Face Forgery Video Detection via Temporal Forgery Cue Unraveling

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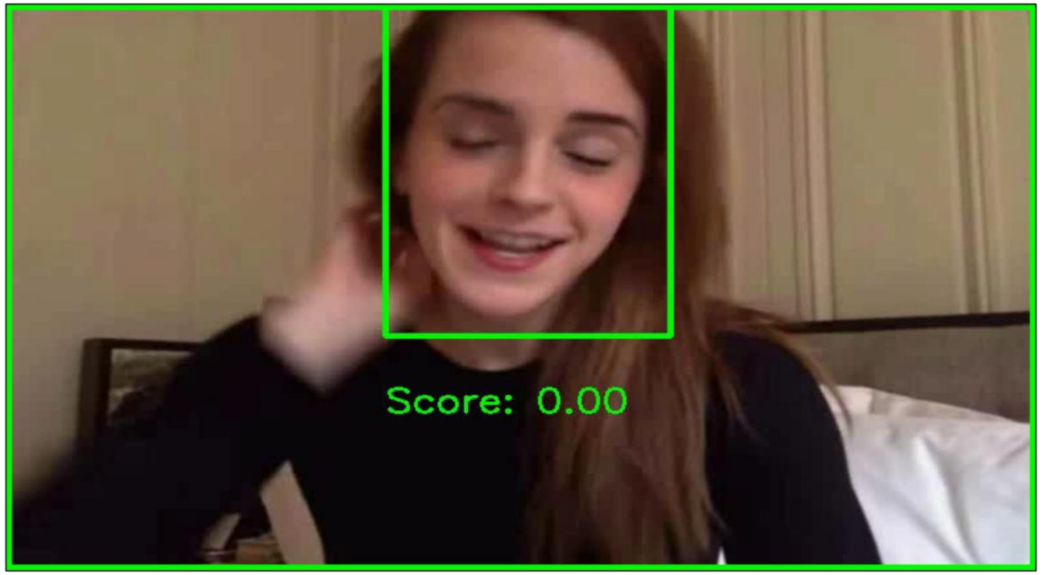
Introduction

Goal

➢ **Face Forgery Video Detection (FFVD)** is a critical yet challenging task in determining whether a digital facial video is authentic or forged.



Introduction

Motivation & Novelty

- Existing FFVD methods typically focus on **isolated spatial features or coarsely fused** spatiotemporal information, failing to leverage temporal forgery cues, resulting in unsatisfactory performance.
- Based on an analysis of the inherent stealth of temporal cues and inspired by the human discrimination process, we abstract temporal forgery cues into three progressive levels: **momentary anomaly, gradual inconsistency, and cumulative distortion**.

