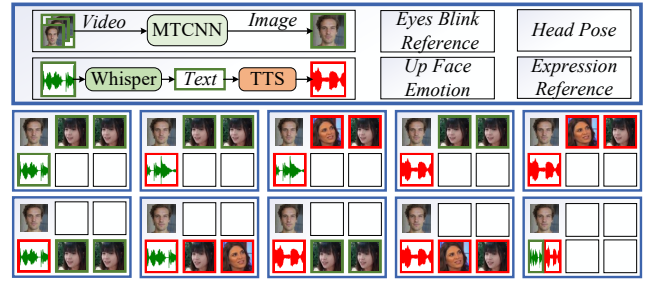


Figure 2: The construction of 11 scenarios. The six boxes in the above big image correspond to the six boxes in each small image below. The green box indicates inputs from the same source, while the red box is the opposite. Green audio denotes genuine audio, whereas red audio signifies forgery audio. Blank means no input.

Audio Collection We additionally collect some speech datasets to enrich our speaker usage scenarios. We extract all the forged audio from FakeAVCeleb. Besides, we collect LibriSpeech (Panayotov et al. 2015) and ASVspoo2019 as driven-audio.

Dataset Construction

FakeVox To simulate the text-guided audio synthesis process in real-world scenarios, we generate additional fake audio using text-to-speech (TTS) technology provided by Tencent. Whisper (Radford et al. 2023) is used to convert the audio data to text. English texts with sentences between 85 and 160 words in length are selected from VoxCeleb. Finally, we respectively generate an emotional and a standard audio datasets, each containing 2000 samples.

Generation Scenario As shown in Figure 2, the green box indicates inputs from the same source, while the red box indicates inputs from different videos. TFG technology requires at least one audio segment, and an image or a video to generate a video. Therefore, we firstly construct two fundamental generation scenarios: genuine audio-driven generation and the forgery one, which are the most common due to their low cost and widespread application, shown in the last small image of Figure 2. Furthermore, aiming to create more realistic videos that contain richer body language, we introduce additional references such as expressions, head movements, and so on. To generate videos that exhibit optimal coherence between visual and auditory semantics, we design a scenario in which the references and the audio originate from the same video. However, the above scenarios do not encompass all complex application scenarios. Thus, another kind of scenario is designed, which is relatively easy to implement and closer to real-world applications. The audio source for this scene is different from the reference video, but all the reference videos are the same one. Finally, we design a kind of scenario where all inputs are completely different, further enriching our dataset scenarios. To achieve the large-scale generation of these not reference scenarios, We collect and utilize HyperLips (Chen et al. 2023), Diff2Lip (Mukhopadhyay et al. 2024) and IP LAP (Zhong

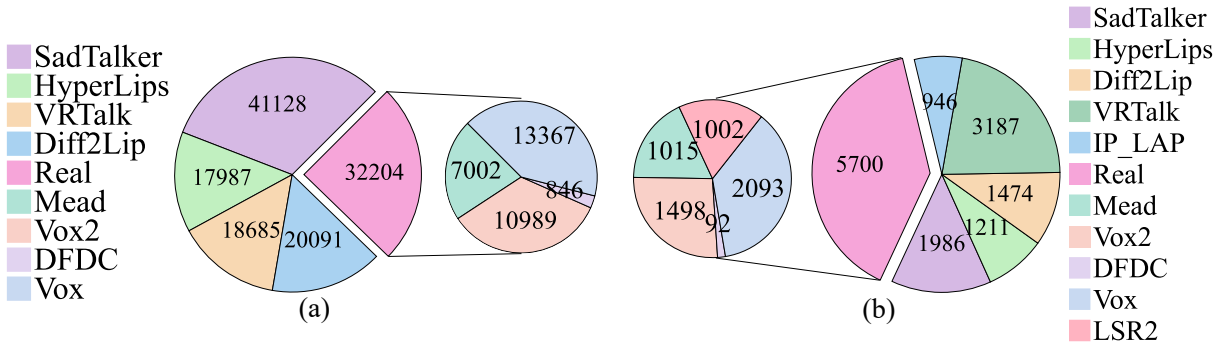


Figure 3: (a) The distribution of training set. (b) The distribution of testing set.

et al. 2023). SadTalker (Zhang et al. 2023) is selected for referenced generation, which includes eyes blinking and head pose. As shown in Figure 2, it is designed with 5 scenarios in the first row of small charts. VideoRetalking (Cheng et al. 2022), which supports inputting references of upper face emotion and expression, is chosen to construct 4 scenarios, shown in the first four subgraphs displayed in the last row.

