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Identity-Preserving Low-Resolution Face Recognition

11/01/2023

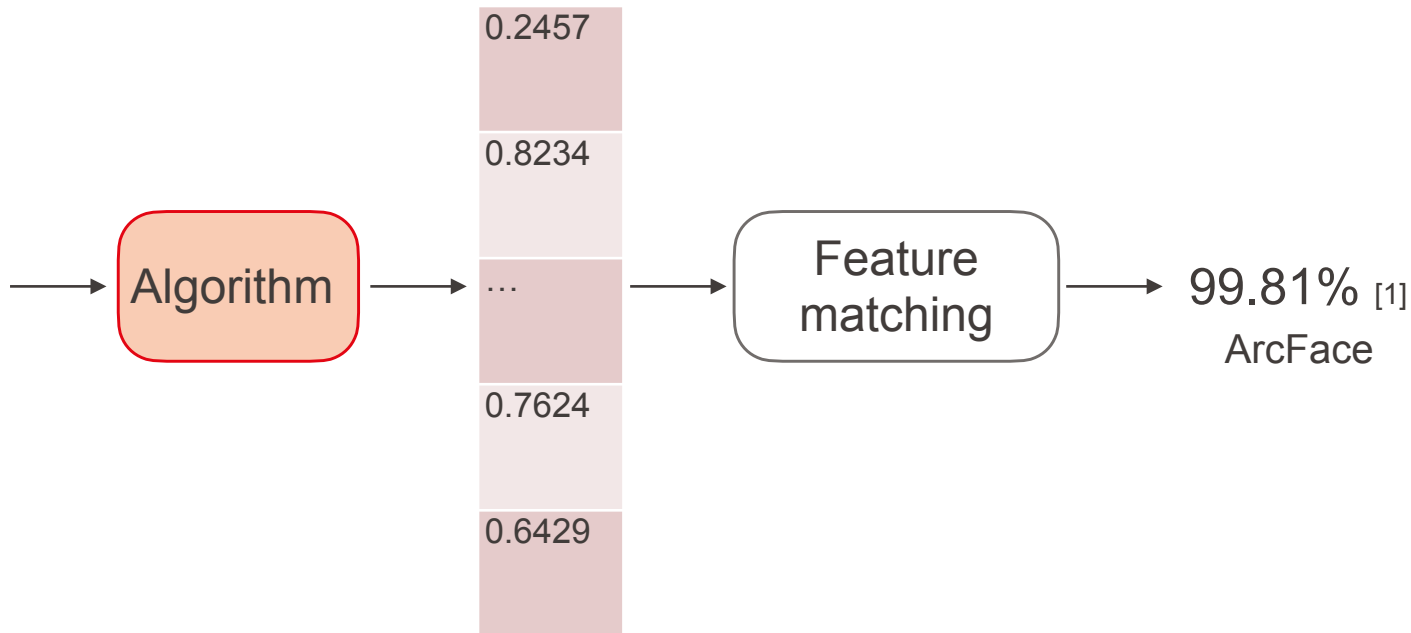
Outline

- Introduction
 - Face Recognition (FR) problem
 - Low Resolution Face Recognition (LRFR)
- Related work
 - Face Recognition pipeline
 - LRFR methods
- LRFR Datasets and Evaluation Protocols
 - LFW
 - QMUL-SurvFace
 - SCface
- Softmax-based Loss Functions
 - Implementation and experiments
- Finetuning for LRFR
 - Octuplet Loss
 - DeriveNet
 - Implementation and experiments
- Proposed methods
- Experiments
- Conclusion

