Latent Factor Guided Convolutional Neural Networks for Age-Invariant Face Recognition

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Introduction

- Age-invariant face recognition (AIFR) still remains a challenging problem despite of considerable progresses on face recognition by deep learning.
- Common deep model is trained on general face dataset. It yields age-sensitive features, resulting in inferior performance on AIFR.
- **Our goal: Learning age-invariant deep features for AIFR.**

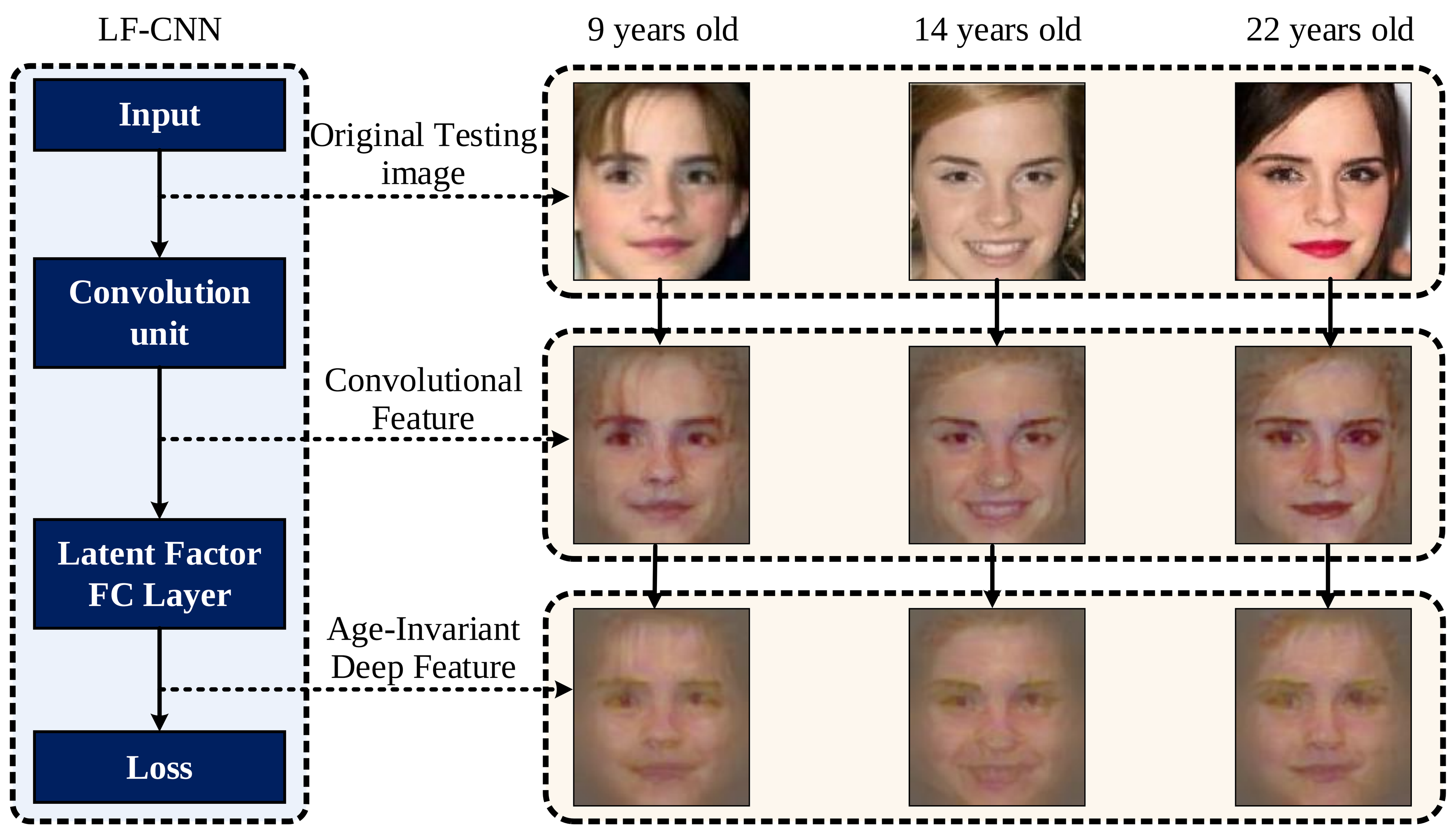

Fig. 1 Cross-age faces processed by the proposed method.

Our contributions

- We propose **latent factor guided convolutional neural networks (LF-CNNs)** to specifically address the AIFR task.
- To our best knowledge, it is the first work to show the effectiveness of deep CNNs in AIFR and achieve the best results on several famous face aging datasets (MORPH, FG-NET, and CACD-VS).