Dataset Distribution

In figure 3, we present the generation distribution of the dataset on each generation method. To simulate the detection of potential novel real-world scenarios, we add a small portion of the LSR2 dataset to our testing set, which remains unexposed to the training phase, thereby increasing the complexity of the presented scenes. Given the rapid advancements in generative artificial intelligence and talking face generation technologies, we incorporate the IP_LAP, which also remains unexposed to the training set, to generate a small portion of testing cases. This cross-domain evaluation emphasizes the necessity for detection methods to exhibit generalization abilities to ensure their superior performance within the testing set. Hence, these configurations facilitate the exploration of generalized, adaptable detection methods, enabling us to effectively tackle unknown and sophisticated forgery challenges.

Furthermore, we combine videos from different shooting scenes and audios on different topics to simulate more than 20 semantic scenarios, resulting in a total of about 40 different scenarios when combined with generation scenarios.

Methodology

Overview

As shown in Figure 5, we propose a global-local multi-modal coherence analysis framework for talking face generation detection. Our framework includes two video streams and one audio stream. Frequency features are extracted from the first video stream. The second one is processed through two global visual coherence detection modules, mapped into a high-dimensional feature vector that contains abundant information on anomalous regions. Processed through wav2vec and residual layers, the audio stream interactive fusions with the information of second video streaming. The

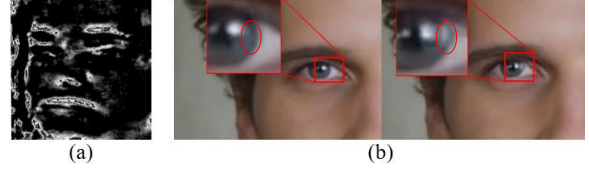


Figure 4: (a) The diagram of the difference between frames. (b) The slight discrepancy in eyeball shape between frames.

fusion information and frequency features are concatenated to further extraction of deep features.

We find that talking face videos often exhibit incoherence during transitions between frames. To address this, a **Region-Focused Smoothness Detection Module** is designed to focus on the principal regions of facial movements at a coarse-grained level, extracting motion information between inter-frames. It employs an attention-like mechanism from a global temporal perspective, effectively capturing the incoherence of frame transitions.

Frame-by-frame generation methodologies inevitably result in incoherence to the global temporal frames. As shown in Figure 4 (b), the same region in a generation video exhibits incoherence across different frames. This slight discrepancy may be interpreted as a motion area by RFSDM, which is an undesired outcome. Through the **Discrepancy Capture-Time Frame Aggregation Module**, we quantify pixel-level spatial discrepancies and propose a differential assessment metric to activate anomalous regions, thereby capturing these subtle inter-frame differences at a fine-grained level. Audiovisual coherence analysis is an effective method for TFG detection. Given the differences in feature extraction between audio and visual data, direct modality interaction often fails to achieve precise temporal alignment, making it inadequate for TFG detection. Therefore, through DCTAM, the spatial information from local temporal frames is aggregated across the multiple granularities of receptive fields.

