TransFIRA: Transfer Learning for Face Image Recognizability Assessment

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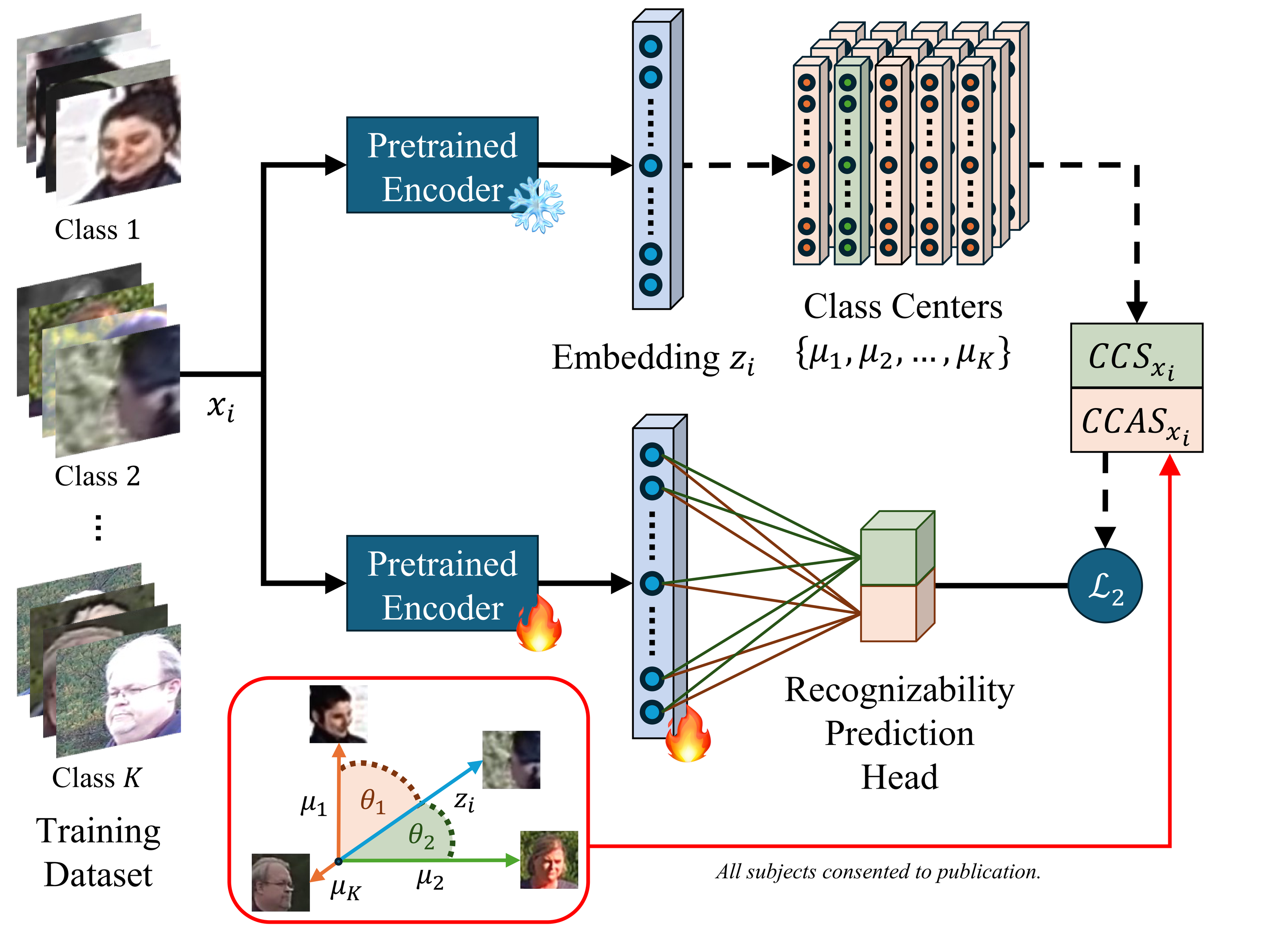
Oral Presentation

transfira.github.io

Motivation

How can we predict encoder-specific face recognizability from images and use it to guide template aggregation?



