

# Leveraging temporal information and GPU acceleration for efficient source attribution of stabilized videos

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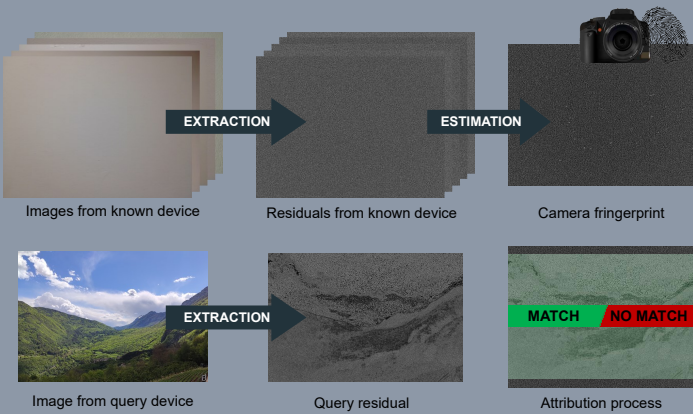
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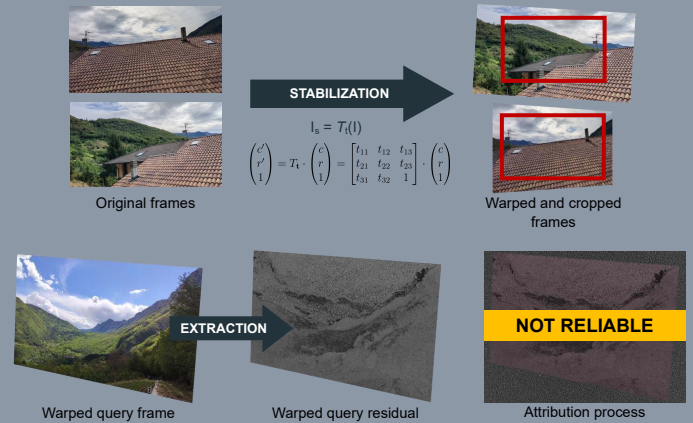
## Abstract

Video stabilization is a common in-camera processing technique applied by modern devices that significantly improves the visual quality of the resulting videos. The applied transformations also distort the Photo Response non-uniformity (PRNU) components in each frame, commonly used for source attribution purposes. The attribution process for stabilized videos relies on estimating the transformation applied to each frame. Several techniques have been proposed to tackle this problem, which typically suffer from a high computational cost due to the size of the inversion parameters space. Our work attempts to reduce the computational load by leveraging the temporal coherence of real videos and accelerate the computation by exploiting the parallelization capabilities of Graphics Processing Units (GPUs). Experiments on a consolidated benchmark dataset confirm the effectiveness of the proposed approach in reducing the required computational time and improving the source attribution accuracy.