Besides, the raw audio is transformed into feature vectors through a pre-trained wav2vec model and residual network layers. Then it is input along with the visual information into an innovative **Visual-Audio Fusion Module**, which is introduced to compute similarity metrics between the audiovisual

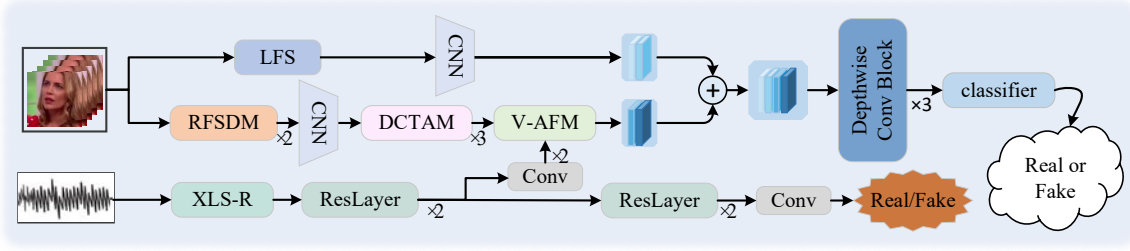


Figure 5: The overall framework of our proposed GLCF. RFSDM and DCTAM extract spatial features, interacting with audio features in V-AFM to get fusion information which is concatenated with frequency domain features extracted by the LFS.

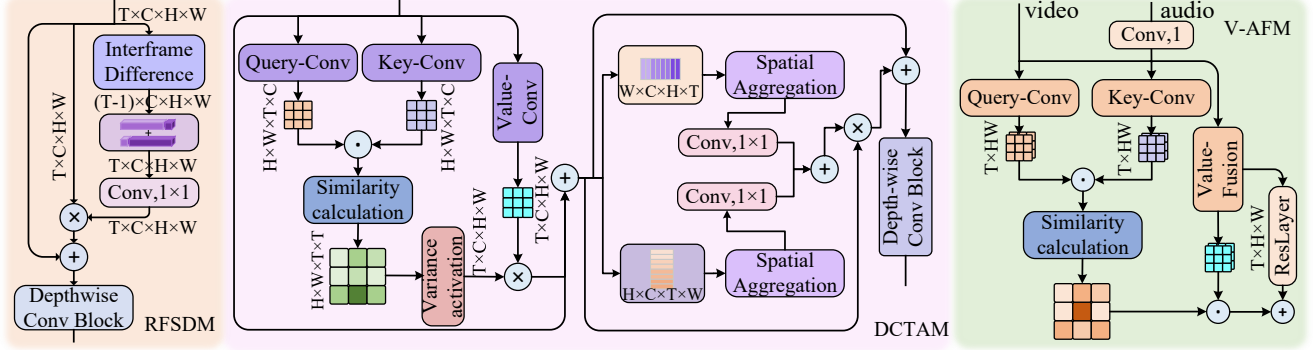


Figure 6: The detail of RFSDM, DCTAM, V-AFM. \oplus and \otimes stand for element-wise addition and multiplication.

modalities from a local temporal perspective. This module facilitates the detection of inter-modal incoherence, which encompasses not only the generation flows of lip movement but also other aspects like head pose.

Spatial analysis is easily disturbed by noise and compression. In contrast, the frequency information can reveal the deep structural characteristics of the image. Based on this, we refer to the **Local Frequency Statistic Method** (LFS) proposed by Qian et al. (Qian et al. 2020). By referring to this module, we successfully extract the statistical frequency domain distribution information, which is concatenated with the audiovisual information for the subsequent depthwise convolution block.

Region-Focused Smoothness Detection Module

Calculating the inter-frame difference is an effective way of reflecting the motion information of video objects. The input frame is denoted as $I \in R^{C \times H \times W}$, C is the number of channels, H and W are spatial dimensions. As input T frames $[I_1 \dots I_T]$, We got input feature $F \in R^{F \times C \times H \times W}$. We calculate the difference between the two leading frames to get the $[D_1 \dots D_{T-1}]$, where $D_{i-1} = I_i - I_{i-1}$. Then we respectively copy the first and last one of $[D_1 \dots D_{T-1}]$ to get $[D_1, D_1, D_2 \dots D_{T-1}]$ and $[D_1, D_2 \dots D_{T-1}, D_{T-1}]$. By adding them, we get $\hat{D} = [\hat{D}_1 \dots \hat{D}_T]$, which denotes the difference between the corresponding frame and the two preceding and following frames. Finally, We use 2D CNN to adaptively learn the weights of the channels, fusing the inter-frame difference information into the original input as regions of interest of the image pixels. This Module can be

formulated as:

$$F_{out} = F_{in} + F_{in} \cdot \text{Conv}_{1 \times 1}(\hat{F}). \quad (1)$$

This module not only enables the feature maps to retain inter-frame transition coherence information but also reflects the motion regions in videos due to the frame difference itself, drawing the model’s attention to the main forged regions such as the mouth. Subsequently, the output is fed into a depth-wise block for further extraction of deep features.