Introduction

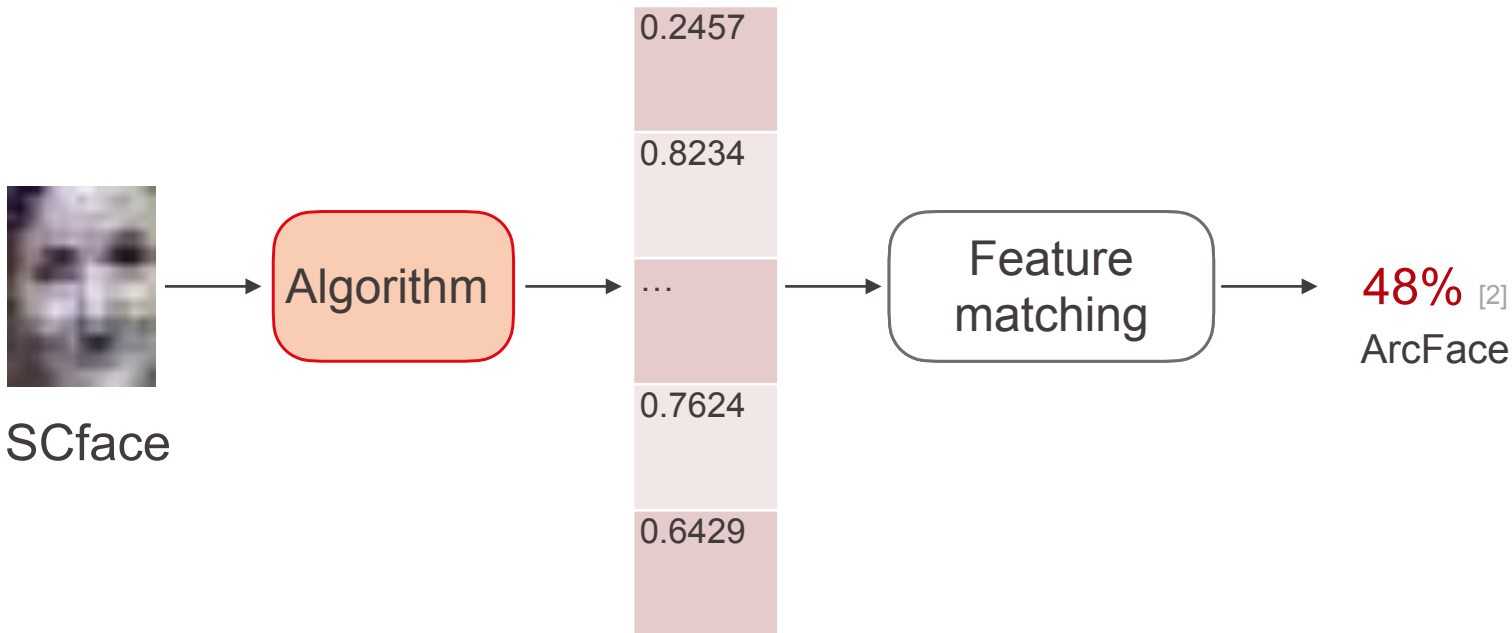


LFW



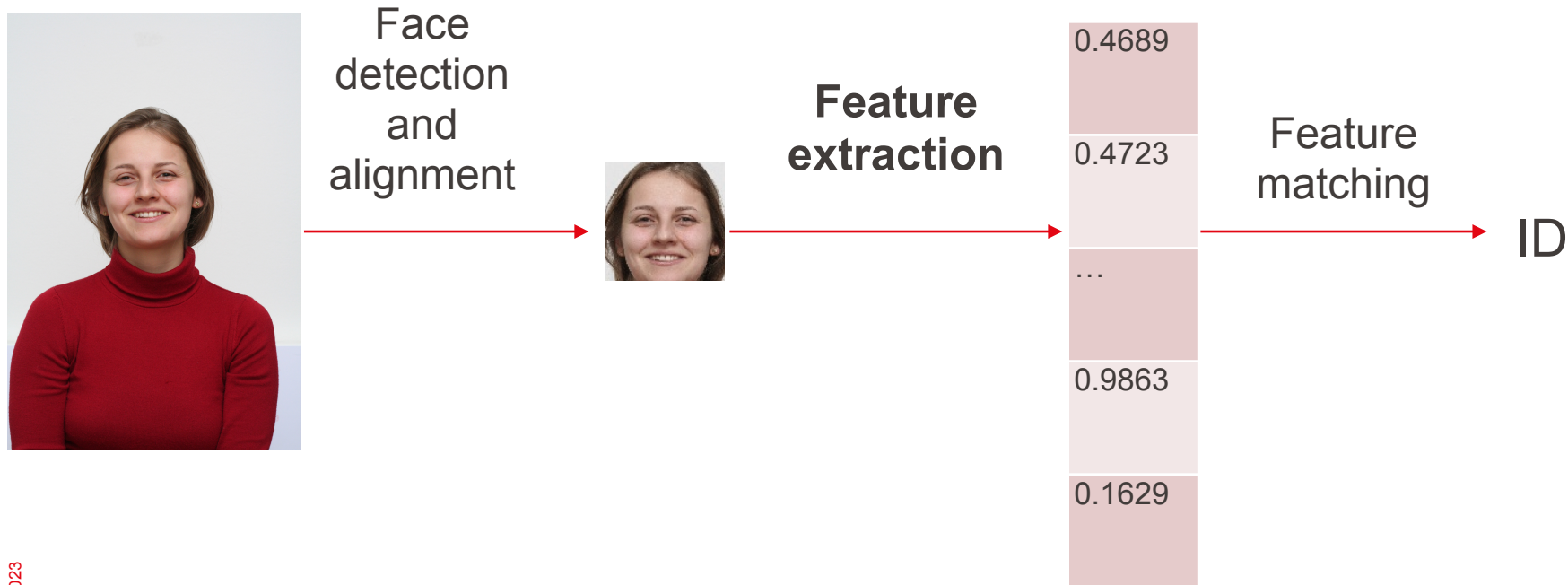
Face Recognition (FR) problem

Introduction



Low Resolution Face Recognition (LRFR) challenge

Face Recognition Pipeline