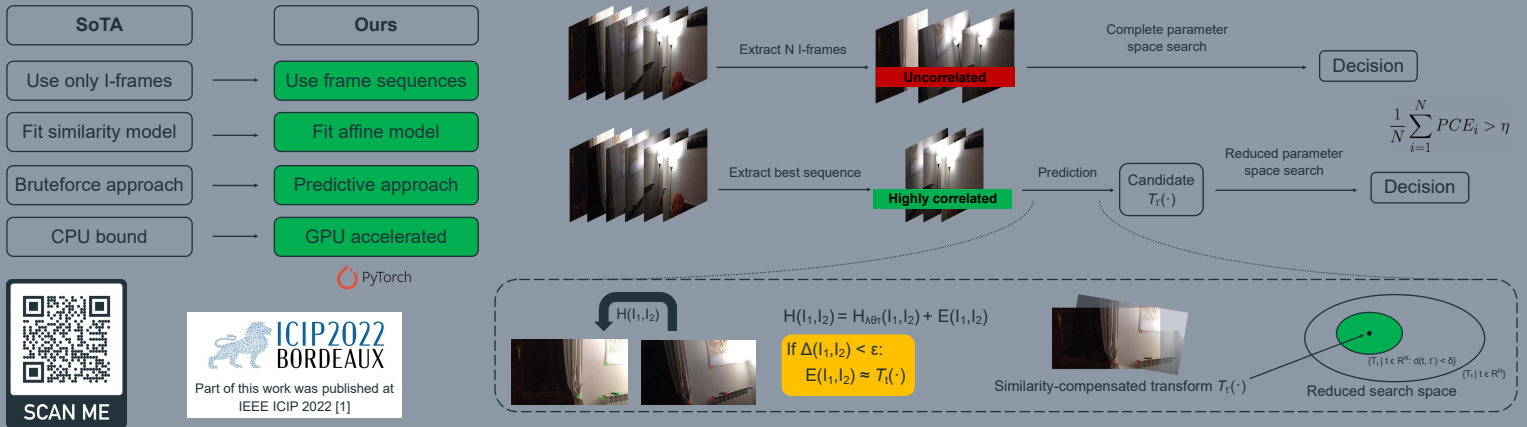
## Source attribution



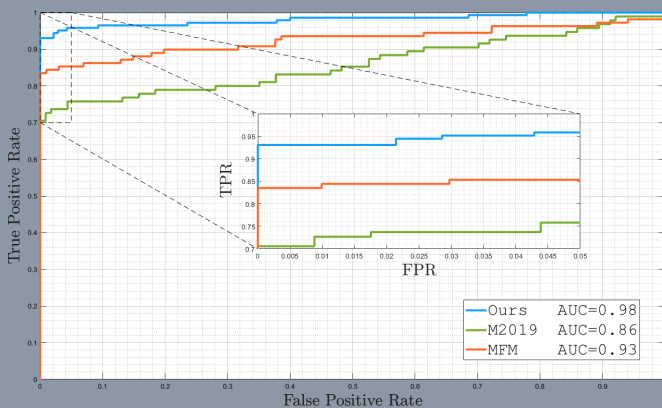
## Video stabilization



## Method



## Results on VISION dataset [4]



Device ID	OUR		M2019 [2]		MFM [3]	
	$\eta_{0.05} = 41.5$		$\eta_{0.05} = 36$		$\eta_{0.05} = 34$	
D02	1	<b>6.41</b>	0.87	61.61	0.89	110.13
D05	1	<b>6.02</b>	0.62	54.08	0.89	107.33
D06	1	<b>6.22</b>	0.88	52.33	0.78	95.05
D10	1	<b>6.71</b>	0.87	51.47	0.89	78.42
D14	0.92	<b>6.98</b>	0.87	51.46	1	72.29
D15	1	<b>8.61</b>	0.63	60.65	0.78	66.32
D18	1	<b>7.06</b>	0.5	47.21	0.89	76.50
D19	1	<b>6.08</b>	0.75	38.27	0.89	57.54
D20	1	<b>6.78</b>	0.88	37.97	1	51.97
D25	0.64	<b>5.95</b>	1	37.88	1	49.50
D29	1	<b>5.90</b>	0.63	53.21	0.67	37.58
D34	1	<b>5.93</b>	0.57	44.88	0.55	39.88

<sup>1</sup> True Positive Rate

<sup>2</sup> Elaboration Time Per Frame

[1] A. Montibeller, C. Pasquini, G. Boato, S. Dell'Anna and F. Pérez-González, "Gpu-Accelerated Sift-Aided Source Identification of Stabilized Videos," 2022 IEEE International Conference on Image Processing (ICIP), Bordeaux, France, 2022, pp. 2616-2620, doi: 10.1109/ICIP46576.2022.9897579

[2] S. Mandelli, P. Bestagini, L. Verdoliva and S. Tubaro, "Facing Device Attribution Problem for Stabilized Video Sequences," in IEEE Transactions on Information Forensics and Security, vol. 15, pp. 14-27, 2020, doi: 10.1109/TIFS.2019.2918644

[3] S. Mandelli, F. Argenti, P. Bestagini, M. Iuliani, A. Piva and S. Tubaro, "A Modified Fourier-Mellin Approach For Source Device Identification On Stabilized Videos," 2020 IEEE International Conference on Image Processing (ICIP), Abu Dhabi, United Arab Emirates, 2020, pp. 1266-1270, doi: 10.1109/ICIP40778.2020.9191001

[4] D. Shuliani, M. Fontani, M. Iuliani, O. Alshaya and A. Piva, "VISION: a video and image dataset for source identification," EURASIP J. on Info. Security 2017, 15 (2017), doi: 10.1186/s-13635-017-0067-2