Discrepancy Capture-Time Frame Aggregation Module

Despite its simplicity and efficacy, the inter-frame differential computation is inadequate for discerning subtle forgery indications between frames. As illustrated in Figure 4, these inconspicuous forgeries may be disregarded or misidentified as motion-related regions or mere motion information, resulting in insufficient attention being paid to them. To address this limitation, we devise the Discrepancy Capture-Time Frame Aggregation Module, which could adaptively capture these subtle differences by the modified attention mechanism.

We transform the input feature $F \in R^{F \times C \times H \times W}$ into the matrix F_Q, F_K, F_V by 2D CNN. We calculate the similarity of F_Q and F_K to obtain the Attention Score Matrix $A \in R^{H \times W \times T \times T}$, which represents the similarity of a pixel point between a particular frame and all frames. It should be noted that the subtle disparities that arise during the frame-by-frame generation process are inherently stochastic. In particular, upon examination of pixels within a specified region, the value of similarity between abnormal frames and normal frames will be much smaller than the

one between normal frames. Consequently, we calculate the variance in the T dimension of the attention score matrix, detecting the aforementioned phenomenon. For the matrix A , we perform a summation operation on its last dimension to get $\bar{A} \in R^{H \times W \times T}$. Then, the variance is calculated along dimension T to generate variance matrix $V \in R^{1 \times 1 \times H \times W}$. We pick the k -th smallest variance to be the threshold of activation, greater than the value masked as 1, less than it is set to 0. This operation is similar to the activation layer, except that we get the threshold of activation by calculating the variance, so we call it the variance-activated layer, which is better than activation directly using the ReLU function. This process could be written as:

$$F = F + \alpha \cdot F_V \cdot \Phi(F_Q \times F_K), \quad (2)$$

where Φ represents the variance activation function, and α is an adaptive weight. One of the challenges associated with multimodal interaction is the precise alignment of audiovisual features at a temporal granularity. Thus, we aggregate temporal information from multiple granularity pairs. As shown in Figure 6, we reshape F into horizontal and vertical feature vectors $F_v \in R^{W \times C \times H \times T}$, $F_h \in R^{H \times C \times T \times W}$, which can retain more detailed visual information. After that, we perform downsampling and convolution of different sizes on the features F_v and F_h , and finally perform upsampling and fusion. This process can be described as:

$$F_v = \frac{1}{3} \cdot (Conv_{1 \times 3} F_v + Up_{1 \times 2}(Conv_{1 \times 3}(Down_{1 \times 2}(F_v))) + Up_{1 \times 4}(Conv_{1 \times 3}(Down_{1 \times 4}(F_v)))) \quad (3)$$

The handling of F_h is similar, except that the convolution kernel is transposed.

Audio Stream and V-AFM

Audio Stream We use a pre-trained wav2vec model and a two-layer residual network to map the input audio stream into the feature space, obtaining F_a . The output will be fed into two streams. One of them introduces a complete forgery audio detection stream, which directly predicts the authenticity of the audio. This stream also facilitates the addition of the audio loss function L_a , better fine-tuning of Wav2Vec and training of ResLayer. The total loss function is:

$$L = L_{va} + L_a. \quad (4)$$

Appropriate intermediate features are conducive to modal fusion. We input another output stream into two 3×3 CNNs to obtain intermediate audio feature vectors. These vectors are input into the audio-visual coherence detection module.