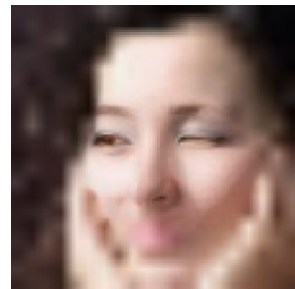
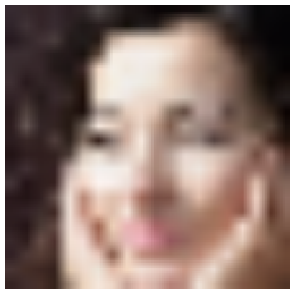
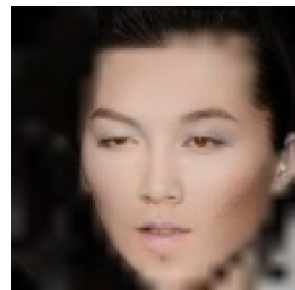
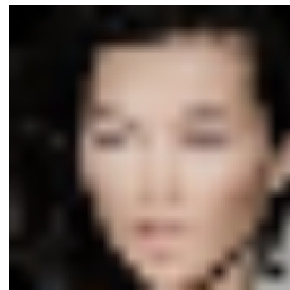
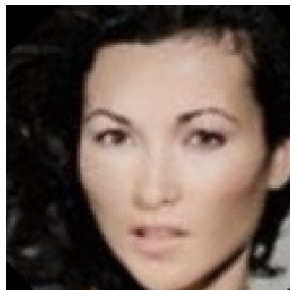