LF-CNN model

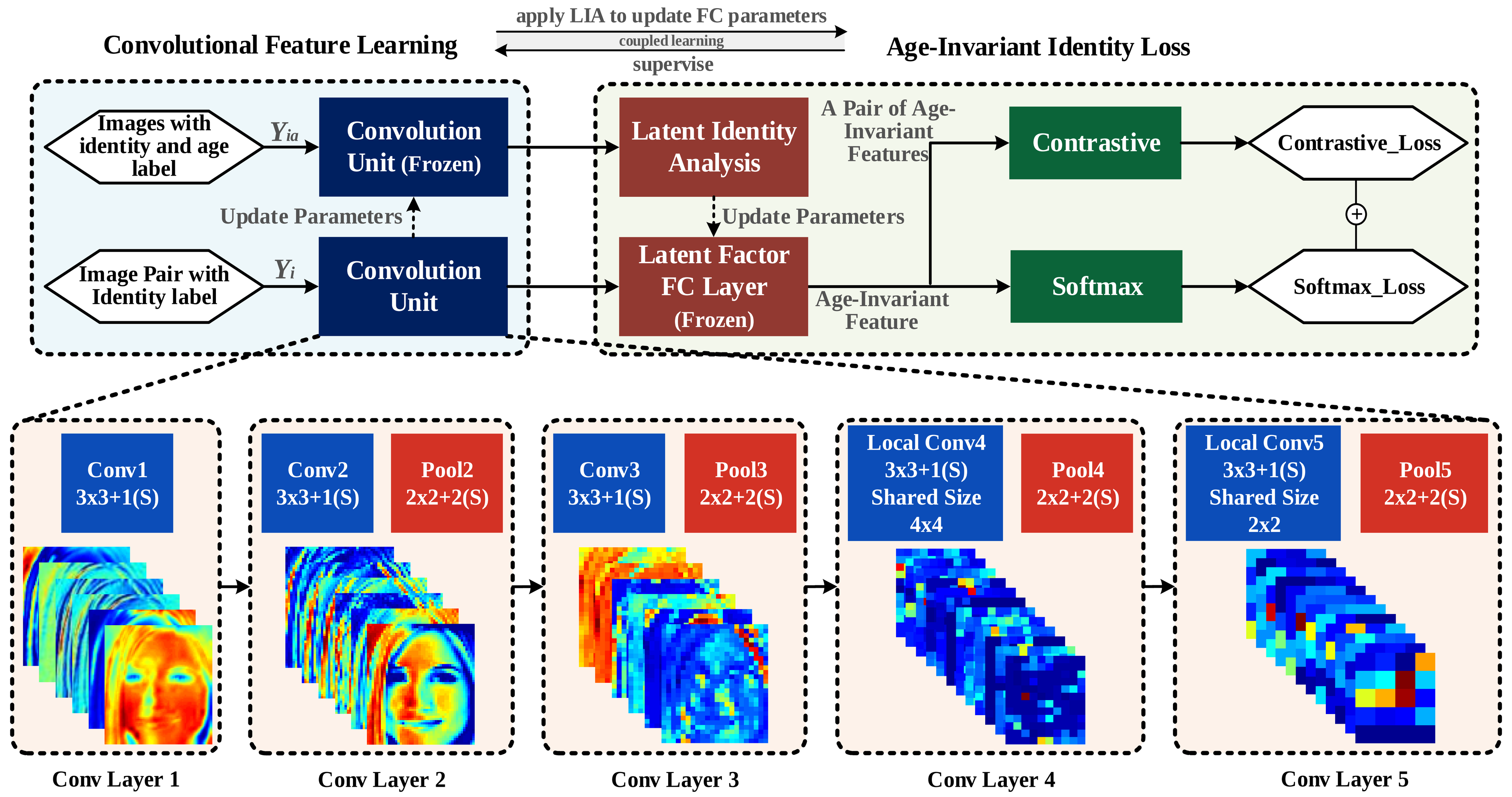

Fig. 2 The architecture of the proposed LF-CNNs and its training process. Frozen layer only performs regular forward and backward calculations, but does not update their parameters. The two parallel convolution units are corresponding to a physical module in two stages (frozen and not frozen).

Discussion

- LF-CNN model is very beneficial to AIFR problem.
  - minimizing the classification error (softmax loss and contrastive loss), aiming to learn discriminative face representations.
  - maximizing the likelihood probability in factor analysis, aiming to improve the age-invariance of the deeply learned features.
- Latent identity analysis (LIA) plays an essential role.
  - inferring the effective identity factor to guide the learning process of the LF-CNNs.
  - largely reducing the parameter scale and preventing the potential over-fitting.

Experimental results

- MORPH Album 2 & FG-NET Dataset

Method	MORPH (Rank-1 Identification Rates)	FG-NET (Rank-1 Identification Rates)
Pak et al. (2010) [24]	-	37.4%
Li et al. (2011) [18]	-	47.5%
HFA (2013) [7]	91.14%	69.0%
CARC (2014) [4]	92.80%	-
MEFA+SIFT+MLBP (2015) [8]	94.59%	76.2%
Method (2015) in [16]	87.13%	-
LPS+HFA (2016) [17]	95.87%	-
CNN-baseline (fine-tuned by MORPH training data)	95.13%	84.4%
LF-CNNs (fine-tuned by MORPH training data)	**97.51%**	**88.1%**

- CACD Verification Subset

Method	Verification Accuracy
High-Dimensional LBP (2013) [5]	81.6%
HFA (2013) [7]	84.4%
CARC (2014) [8]	87.6%
Human, Average (2015)	85.7%
Human, Voting (2015)	94.2%
LF-CNNs	**98.5%**

- LFW Dataset

Method	Images	Networks	Acc.
DeepFace (2014) [33]	4M	3	97.35%
DeepID-2+ (2015) [32]	-	25	99.47%
FaceNet (2015) [29]	200M	1	99.65%
Deep Embedding (2015) [20]	1.2M	10	99.77%
Deep FR (2015) [25]	2M	1	98.95%
LF-CNNs (single)	**700K**	**1**	**99.10%**
LF-CNNs (ensemble)	**700K**	**25**	**99.50%**