Video-Audio Fusion Module We design an audiovisual fusion module based on a multi-head cross-attention mechanism, the main purpose of which is to detect the coherence between audiovisual modes. Specifically, We input audio features into a 1D CNN to align the feature dimension with the visual feature vector, and then further input a 3D CNN to obtain $Query \in R^{C \times T \times H \times W}$. Similarly, visual features are entered into the 3D CNN to get the $Key \in R^{C \times T \times H \times W}$. $Value$ is a linear combination of audiovisual

features, and the entire calculation process can be expressed as:

$$F_{vai} = V_i \times \text{softmax}(\frac{Q_i K_i^T}{H}), \quad (5)$$

$$F_{va} = \Psi(V) + Conv_{1 \times 1}(\text{Concat}(F_{vai})), \quad (6)$$

where Ψ represents the Residual layer, i represents the head.

Experiments

Experimental Settings

Datasets To evaluate our dataset and methodology, we conduct experiments on our MSTF and three other challenging datasets: FaceForensics++, FakeAVCeleb, and DFDC.

- MSTF is our large-scale talking face dataset, comprising 130,095 training videos and 14,504 testing videos,
- FaceForensics++ is a conventional deepfake dataset. We utilized its visually blurred low-quality (LQ) version to contrast and evaluate the challenges posed by MSTF. Given the incompatibility of multimodal methods on this dataset, we exclusively employ unimodal forgery detection methods for our experiments.
- DFDC incorporates advanced face-swapping forgeries, posing a significant challenge for detection. We use 4080 fake videos and 1133 real videos for the experiment.
- FakeAVCeleb, a popular deepfake multimodal dataset, contains 500 real and 20,000 forged videos for evaluating forgery detection methods.

Evaluation metrics In our experiments, we use the accuracy rate (ACC) for evaluation.

Implementation Details We use MTCNN to detect faces in all datasets and then crop them. We adjust the face images to 256×256 to retain more facial information. We use NVIDIA A100 Tensor Core GPU.

Performance Comparisons

Intra-Dataset Comparisons We select several frame-based detection methods for comparison, including F3Net (Qian et al. 2020), RFM (Wang and Deng 2021), Multiatt (Zhao et al. 2021), RECCE (Cao et al. 2022), MiNet (Ba et al. 2024). Additionally, we incorporate several multimodal video detection approaches, including Joint A-V (Zhou and Lim 2021), AVSSD (Sung, Chen, and Chen 2023), and AVD2-DWF (Wang et al. 2024). It is noteworthy that the code for ReCCE, Joint A-V, and AVD2-DWF are not fully open-sourced, thus we try our best to replicate it based on the original documentation. All these methods have been published in reputable journals or conferences. The experimental results are presented in Table 2.

Experimental results show that our raw MSTF dataset is even harder to detect content from than the well-known and challenging FF++ dataset(C40), revealing the necessity of specialized detection for talking face generation and the effectiveness and validity of the MSTF dataset in facilitating such endeavors. In the meantime, our method achieves the best performance on the FakeAVCeleb, DFDC, and MSTF datasets. On the MSTF dataset, it surpasses the second-best

Methods	FF++	FakeAV	DFDC	MSTF
F3Net	0.8767	0.9829	0.9245	0.8516
RFM	0.8410	0.9634	0.6406	0.8521
Multi-att	0.8740	0.9833	0.8976	0.7871
RECCE	0.8742	0.9831	0.9125	0.8191
MiNet	0.8626	0.9768	0.8933	0.8612
Joint A-V	—	0.9769	0.7773	0.8454
AVSSD	—	0.9760	0.6445	0.8292
AVD2-DWF	—	0.9736	0.6758	0.7821
Ours	—	0.9892	0.9258	0.8849

Table 2: Comparison result on FF++(C40), FakeAVCeleb, DFDC and MSTF in terms of a accuracy

Methods	FakeAVCeleb	MSTF
F3Net	0.9829	0.5611
RFM	0.9634	0.5783
Multi-att	0.9833	0.5148
RECCE	0.9831	0.5941
MiNet	0.9768	0.5438
Joint A-V	0.9769	0.4124
AVSSD	0.9760	0.5981
AVD2-DWF	0.9736	0.6000
Ours	0.9892	0.6194