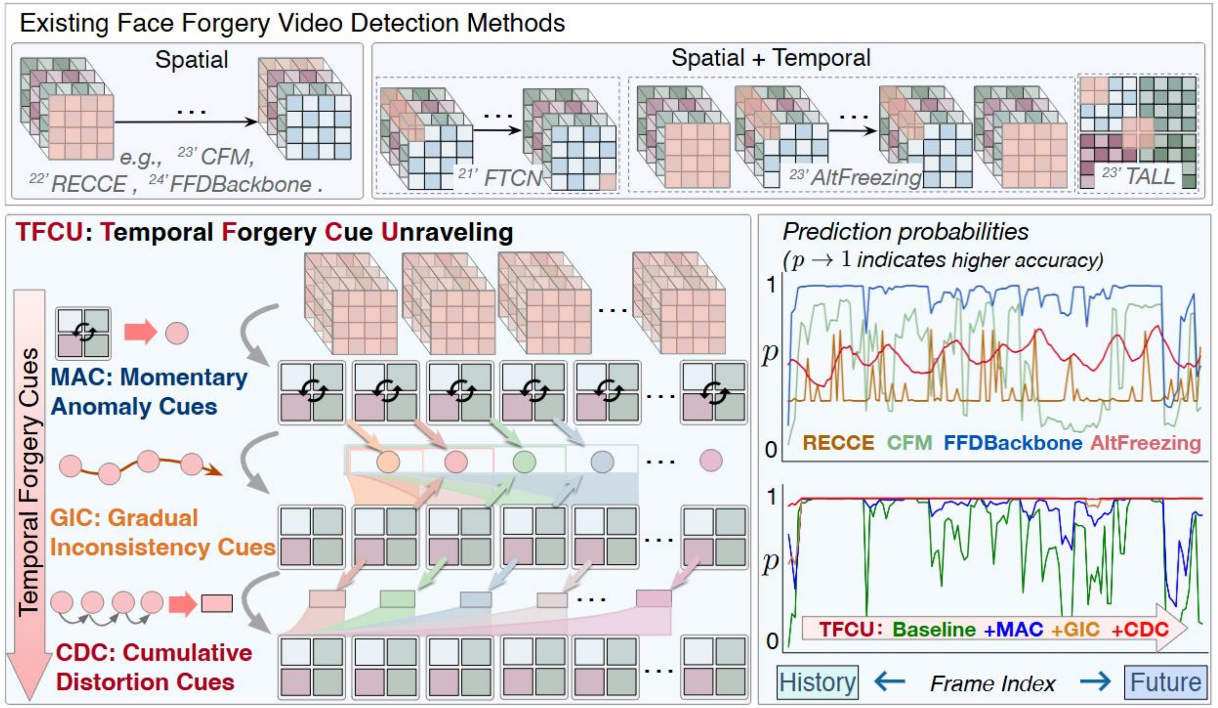
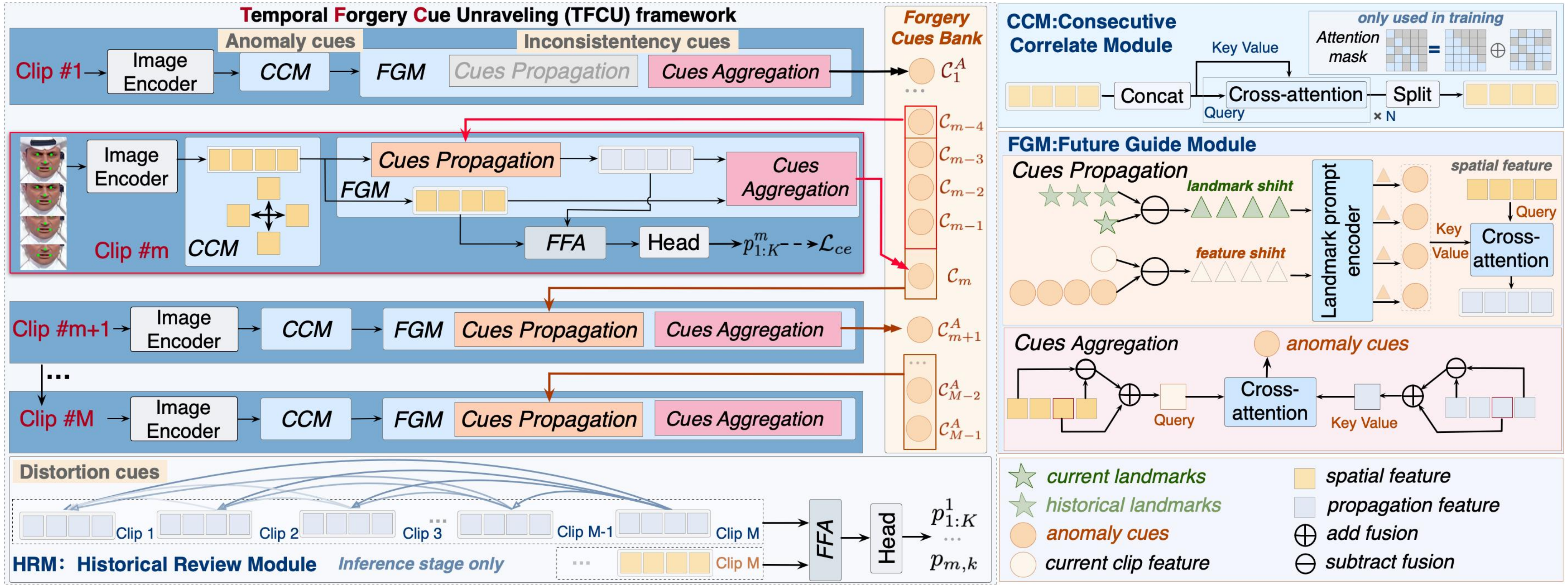


Figure 1. Temporal forgery cues are coarsely explored by adjusting 3D CNNs' kernels or combining frames (*top-right*), leading to significant inter-frame prediction fluctuations (*middle-right*). In contrast, our TFCU meticulously unravels these cues in three progressive levels: momentary anomaly, gradual inconsistency, and cumulative distortion, highlighting general forgery features bidirectionally between historical and future frames (*bottom-left*), thereby achieving stable and precise predictions (*bottom-right*).

Framework

- We strive to unravel these cues across three progressive levels: **momentary anomaly**, **gradual inconsistency**, and **cumulative distortion**.
- We design the Temporal Forgery Cue Unraveling (TFCU) framework to sequentially highlight spatially discriminative features by bidirectionally unraveling temporal forgery cues between **historical and future frames**.