LRFR Methods

Resolution-invariant

- Adapting HRFR techniques
- Finetuning
- Cross Resolution Loss Functions

Super Resolution



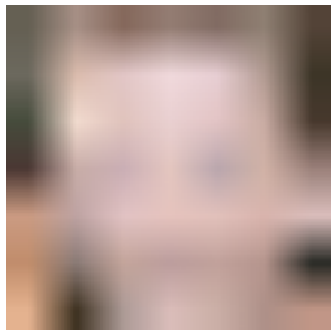
Original

Downsampled

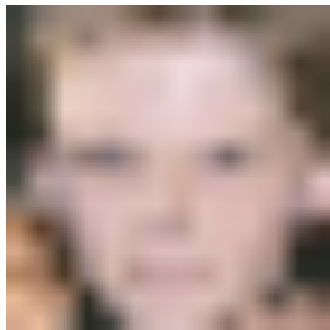
GPEN[3] results

LRFR Datasets: LFW

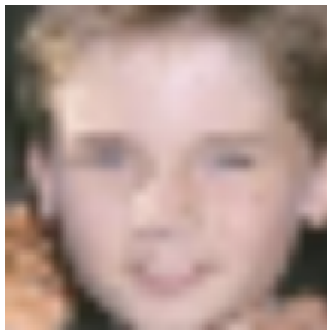
<i>Images</i>	13000
<i>ID</i>	1680
<i>Detection method</i>	MTCNN
<i>Problem</i>	Verification
<i>Protocol</i>	Image Restricted Configuration: pairs and synthetically downsampled to (7x7, 14x14, 28x28, 56x56) LR



7x7



14x14



28x28



56x56

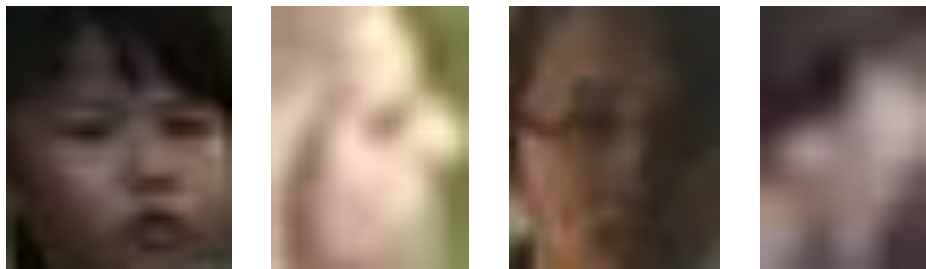
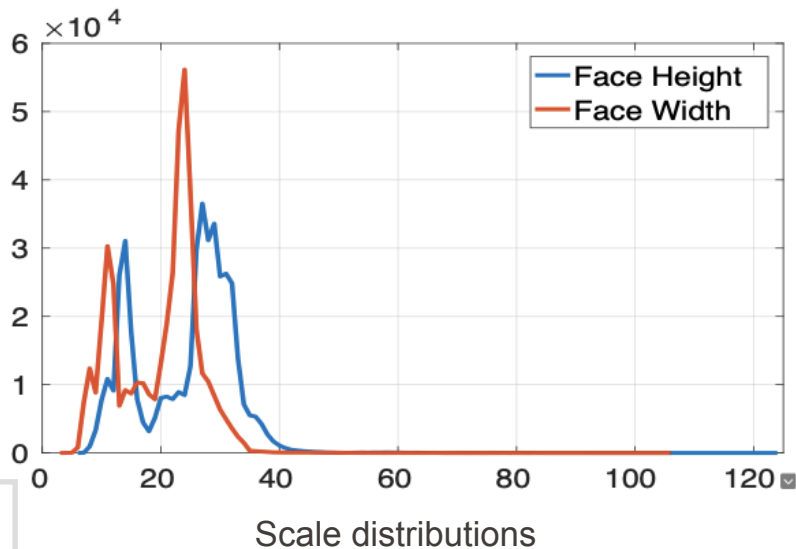


112x112

Downsampled LFW [4]

QMUL-SurvFace

<i>Images</i>	463507
<i>ID</i>	15573
<i>Detection method</i>	-
<i>Problem</i>	Verification
<i>Protocol</i>	Image Restricted Configuration



QMUL-SurvFace[5] examples

SCface[6] Camera 1



Gallery



Night



Day

Distance 1

Distance 2

Distance 3

<i>Images</i>	4160
<i>ID</i>	130
<i>Detection method</i>	MTCNN
<i>Problem</i>	Identification
<i>Protocol</i>	<ul style="list-style-type: none"> - Day (5 cameras) / night (3 cameras) - Distance: 1, 2, 3

Softmax-based Loss Functions

$$L = -\log \frac{\exp(f(\theta_{y_i}, m))}{\exp(f(\theta_{y_i}, m)) + \sum_{j \neq y_i}^n \exp(s \cos \theta_j)}$$

SphereFace [7] $f(\theta_j, m) = \begin{cases} s \cos(m\theta_j) & j = y_i \\ s \cos(\theta_j) & j \neq y_i \end{cases}$

