# 6 Appendix

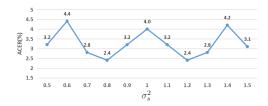
# A. Impact of Spatial Neighborhood Distance in DBO

The full version of deep bilateral operator (DBO) with spatial neighborhood distance term can be formulated as

$$DBO_{full}(\mathcal{F})_{p} = \frac{1}{k} \sum_{q \in \mathcal{F}} g_{\sigma_{s}}(\|p - q\|) g_{\sigma_{r}}(|\mathcal{F}_{p} - \mathcal{F}_{q}|) \mathcal{F}_{q},$$

$$with: \qquad k = \sum_{q \in \mathcal{F}} g_{\sigma_{s}}(\|p - q\|) g_{\sigma_{r}}(|\mathcal{F}_{p} - \mathcal{F}_{q}|).$$
In this ablation study, the impact of spatial neighborhood distance  $g_{\sigma_{s}}(\|p - q\|)$  would be explorted. Here, the default setting  $\sigma^{2} = 1.0$  is utilized. It can be seen from Fig. 8

In this ablation study, the impact of spatial neighborhood distance  $g_{\sigma_s}(\|p-q\|)$  would be evaluated. Here the default setting  $\sigma_r^2=1.0$  is utilized. It can be seen from Fig. 8 that there are no improvements (2.4% and 2.1% ACER for with and without spatial neighborhood distance, respectively) when introducing spatial neighborhood distance term into BCN.

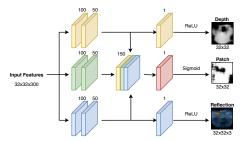


**Fig. 8.** Impact of  $\sigma_s$  in BCN.

Note that the ablation study about distance term  $\sigma_s$  here is not enough thus it might be a sub-optimal solution. The optimal hyperparameter setting could be found via strict grid search, which is one of our future works. Long-range spatial impact of distance term  $\sigma_s$  under large kernel size (e.g., 5x5 and 7x7) is also worth exploring in future.

#### B. Network Details of Multi-head Supervision

The detailed layers are illustrated in Fig. 9. With the supervision from three kinds of cues, the backbone network is able to learn more holistic material-based features.



**Fig. 9.** Network structure of multi-head supervision. The number of filters are shown on top of each convolution, the size of all filters is  $3\times3$  with stride 1.

#### C. Intra Testing Results on SiW

As shown in Table 6, the proposed method performs the best for all three protocols, revealing the excellent generalization capacity.

**Table 6.** The results of intra testing on three protocols of SiW [16].

Prot.	Method	APCER(%)	BPCER(%)	ACER(%)
	Auxiliary [16]	3.58	3.58	3.58
1	STASN [38]	_	_	1.00
	FAS-TD [37]	0.96	0.50	0.73
	BASN [32]	_	_	0.37
	Ours	0.55	0.17	0.36
	Auxiliary [16]	$0.57\pm0.69$	$0.57\pm0.69$	$0.57\pm0.69$
2	STASN [38]	_	_	$0.28\pm0.05$
l	FAS-TD [37]	$0.08\pm0.14$	$0.21\pm0.14$	0.15±0.14
	BASN [32]	_	_	0.12±0.03
İ	Ours	$0.08\pm0.17$	$0.15\pm0.00$	$0.11 \pm 0.08$
	STASN [38]	-	-	$12.10\pm1.50$
3	Auxiliary [16]	8.31±3.81	$8.31\pm3.80$	8.31±3.81
İ	BASN [32]	_	_	6.45±1.80
	FAS-TD [37]	$3.10\pm0.81$	$3.09\pm0.81$	$3.10\pm0.81$
	Ours	$2.55\pm0.89$	$2.34\pm0.47$	$2.45{\pm}0.68$

## D. Cross-type Testing on CASIA-MFSD, Replay-Attack and MSU-MFSD

In these cross-type testing, three datasets CASIA-MFSD [64], Replay-Attack [65] and MSU-MFSD [66] are utilized to perform intra-dataset cross-type testing between replay and print attacks. For instance, the second column 'Video' in Table 7 means that model should be trained from 'Cut Photo' and 'Wrapped Photo' while tested on 'Video'. Table 7 shows that our proposed method achieves the best overall performance (96.77% AUC), indicating the learned features generalized well among unknown attacks.

**Table 7.** The results of cross-type testings. The evaluation metric is AUC (%).

Method	CASIA-MFSD [64]		Replay-Attack [65]		MSU-MFSD [66]		Overall			
Method	Video	Cut Photo	Wrapped Photo	Video	Digital Photo	Printed Photo	Printed Photo	HR Video	Mobile Video	Overan
OC-SVM+BSIF [69]	70.74	60.73	95.90	84.03	88.14	73.66	64.81	87.44	74.69	$78.68 \pm 11.74$
SVM+LBP [63]	91.94	91.70	84.47	99.08	98.17	87.28	47.68	99.50	97.61	$88.55{\pm}16.25$
NN+LBP [70]	94.16	88.39	79.85	99.75	95.17	78.86	50.57	99.93	93.54	$86.69 \pm 16.25$
DTN [33]	90.0	97.3	97.5	99.9	99.9	99.6	81.6	99.9	97.5	$95.9\pm6.2$
AIM-FAS [10]	93.6	99.7	99.1	99.8	99.9	99.8	76.3	99.9	99.1	96.4±7.8
Ours	99.62	100.00	100.00	99.99	99.74	99.91	71.64	100.00	99.99	$96.77 \pm 9.99$

## E. Cross-dataset Testing on CASIA-MFSD and Replay-Attack

As shown in Table 8, our proposed method has 16.6% HTER on protocol CR, outperforming all prior state-of-the-arts. For protocol RC, we also achieve comparable performance with 36.4% HTER.

Table 8. Cross-dataset testing between CASIA-MFSD and Replay-Attack.

	Protocol C	R (HTER)	Protocol RC (HTER)		
Method	Train	Test	Train	Test	
			Replay-Attack	CASIA-MFSD	
STASN [38]	31.5%		30.9%		
Color Texture [5]	30.3%		37.7%		
FaceDs [13]	28.5%		41.1%		
Auxiliary [16]	27.6%		28.4%		
BASN [32]	23.6%		29.9%		
FAS-TD [37]	17.5%		24.0%		
Ours	16.	6%	36.	4%	