1. Consecutive Correlate for Anomaly Cues

- We propose a consecutive correlate module to capture momentary anomaly cues by correlating interactions among consecutive frames.
- We design the cross-attention module for inter-frame interaction with a unit frame-wise lower triangular mask and random masking for the cross-attention weight w .

$$M_{ij}^{d} = \begin{cases} 1, & \lceil \frac{i}{N} \rceil \geq \lfloor \frac{j}{N} \rfloor \\ -\infty, & \lfloor \frac{i}{N} \rfloor < \lceil \frac{j}{N} \rceil \end{cases}, M_{ij}^{r} = \begin{cases} 1, & p \\ -\infty, & 1-p \end{cases} \qquad w' = w \odot (M_d + M_r)$$

2. Future Guide for Inconsistency Cues

- We devise a future guide module to unravel inconsistency cues by iteratively aggregating historical anomaly cues and gradually propagating them into future frames.

- **Anomaly Cue Aggregation**: For subsequent clips, $\mathbf{E_{ca}}$ takes features from consecutive correlation module (f^{cc}) and output from inconsistency cue propagation (f^{ip}) as input to aggregate anomaly cues $(\mathcal{C}_m)$.

$$\mathcal{C}_m = \mathbf{E}_{ca}\left(f_m^{cc}, f_m^{ip}\right), f_m^{cc} = f_{\lceil \frac{K}{2} \rceil}^{cc} + \left(f_K^{cc} - f_1^{cc}\right)$$

- **Inconsistency Cue Propagation**: We leverage $\mathbf{E_{cp}}$ to propagate forgery cues by interacting current clip $f_{m,k}^{cc}$ with nearest T historical $\mathcal{C}$. In addation, we encode the Landmark shifts using $\mathbf{E_{lp}}$ to update $\mathcal{C}$,and process them with $\mathbf{E_{cp}}$ to enhance spatial features.

$$\mathcal{C}_R^{'} = \mathbf{E_{lp}}\left(L_{\lceil \frac{K}{2} \rceil}^{m} - L_{\lceil \frac{K}{2} \rceil}^{R}, f_m^{cc} - \mathcal{C}_R\right)$$

$$f_{m,1:K}^{ip} = \mathbf{E_{cp}}\left(f_{m,1:K}^{cc}, \{\mathcal{C}_i^{'} + \mathcal{C}_i\}_{i=m-T}^{m-1}\right)$$

3. Historical Review for Distortion Cues

- We introduce a historical review module that unravels distortion cues via momentum accumulation from future to historical frames.
- We perform backward updates across all M clips, where for the m-th clip: its value is iterative updated using future s-th clip, formulated as:

$$f''^{ip}_{m,1:K} = \alpha^s_m f'^{ip}_{m,1:K} + (1 - \alpha^s_m)\frac{1}{K}\sum_{i=1}^{K} f'^{ip}_{s,k}$$

where $s \in \{m+1, m+2, \ldots, M\}$

1. Cross-datasets and Cross-manipulation Evaluations

- Extensive experiments demonstrate the effectiveness of our TFCU method, achieving state-of-the-art performance across diverse unseen datasets and manipulation methods.

Method	Celeb-DF		DFDC		FFIW	
	video	frame	video	frame	video	frame
22' RECCE‡ [5]	73.50	64.82	65.64	62.54	63.41	60.93
22' SBI† [29]	<u>92.88</u>	84.86	72.06	68.16	85.05	81.63
22' D-adv‡ [34]	81.95	76.74	74.43	71.59	71.44	70.71
22' UIA-ViT† [48]	84.75	77.51	75.00	72.61	75.26	69.18
23' CADDM† [9]	86.00	77.45	71.80	66.97	80.64	75.18
23' CFM† [21]	85.27	78.08	75.02	71.96	80.49	78.27
24' LSDA* [40]	91.10	<u>86.70</u>	77.00	73.60	-	-
24' FFDBackbone† [14]	90.88	83.31	<u>85.41</u>	<u>82.45</u>	<u>90.87</u>	<u>87.06</u>
21' FTCN† [46]	85.88	80.64	67.61	66.58	70.85	68.89
23' AltFreezing† [35]	85.06	72.58	71.74	66.23	72.97	69.13
23' TALL* [37]	90.79	-	76.78	-	-	-
24' NACO* [44]	89.50	-	76.70	-	-	-
TFCU	**93.18**	**91.38**	**86.05**	**85.43**	**91.27**	**90.21**

"†": author's released model "*": results from original paper
"‡": re-implementation model with public code

Table 1. **Cross-dataset evaluations.** "video" and "frame" denote video-wise and frame-wise AUC↑ (%) respectively. The method's superscript indicates paper's publication or release year.