CosFace [8] $f(\theta_j, m) = \begin{cases} s(\cos \theta_j - m) & j = y_i \\ s \cos(\theta_j) & j \neq y_i \end{cases}$

ArcFace [9] $f(\theta_j, m) = \begin{cases} s \cos(\theta_j + m) & j = y_i \\ s \cos(\theta_j) & j \neq y_i \end{cases}$

Idea:
Constant margin

Adapting HRFR techniques : Training Settings

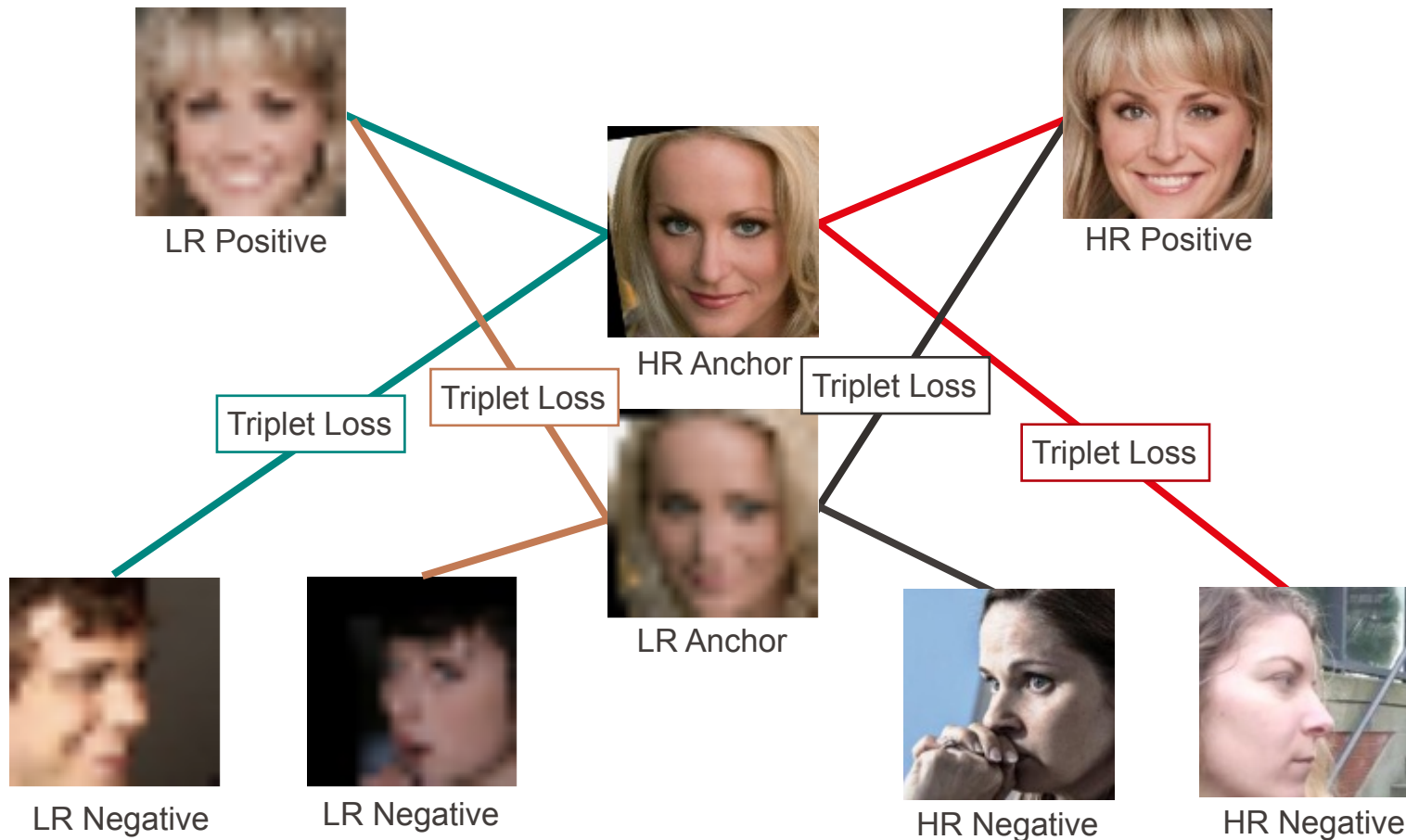
<i>Backbone</i>	ResNet50
<i>Data Loader</i>	Cross Resolution Batch Training [10]
<i>Optimizer</i>	SGD
<i>Epochs</i>	18
<i>Training dataset</i>	CASIA-WebFace [11]
<i>Images in training dataset</i>	494414
<i>Classes in training dataset</i>	10575

