Towards Diverse Liveness Feature Representation and Domain Expansion for Cross-Domain Face Anti-Spoofing

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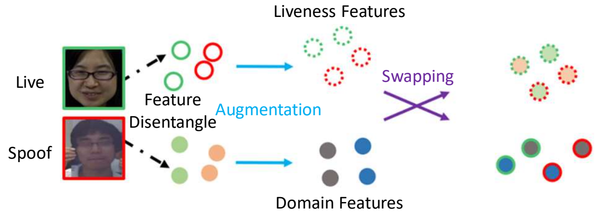
Face Anti-Spoofing (FAS)

Challenges in Cross-Domain Testing

- Representation dominated by domain-dependent variations
- Lack of out-of-domain information

Goal

- To enrich diversity of liveness feature
  - ➢ Generate out-of-domain features
  - ➢ Maintaining discriminative characteristics
- To enlarge generalization ability of domain features
  - ➢ Generate unseen features



DFANet : Disentangled Feature Augmentation Network

Feature Disentanglement and Reconstruction

- Disentanglement of liveness feature and domain feature

$$\mathcal{L}_{rec} = \sum_{\forall \mathbf{f}_{ls,dm}} (\|\mathbf{f}_{ls,dm} - \bar{\mathbf{f}}_{ls,dm}\|_2^2)$$

Augmentation of Liveness Features

- Affine feature transform

$$\hat{\mathbf{f}_{ls}} = \mathbf{E}_{fwt}(\mathbf{f}_{ls}) = \underbrace{\mathbf{s} \odot \mathbf{f}_{ls} + \mathbf{b}}_{\text{Learnable}}$$

- Increase diversity of transformed features

$$\mathcal{L}_{dis} = \mathbf{sim}(\hat{\mathbf{f}}_{ls}, \mathbf{f}_{ls}) = \frac{\hat{\mathbf{f}}_{ls} \cdot \mathbf{f}_{ls}}{\|\hat{\mathbf{f}}_{ls}\| \, \|\mathbf{f}_{ls}\|}$$

- Preserve live/spoof discriminative characteristics

$$\mathcal{L}_{ls-aft} = -\sum_{\forall \bar{\mathbf{f}}_{\hat{ls}}} (y^{ls} log(\mathbf{C}_{ls}(\bar{\mathbf{f}}_{\hat{ls}})))$$

Augmentation of Domain Features

- Learnable AdaIN

$$\hat{\mathbf{f}}_{dm} = \mathbf{E}_{adl}(\mathbf{f}_{dm}) = \alpha \cdot \left(\frac{\mathbf{f}_{dm} - \mu_{\mathbf{f}_{dm}}}{\sigma_{\mathbf{f}_{dm}}}\right) + \beta$$

Learnable

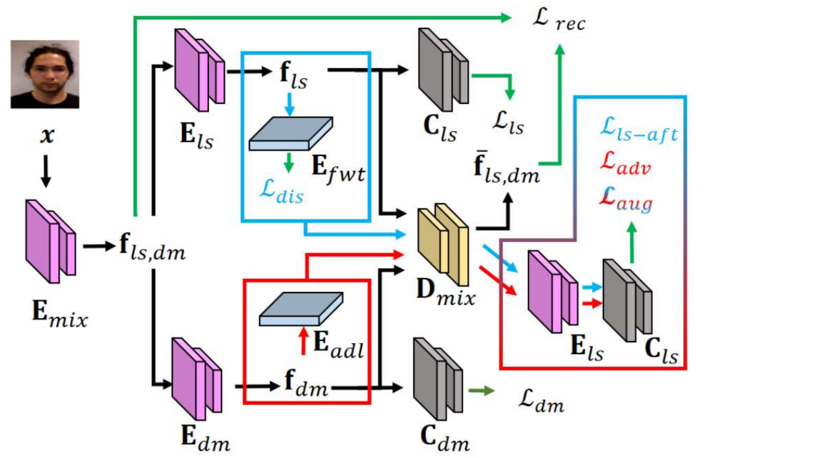
- Adversarial domain learning

$$\mathcal{L}_{adv} = -\sum_{\forall \bar{\mathbf{f}}_{ls}} ((1 - y^{ls}) log(\mathbf{C}_{ls}(\bar{\mathbf{f}}_{ls})))$$

Model Training

- Augmented Feature Learning

$$\mathcal{L}_{aug} = -\sum_{\forall \bar{\mathbf{f}}_{\hat{ls}}} y^{ls} log(\mathbf{C}_{ls}(\bar{\mathbf{f}}_{\hat{ls}})) - \sum_{\forall \bar{\mathbf{f}}_{ls}} y^{ls} log(\mathbf{C}_{ls}(\bar{\mathbf{f}}_{ls}))$$



Experiments

Datasets

- OULU-NPU (O), MSU-MFSD (M), CASIA-MFSD (C), Replay-Attack (I)

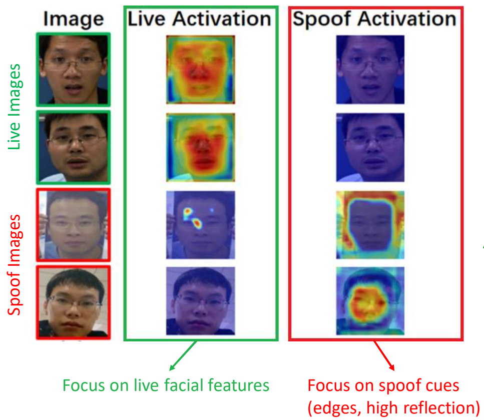
Evaluation Metrics

- Half Total Error Rate (HTER)
- Area Under Curve (AUC)

Cross domain testing

Method	[O,C,I]→ M		[O,M,I]→ C		[O,C,M]→ I		[I,C,M]→ O	
	HTER	AUC	HTER	AUC	HTER	AUC	HTER	AUC
MADDG [5] (*CVPR 19*)	17.69	88.06	24.50	84.51	22.19	84.99	27.89	80.02
DR-MD-Net [6] (*CVPR 20*)	17.02	90.10	19.68	87.43	20.87	86.72	25.02	81.47
SSDG-R [21] (*CVPR 20*)	7.38	97.17	10.44	95.94	11.71	96.59	15.61	91.54
RFM [22] (*AAAI 20*)	13.89	93.98	20.27	88.16	17.30	90.48	16.45	91.16
D^2AM [9] (*AAAI 21*)	12.70	95.66	20.98	85.58	15.43	91.22	15.27	90.87
RAEDFL [1] (*ACPR 21*)	16.67	87.93	17.78	86.11	14.64	85.64	18.06	90.04
SSAN-M [7] (*CVPR 22*)	10.42	94.76	16.47	90.81	14.00	94.58	19.51	88.17
SSAN-R [7] (*CVPR 22*)	6.67	**98.75**	10.00	96.67	8.88	96.79	13.72	93.63
PatchNet [23] (*CVPR 22*)	7.10	98.46	11.33	94.58	14.6	92.51	11.82	95.07
LDCN [10] (*BMVC 22*)	9.29	96.86	12.00	95.67	9.43	95.02	13.51	93.68
Ours	**5.24**	97.98	**8.78**	**97.03**	**8.21**	**96.84**	**9.34**	**96.43**

Activation Maps



T-SNE Visualization