Table 3: Comparison result on cross-dataset generalization in terms of accuracy.

performer, MiNet, by 2.37%. For the FakeAVCeleb dataset, focusing on the binary classification of genuine and fake samples, our method also outperforms the second-best performer, Multi-att, by 0.59%. Similarly, on DFDC, we outperform F3Net, the second-best performer, by a narrow margin of 0.13%. Experimental results demonstrate that our methodology is not merely confined to the specific domain of talking face generation detection but also exhibits a significant degree of generalizability, enabling it to adeptly address a wide array of forgery tactics, including traditional deepfake.

Inter-Dataset Comparisons We perform training on the FakeAVCeleb and perform testing on FakeAVCeleb and our proposed MSTF. The experimental results are shown in Table 3. Our method simultaneously achieves the best performance on both datasets. This indicates that our method captures the common forgery traces between traditional deepfake and talking face videos, rather than relying on overfitting.

Overall, methods trained on deepfake datasets do not exhibit good generalization on the MSTF, further highlighting the importance of dedicated datasets of talking face videos.

Ablation Study

Given our method’s focus on talking face generation, we conduct a series of ablation studies on the MSTF dataset to evaluate the importance of our four primary modules. As shown in Table 4, our innovative RFSDM, DCTAM,

Method				MSTF
LFS	RFSDM	DCTAM	V-AFM	
—	✓	✓	✓	0.8625
✓	—	✓	✓	0.8503
✓	✓	—	✓	0.8470
✓	✓	✓	—	0.8022
✓	✓	✓	✓	0.8849

Table 4: The Ablation Study on MSTF

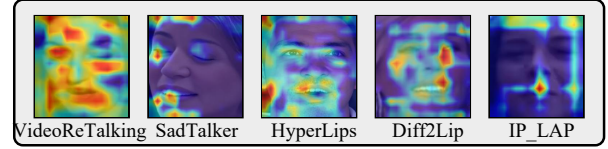


Figure 7: Grad-CAM (Selvaraju et al. 2017) of model outputs.

and V-AFM modules each contributed to an increase in model performance by at least 3%, with the V-AFM module, specifically designed for modal consistency detection, demonstrating an even more substantial improvement of 8.27%. Although the LFS module has the least impact on model performance, it indicates that feature completion in the frequency domain is beneficial for detecting talking face forgery. Achieving better results may require further design for TFG.

Visualization Analysis

In Figure 7, we draw the attention map, which shows that the model can pay attention to the forged traces in different areas, especially the mouth and eyes. It also demonstrates the effectiveness of our V-AFM for audiovisual coherence detection. The model also focuses on major motion regions such as the head and some other small regions, demonstrating the effectiveness of our RFSDM and DCTAM.

Limitations

Further research is needed in the future to develop detection methods specifically aimed at TFG videos compressed by social media platforms.

Conclusion

In this paper, we propose the first large-scale multi-scenario talking face dataset. For TFG detection, we propose RFSDM, which analyzes the coherence of the transition of video frames. DCTAM is introduced to bridge the process by capturing subtle inter-frame differences and adaptively aggregating spatial information. V-AFM is proposed to detect the coherence between the fused information and the corresponding audio information in the local temporal segment. Experiments demonstrate the challenge and necessity of our dataset. Our Framework also achieves optimal performance in both talking face detection and deepfake detection.

Acknowledgments

This work is supported by the National Natural Science Foundation of China (No. U2001202, No. 62072480, No. 62172435, No. U23A20305), the National Key Research and Development Program of China (No. 2022YFB3102900), the Macau Science and Technology Development Foundation (No. SKLIOTSC-2021-2023, 0022/2022/A), the Natural Science Foundation of Guangdong Province of China (No. EF2023-00116-FST), the Open Research Project of the Key Laboratory of Artificial Intelligence Security, Ministry of Public Security (RGZNAQ-2403).

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