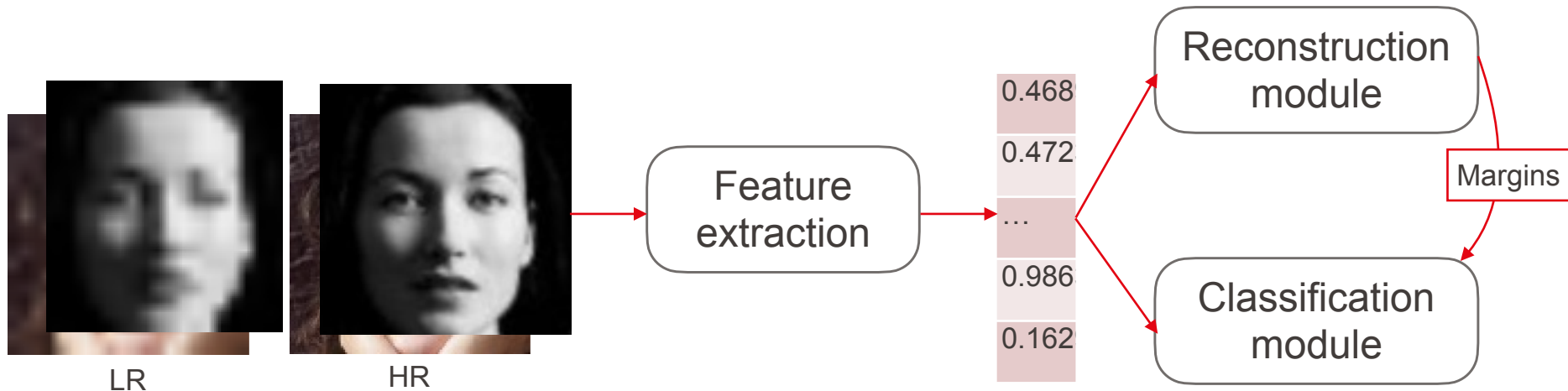


Softmax-based Loss Functions and their performance

	CosFace	<i>SphereFace</i>	ArcFace
LFW (112x112)	0.979	0.9641	0.9773
LFW (56x56)	0.9801	0.9625	0.97399
LFW (28x28)	0.9721	0.9025	0.96933
LFW (14 x 14)	0.9266	0.7155	0.9189
LFW (7x 7)	0.7543	0.5926	0.74666
QMUL-SurvFace	0.6411	0.5953	0.6303
SCface dist 1	0.6873	0.1253	0.7349
SCface dist 2	0.9336	0.3487	0.95679
SCface dist 3	0.9229	0.5654	0.9322