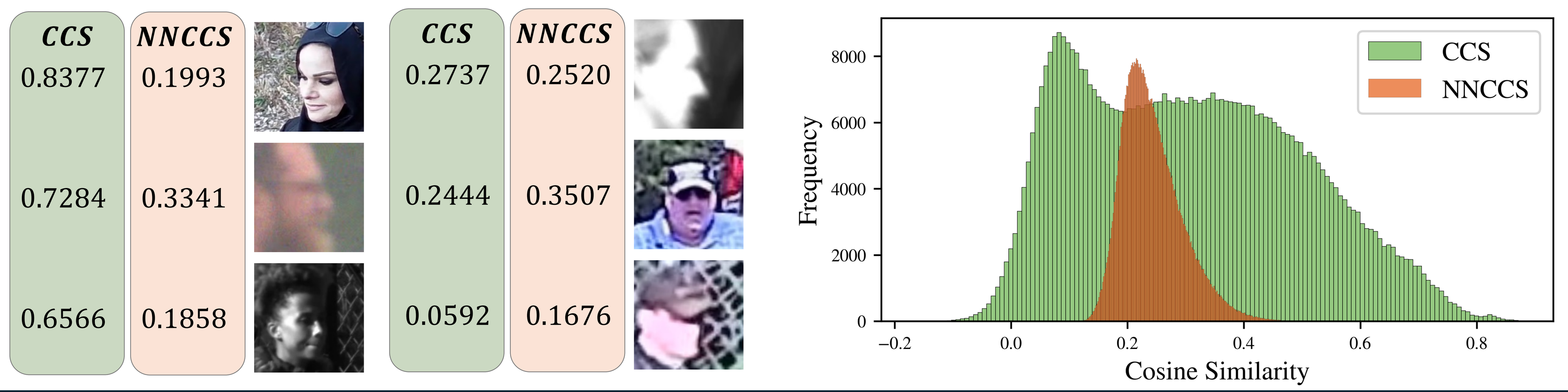
Recognizability: the likelihood that an image will be correctly identified by a given encoder.

Background

Template-based face recognition aggregates multiple images into a single representation, where even a few unrecognizable frames can corrupt it. Key benchmarks operate under **highly unconstrained conditions**:

- **BRIAR**: Video surveillance at altitude and range (private)
- **IJB-C**: Diverse web and video imagery (public)

Encoders must contend with extreme variation in pose, blur, illumination, and occlusion. Predictions from existing **face image quality assessment (FIQA)** metrics often fail to determine whether images are recognizable because they are detached from the **encoder's decision geometry**.



Method

TransFIRA adapts any pretrained encoder to predict recognizability from its own embedding geometry.

Our framework consists of three stages:

1. Image Recognizability

For each image x_i with embedding $z_i = \phi(x_i)$, we compute class-center similarities that measure its alignment with its identity.

- **Class Center Angular Similarity (CCS)** measures how closely an embedding aligns with the center of its own class:

$$CCS_{x_i} = \frac{z_i^\top \mu_{y_i}}{\|z_i\|_2 \, \|\mu_{y_i}\|_2}.$$

- **Nearest Nonmatch Class Center Angular Similarity (NNCCS)** measures its similarity to the most confusable imposter class:

$$NNCCS_{x_i} = \max_{j \neq y_i} \frac{z_i^\top \mu_j}{\|z_i\|_2 \, \|\mu_j\|_2}.$$

- **Class Center Angular Separation (CCAS)** is their difference:

$$CCAS_{x_i} = CCS_{x_i} - NNCCS_{x_i}.$$

$CCAS > 0$ indicates when z_i is closest to its own class center.

2. Recognizability Prediction Network

We extend the pretrained backbone with a **recognizability prediction head** to predict CCS and CCAS scores:

$$\hat{\mathbf{r}}_i = [\hat{CCS}_{x_i}, \hat{CCAS}_{x_i}]^\top = h_\psi(\phi(x_i)).$$

Fine-tuning both the backbone and head to predict the ground truth scores ensures **recognizability remains encoder-specific and fully aligned with the model's internal representation.**

3. Recognizability-Informed Template Aggregation

The predicted CCS and CCAS scores guide template aggregation:

- **Filtering:** Images with predicted $CCAS > 0$ are retained, ensuring only confidently recognized frames are included.
- **Weighting:** Embeddings are weighted by predicted CCS before averaging, emphasizing reliable samples near the class center.

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Results

TransFIRA achieves **state-of-the-art results on BRIAR and IJB-C,** outperforming all prior FIQA methods.