Method	SadTalker[45]		FOMM[30]		FaceDancer[26]		MobileSwap[38]		SimSwap[6]		InSwapper[3]		UniFace[36]	
	video	frame	video	frame	video	frame	video	frame	video	frame	video	frame	video	frame
22' RECCE‡ [5]	83.58	84.24	99.15	94.15	81.84	71.96	97.23	94.21	79.36	74.06	92.75	88.26	94.15	87.55
22' SBI† [29]	77.24	81.18	<u>99.49</u>	96.88	77.98	73.69	**99.63**	<u>98.02</u>	<u>97.18</u>	94.59	91.99	88.26	95.09	92.80
22' D-adv‡ [34]	81.20	<u>86.85</u>	99.23	<u>97.59</u>	80.58	73.60	97.70	95.38	82.62	81.47	89.64	86.12	93.31	90.26
22' UIA-ViT† [48]	78.59	77.75	94.56	89.24	86.30	80.73	95.64	90.05	70.90	68.05	91.04	86.15	88.99	83.05
23' CADDM† [9]	51.14	61.57	78.40	77.07	72.20	66.56	95.96	89.94	93.27	86.11	76.76	72.29	90.17	83.52
23' CFM† [21]	84.26	83.78	98.69	95.58	93.62	88.20	99.04	95.42	90.16	85.85	94.50	90.25	97.13	93.54
24' FFDBackbone† [14]	88.14	86.66	99.45	96.69	<u>95.72</u>	89.83	<u>99.40</u>	96.60	96.58	92.31	<u>97.83</u>	93.16	99.10	96.60
21' FTCN† [46]	82.70	82.81	80.24	81.13	94.78	<u>93.45</u>	78.81	79.68	96.39	<u>95.11</u>	97.10	<u>96.19</u>	98.03	97.43
23' AltFreezing† [35]	<u>88.30</u>	79.81	72.86	66.36	90.18	80.43	92.89	82.97	**97.29**	90.85	**98.67**	95.16	**99.69**	<u>98.19</u>
TFCU	**90.16**	**91.16**	**99.59**	**99.21**	**95.91**	**94.82**	99.22	**98.63**	96.81	**95.82**	97.36	**96.47**	<u>99.17</u>	**98.67**

"†": author's released model "‡": re-implementation model with public code

Table 2. **Cross-manipulation evaluations.** The first row shows the classical and representative face manipulation methods, with the corresponding test dataset from DF40 [41]. "video" and "frame" denote video-wise and frame-wise AUC↑ (%) respectively.

Experiments on Face Forgery Video Detection

2. Discriminant Performance on DFDC

FTCN （ICCV 2021） AltFreezing （CVPR 2023） TFCU (Ours)

Experiments on Face Forgery Video Detection

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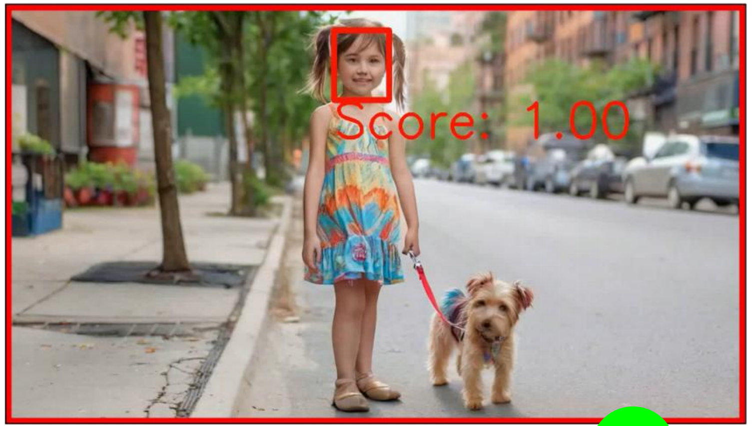
3. Discriminant Performance on Text-to-Video Generation Videos

Kling1.5

Our model: ***Fake***

Luma 1.6



Our model: ***Fake***

QingYing

Our model: ***Fake***

Mochi1

Our model: ***Fake***

Minimax

Our model: ***Fake***

Pixverse

Our model: ***Fake***

Prompt: Static camera, a little girl is walking on the street with a small dog in front of her.