Finetuning: Octuplet Loss

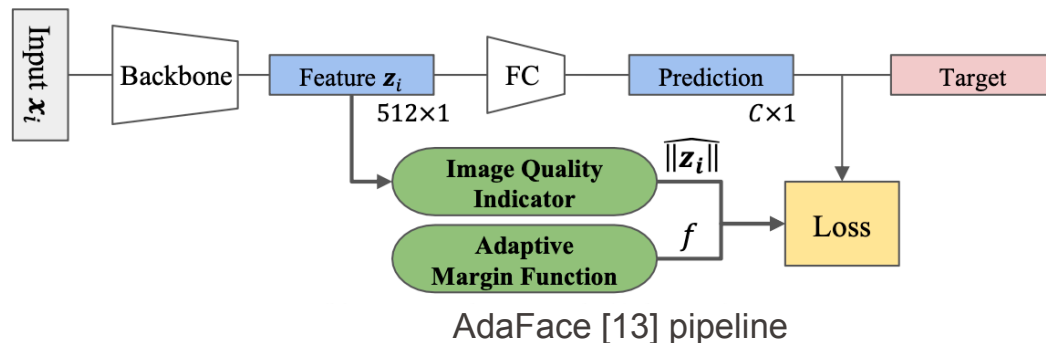
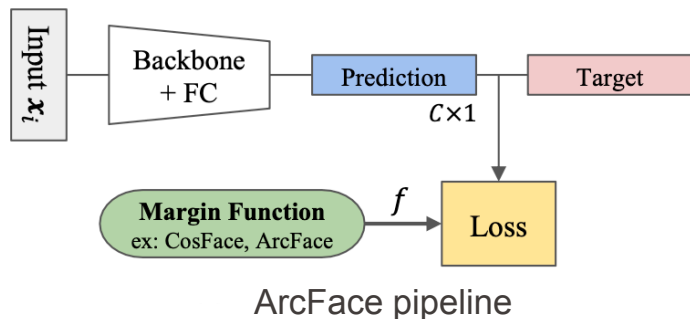




Finetuning for LRFR

	<i>Octuplet Loss</i>	<i>DeriveNet</i>
<i>LFW (112x112)</i>	0.9208	0.9878
<i>LFW (56x56)</i>	0.9211	0.9873
<i>LFW (28x28)</i>	0.9135	0.9471
<i>LFW (14 x 14)</i>	0.8616	0.7103
<i>LFW (7x 7)</i>	0.7375	0.5708
<i>QMUL-SurvFace</i>	0.6602	0.56184
<i>SCface dist 1</i>	0.5095	0.346
<i>SCface dist 2</i>	0.6296	0.8302
<i>SCface dist 3</i>	0.4175	0.9583

Cross Resolution Loss Functions: AdaFace



Idea:
Adaptive margin function
depends on the norm of
input image

Proposed method 1

Case 1



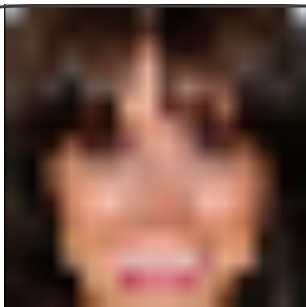
Original

margin

0.35

ArcFace

Case 2



Downsampled
to 16x16

margin

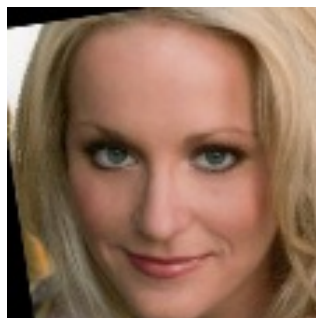
0.5

ArcFace

Idea:

