

SUPPLEMENTAL MATERIAL

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1 EFFECTIVENESS OF FREQUENCY CLUES

We follow previous work to utilize frequency information to provide richer forgery clues. Currently, we concatenate all 4 types of Haar wavelet coefficients and report results. Here we conduct ablation study on different transformation methods (e.g., Discrete Cosine Transform and Discrete Fourier Transform). Specifically, we replace the frequency domain module with the frequency domain operator of the previous work while keeping the CRL unchanged. The superiority of wavelet of the proposed method can be seen in Table 1.

Table 1: Comparison with methods leveraging different type of frequency clues. The proposed method uses Wavelet transformation to extract frequency features. The FF++ (HQ (c23)) dataset is used for training and testing.

	ACC	AUC
Discrete Cosine Transform	97.41	98.64
Discrete Fourier Transform	97.02	99.13
Haar Wavelet Transform	97.57	99.53

2 MORE RESULTS ON GENERALIZABILITY COMPARISONS

Here we demonstrate more cross-datasets evaluations based on more deepfake datasets including CelebDF (Li et al., 2020b) and DeeperForensics-1.0 (DF1.0) (Jiang et al., 2020). To comprehensively evaluate the generalizability of our method, we compared with several state-of-the-art methods including Xception (Rossler et al., 2019), Face X-ray (Li et al., 2020a), F³-Net (Qian et al., 2020), and SLADD (Chen et al., 2022).

In these experiments, we train the compared models on each of the four methods in FaceForensics++ (FF++) (Rossler et al., 2019), and evaluate it on the benchmark datasets including CelebDF and DF1.0. This setting is rather challenging since the forgery clues in the test dataset are unseen in the training dataset. Table 2 shows the results of comparisons of several approaches. Results are reported using the Area Under Curve (AUC) metric. As can be seen, the proposed method outperforms other models in the majority of situations and delivers the best overall performance. This clearly demonstrates the method’s generalizability benefit.

Table 2: Comparisons of generalizability to SOTA methods in terms of AUC. Bold font denotes the best results. The training dataset is shown in the first row of the table, and the equivalent test dataset is shown in the second row. Among the compared models, the proposed method performs well.

	DF		F2F		FS		NT	
	CelebDF	DF1.0	CelebDF	DF1.0	CelebDF	DF1.0	CelebDF	DF1.0
Xception (Rossler et al., 2019)	68.10	61.70	59.80	74.50	60.10	60.50	62.50	83.80
Face X-ray (Li et al., 2020a)	55.40	66.80	68.40	76.60	69.70	79.50	70.30	86.60
F ³ -Net (Qian et al., 2020)	66.40	65.80	65.40	76.10	63.60	65.10	68.90	93.20
SLADD (Chen et al., 2022)	73.00	74.20	78.10	78.60	80.00	69.50	75.90	88.90
Ours	74.15	77.12	79.38	78.42	82.14	70.28	78.36	89.92

3 COMPARISONS WITH MULTIPLE LOSS FUNCTIONS

To demonstrate the effectiveness of CRL, we conduct additional experiments on various losses, including traditional softmax loss, Euclidean margin loss, SphereFace Liu et al. (2017), ArcFace Deng et al. (2019), and Elasticface Boutros et al. (2022). As shown in Table 3, the proposed CRL achieves the best results by forcing natural faces to be gathered and separated from manipulated faces, which are distributed less compactly.

Table 3: Effectiveness of CRL. We report frame-level results on FF++ (HQ (c23)) dataset. Compared to existing losses, the proposed CRL achieves the best results.

Loss function	ACC	AUC
Softmax loss	90.45	95.01
Euclidean margin loss	91.06	95.63
SphereFace Liu et al. (2017)	91.48	95.91
Arcface Deng et al. (2019)	92.32	97.85
Elasticface Boutros et al. (2022)	92.77	97.98
CRL	94.04	98.23

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