

Face Reconstruction from Facial Templates by Learning Latent Space of a Generator Network

Hatef Otroshi Shahreza^{1,2}, Sébastien Marcel^{1,3}

¹ Idiap Research Institute, Martigny, Switzerland
² École Polytechnique Fédérale de Lausanne (EPFL), Lausanne, Switzerland
³ Université de Lausanne (UNIL), Lausanne, Switzerland





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Introduction

Problem definition ٠



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face images to enter the same or different face recognition system (F_{target}).

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- Adversary's knowledge:
 - The leaked face templates enrolled in the database.
 - The whitebox/blackbox knowledge of the feature extractor model (F_{database})
 - face recognition model to use in training (F_{loss}).

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 - In case of blackbox scenario, the adversary has a whitebox knowledge of another face recognition model to use in training (F_{loss}).
- Adversary's capability: The adversary can inject the reconstructed face image as a query to the target face recognition system (F_{target}).

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- Adversary's capability: The adversary can inject the reconstructed face image as a query to the target face recognition system (F_{target}).
- Adversary's strategy: The adversary trains a face reconstruction model to invert the leaked facial templates. Then, the adversary can use the reconstructed face images and inject as a query to the target face recognition system (F_{target}).

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Proposed Method



WGAN loss

 $\rightarrow \mathcal{L}_{rec}$

$$\mathcal{L}_{C}^{\text{WGAN}} = \mathbb{E}_{\boldsymbol{w} \sim \mathcal{W}}[C(\boldsymbol{w})] - \mathbb{E}_{\hat{\boldsymbol{w}} \sim M_{\text{rec}}([\boldsymbol{n},\boldsymbol{x}])}[C(\boldsymbol{w})]$$
$$\mathcal{L}_{M_{\text{rec}}}^{\text{WGAN}} = \mathbb{E}_{\hat{\boldsymbol{w}} \sim M_{\text{rec}}([\boldsymbol{n},\boldsymbol{x}])}[C(\hat{\boldsymbol{w}})]$$

Reconstruction loss $\mathcal{L}_{\rm rec} = \mathcal{L}_{\rm pixel} + \mathcal{L}_{\rm ID}$ $\mathcal{L}_{\text{pixel}} = \mathbb{E}_{\boldsymbol{x} \sim \mathcal{X}} [\|\boldsymbol{I} - \boldsymbol{G}(\boldsymbol{x})\|_2^2],$ $\mathcal{L}_{\text{ID}} = \mathbb{E}_{\boldsymbol{x} \sim \mathcal{X}} [\|F_{\text{loss}}(\boldsymbol{I}) - F_{\text{loss}}(G(\boldsymbol{x}))\|_2^2].$



Proposed Method

	F _{database}	$\mathbf{F}_{\mathbf{loss}}$	Evaluation	Adversary's Knowledge of Original and Target Systems	Difficulty of Attack		
Attack 1	whitebox	$F_{database}$	same system	whitebox knowledge of F_{database} and F_{target}	very easy		
Attack 2	whitebox	F_{database}	different system (transferability)	whitebox knowledge of $F_{database}$	easy		
Attack 3	blackbox	adversary's own	same system	blackbox knowledge of $F_{database}$ and F_{target}	difficult		
Attack 4	blackbox	F_{target}	different system (transferability)	blackbox knowledge of F_{database} and whitebox knowledge of F_{target}	difficult		
Attack 5	blackbox	adversary's own	different system (transferability)	only blackbox knowledge of $F_{database}$	very difficult		

Sample Reconstructed Face Images



0.815

0.618

0.629

0.728

0.602

0.742

Table 4: Evaluation of attacks with *whitebox* knowledge of the system from which the template is leaked (i.e., $F_{\text{loss}} = F_{\text{database}}$) against SOTA FR models in terms of adversary's success attack rate (SAR) using our proposed method on the MOBIO and LFW datasets. The values are in percentage and correspond to the threshold where the target system has $FMR = 10^{-3}$. Cells are color coded according the type of attack as defined in Section 2 for attack 1 (light gray) and attack 2 (dark gray).

F _{database}		MO		LFW						
	ArcFace	ElasticFace	HRNet	AttentionNet	Swin	ArcFace	ElasticFace	HRNet	AttentionNet	Swin
ArcFace	92.38	81.90	71.43	70.48	74.29	86.82	74.20	36.57	36.40	58.86
ElasticFace	78.10	87.62	64.29	64.76	69.05	78.25	82.52	41.80	40.25	61.09

Table 5: Evaluation of attacks (with *blackbox* knowledge of the system from which the template is leaked i.e., $F_{database}$) against SOTA FR models in terms of adversary's success attack rate (SAR) using different methods on the MOBIO and LFW datasets. The values are in percentage and correspond to the threshold where the target system has FMR = 10^{-3} . M1: NbNetB-M [Mai et al., 2018], M2: NbNetB-P [Mai et al., 2018], M3: [Dong et al., 2021], M4: [Vendrow and Vendrow, 2021], and M5: [Dong et al., 2023]. Cells are color coded according the type of attack as defined in Section 2 for attack 3 (lightest gray), attack 4 (middle dark gray), and attack 5 (darkest gray).

Fdatabase	$\mathbf{F}_{\mathbf{loss}}$	\mathbf{F}_{target}	MOBIO						LFW					
			M1	M2	M3	M4	M5	Ours	M1	M2	M3	M4	M5	Ours
ArcFace	ElasticFace	ArcFace	1.90	15.24	2.38	28.10	58.57	81.90	10.68	40.25	12.91	58.88	75.31	77.16
		ElasticFace	1.43	11.43	4.29	15.24	37.61	73.81	8.36	34.39	6.35	29.10	50.17	68.06
		HRNet	0.95	6.19	2.86	10.00	30.48	57.14	1.30	7.78	1.75	9.20	24.72	28.45
		AttentionNet	0	6.67	3.33	4.29	26.67	54.29	1.33	7.17	2.29	9.17	24.16	28.87
		Swin	1.43	13.33	3.81	10.95	40.00	67.14	4.27	23.85	5.97	21.75	41.27	48.28
ElasticFace	ArcFace	ArcFace	2.38	18.57	2.86	16.19	48.09	87.14	15.33	48.67	11.81	37.45	65.40	83.20
		ElasticFace	3.81	43.81	4.76	43.33	72.38	89.05	21.44	58.16	11.59	52.88	74.08	83.43
		HRNet	0.48	20.00	1.43	10.48	42.86	73.81	3.46	18.36	2.74	11.82	32.99	49.02
		AttentionNet	1.90	18.10	3.33	9.05	40.00	71.90	2.89	16.31	2.91	10.95	31.15	46.63
		Swin	0.95	26.19	2.86	15.24	46.67	75.24	9.22	38.79	8.26	24.62	51.20	66.89

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tacks, attacks 1-2 (second raw) and attacks 3-5 (second raw, using ElasticFace for F_{loss}). The values below each image show the cosine similarity between the corresponding ArcFace templates of original and reconstructed face images.

Important Areas in the Reconstructed Face Images



0.773

0.738

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0.661

0.768

0.695

Using a Different Face Generator Network (StyleSwin)



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0.624

0.611

0.614

0.645

Thanks for your attention!



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