Adaptive margin function
depends on
downsampling of image

Image Quality



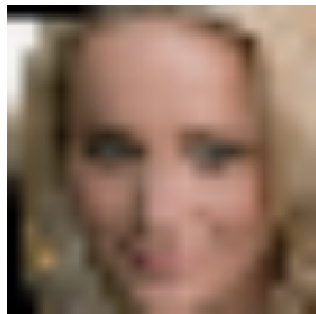
HR image

Laplacian



$\text{mean}(\|x\|_2^2)$

15.721



LR image

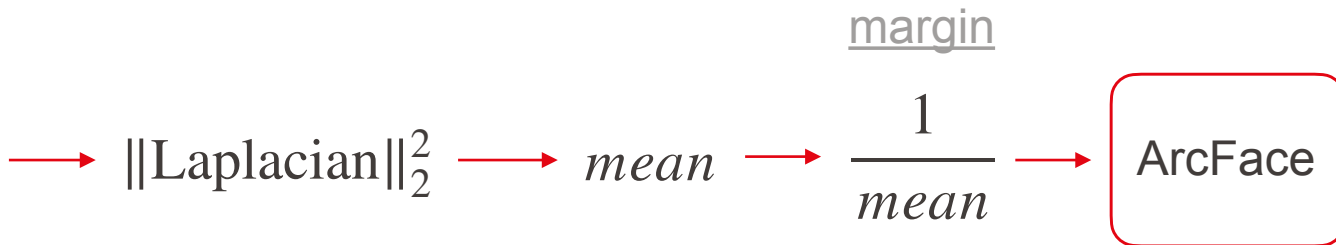
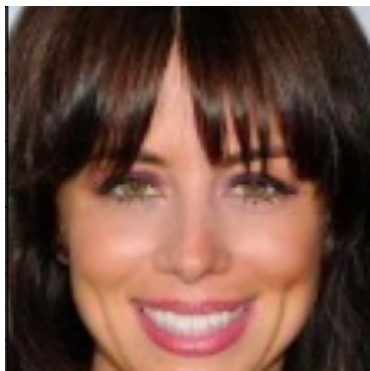
Laplacian



$\text{mean}(\|x\|_2^2)$

2.317

Proposed method 2



Idea:

Adaptive margin function
depends on mean
discriminative laplacian

Experiments: LFW

	<i>AdaFace</i>	<i>Appr. 1</i>	<i>Appr. 2</i>
112x112	0.9906	0.977	0.9623
56x56	0.9869	0.974	0.9645
28x28	0.9685	0.969	0.9584
14x14	0.6321	0.9236	0.9138
7x7	0.5653	0.7685	0.7905

QMUL-SurvFace

	<i>AdaFace</i>	<i>Appr. 1</i>	<i>Appr. 2</i>
<i>mean accuracy</i>	0.5324	0.6281	0.7125
<i>std</i>	0.04875	0.02956	0.0265

	<i>AdaFace</i>	<i>Appr. 1</i>	<i>Appr. 2</i>
<i>Dist 1 Day</i>	0.50634	0.7539	0.7492
<i>Dist 2 Day</i>	0.96913	0.9506	0.9182
<i>Dist 3 Day</i>	0.99691	0.9491	0.8104

	<i>CosFace</i>	<i>SphereFace</i>	<i>ArcFace</i>	<i>Octuplet Loss</i>	<i>DeriveNet</i>	<i>AdaFace</i>	<i>Approach 1</i>	<i>Approach 2</i>
<i>LFW (112x112)</i>	0.979	0.9641	0.9773	0.9208	0.9878	0.9906	0.977	0.9623
<i>LFW (56x56)</i>	0.9801	0.9625	0.97399	0.9211	0.9873	0.9869	0.974	0.9645
<i>LFW (28x28)</i>	0.9721	0.9025	0.96933	0.9135	0.9471	0.9685	0.969	0.9584
<i>LFW (14 x 14)</i>	0.9266	0.7155	0.9189	0.8616	0.7103	0.6321	0.9236	0.9138
<i>LFW (7x 7)</i>	0.7543	0.5926	0.74666	0.7375	0.5708	0.5653	0.7685	0.7905
<i>QMUL-SurvFace</i>	0.6411	0.5953	0.6303	0.6602	0.5618	0.5324	0.6281	0.7125
<i>SCface dist 1</i>	0.6873	0.1253	0.7349	0.5095	0.346	0.50634	0.7539	0.7492
<i>SCface dist 2</i>	0.9336	0.3487	0.95679	0.6296	0.8302	0.96913	0.9506	0.9182
<i>SCface dist 3</i>	0.9229	0.5654	0.9322	0.4175	0.9583	0.99691	0.9491	0.8104

Conclusion

- Studied the state-of-the-art deep learning-based LRFR methods
- Implemented the deep learning FR pipeline based on the state-of-the-art implementation
- Investigated LRFR datasets: LFW, QMUL-SurvFace, SCface; and set up evaluation protocols
- Implemented FR methods: CosFace, SphereFace, ArcFace; and adapted them to LRFR using Cross Resolution Batch Training
- Implemented LRFR finetuning methods: OctupletLos, DeriveNet
- Proposed 2 methods for LRFR that obtained better performance on low-resolution faces when compared to AdaFace
- Compared the performance of implemented methods

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Thank you!

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