Experiments on Face Forgery Video Detection

4. Discriminant Performance on Image-to-Video Generation Videos

Kling1.5

Our model: ***Fake***

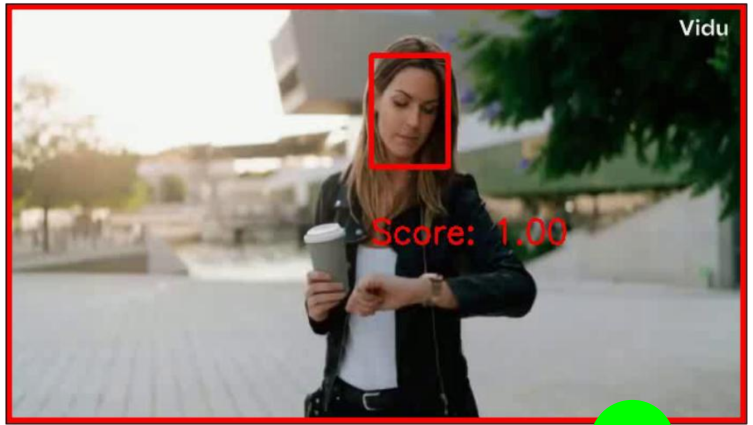
Luma 1.6

Our model: ***Fake***

QingYing

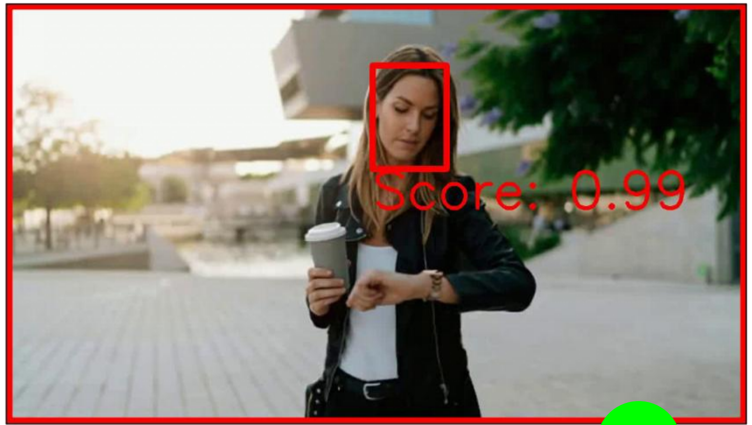
Our model: ***Fake***

Vidu



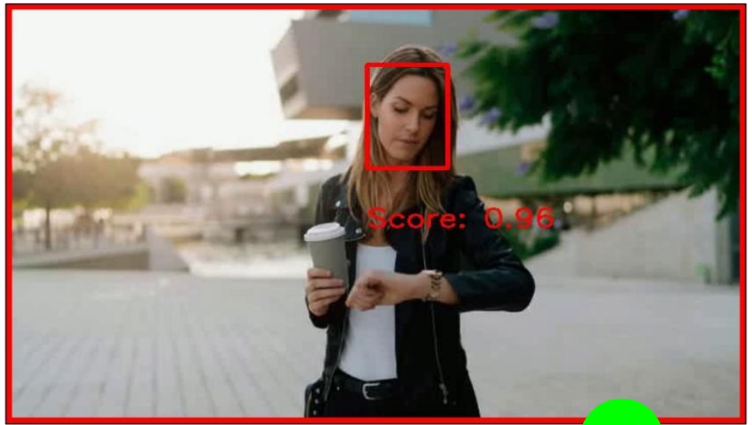
Our model: ***Fake***

OpenSora 1.2



Our model: ***Fake***

Cog5B



Our model: ***Fake***

Prompt: *camera remains still, the woman holds a coffee cup and walks towards.*

Conclusion

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- We develop an FFVD framework that meticulously unravels temporal forgery cues from **momentary anomalies** to gradual inconsistencies and ultimately to cumulative distortions.
- We devise cue aggregation and propagation mechanisms that aggregate historical anomalies and propagate **inconsistencies** to highlight future spatial forgery features.
- We design a momentum accumulation operation to reinforce historical spatial forgery features by accumulating future **distortions**.
- We conduct comprehensive experiments demonstrating the effectiveness of our method, achieving state-of-the-art performance across various cross-datasets and cross-manipulations.

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- We conduct comprehensive experiments demonstrating the effectiv-eness of our method, achieving state-of-the-art performance across various cross-datasets and cross-manipulations.

We hope that our work opens up new avenues for further study of face forgery video detection tasks.

Thanks for your attention !

Face Forgery Video Detection via Temporal Forgery Cue Unraveling

https://github.com/zhenglab/TFCU