Method	BRIAR Protocol 3.1 [5]: FNMR-ERC AUC							
	CosFace (BRIAR) [5,25]				ArcFace (WebFace) [9,27]			
	SC	10^{-3}	10^{-4}	10^{-6}	SC	10^{-3}	10^{-4}	10^{-6}
FaceQNet [10, 12]	0.1589	0.3957	0.5225	0.6903	0.1194	0.5037	0.7606	0.8924
MagFace [19]	0.1367	0.4314	0.5616	0.7336	0.0467	0.5426	0.8054	0.9200
SDD-FIQA [20]	0.0293	0.4513	0.5771	0.7335	0.0112	0.5527	0.8069	0.9148
CR-FIQA (S) [4]	0.1107	0.4199	0.5463	0.7093	0.0570	0.5409	0.7874	0.8975
CR-FIQA (L) [4]	0.4143	0.2708	0.3839	0.5640	0.3654	0.4387	0.6815	0.8386
DifFIQA (R) [1]	0.4416	0.2782	0.3820	0.5490	0.4657	0.4375	0.6622	0.8194
eDifFIQA (S) [2]	0.3610	0.2978	0.4064	0.5763	0.2577	0.4644	0.7035	0.8433
eDifFIQA (M) [2]	0.2870	0.3249	0.4267	0.5836	0.2265	0.4517	0.6895	0.8316
eDifFIQA (L) [2]	0.4377	0.2840	0.3855	0.5489	0.4415	0.4407	0.6658	0.8198
GraFIQs (S) [15]	0.0350	0.4363	0.5646	0.7344	-0.0194	0.5325	0.8102	0.9287
GraFIQs (L) [15]	0.1831	0.3881	0.5059	0.6732	0.1434	0.5074	0.7643	0.8914
CLIB-FIQA [21]	0.5004	0.2536	0.3591	0.5340	0.4404	0.4508	0.6758	0.8281
Ours (CCAS)	**0.8230**	**0.1558**	**0.2734**	**0.4752**	**0.6568**	**0.4071**	**0.6335**	**0.8068**
Ours (CCS)	**0.8566**	**0.1536**	**0.2722**	**0.4753**	**0.6401**	**0.3934**	**0.6315**	**0.8076**

InsightFace ArcFace verification on BRIAR improves **from 0.4269 to 0.8715 TAR at 10^{-3} FMR,** despite ArcFace never being trained on BRIAR.

Method	BRIAR Protocol 3.1 [5]: TAR at Fixed FMR					
	CosFace (BRIAR) [5,25]			ArcFace (WebFace) [9,27]		
	10^{-3}	10^{-4}	10^{-6}	10^{-3}	10^{-4}	10^{-6}
Average (Baseline)	0.9077	0.8423	0.7500	0.4269	0.1923	0.0846
FaceQNet [10, 12]	0.9077	0.8500	0.7577	0.4385	0.2385	0.0923
MagFace [19]	0.9077	0.8423	0.7538	0.4385	0.2154	0.0923
SDD-FIQA [20]	0.9038	0.8462	0.7538	0.4269	0.2154	0.0923
CR-FIQA (S) [4]	0.9038	0.8462	0.7577	0.4538	0.2577	0.1077
CR-FIQA (L) [4]	0.9231	0.8731	0.8077	0.5346	0.3231	0.1654
DifFIQA (R) [1]	0.9423	0.8769	0.8269	0.6192	0.4885	0.3885
eDifFIQA (S) [2]	0.8885	0.8462	0.7962	0.5500	0.3731	0.2808
eDifFIQA (M) [2]	0.6769	0.5923	0.4423	0.3962	0.3000	0.2115
eDifFIQA (L) [2]	0.8500	0.8000	0.7154	0.6154	0.4692	0.3577
GraFIQs (S) [15]	0.9077	0.8423	0.7500	0.4269	0.1923	0.0846
GraFIQs (L) [15]	0.9077	0.8423	0.7500	0.4269	0.1923	0.0846
CLIB-FIQA [21]	0.9154	0.8654	0.7885	0.5038	0.3115	0.1769
Ours (CCAS Filter)	**0.9846**	**0.9231**	**0.8846**	**0.8715**	**0.7510**	**0.5703**
Ours (CCS Weight)	0.9615	0.9038	0.8462	0.6269	0.4308	0.2692
Ours (Filter + Weight)	**0.9885**	**0.9269**	**0.8885**	**0.8715**	**0.7510**	**0.5984**

We extend **TransFIRA** to **body recognizability prediction,** improving template aggregation on BRIAR.

Method	TAR@1e-3	TAR@1e-4	TAR@1e-6
Average (Baseline)	0.5934	0.3278	0.0851
Calibrated CCAS Filter	0.6037	0.3485	0.0933
Calibrated CCAS Weight	**0.6452**	**0.3693**	0.1037
Calibrated Filter + Weight	0.6328	0.3568	**0.1079**

See our paper for IJB-C results and explainability analyses.