Deep Feature Learning for Facial Age Estimation

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1. Overview

Motivation

- Human age labels are chronologically correlated.
- Densely collecting face samples across a large range of age labels is difficult (unbalanced training data).

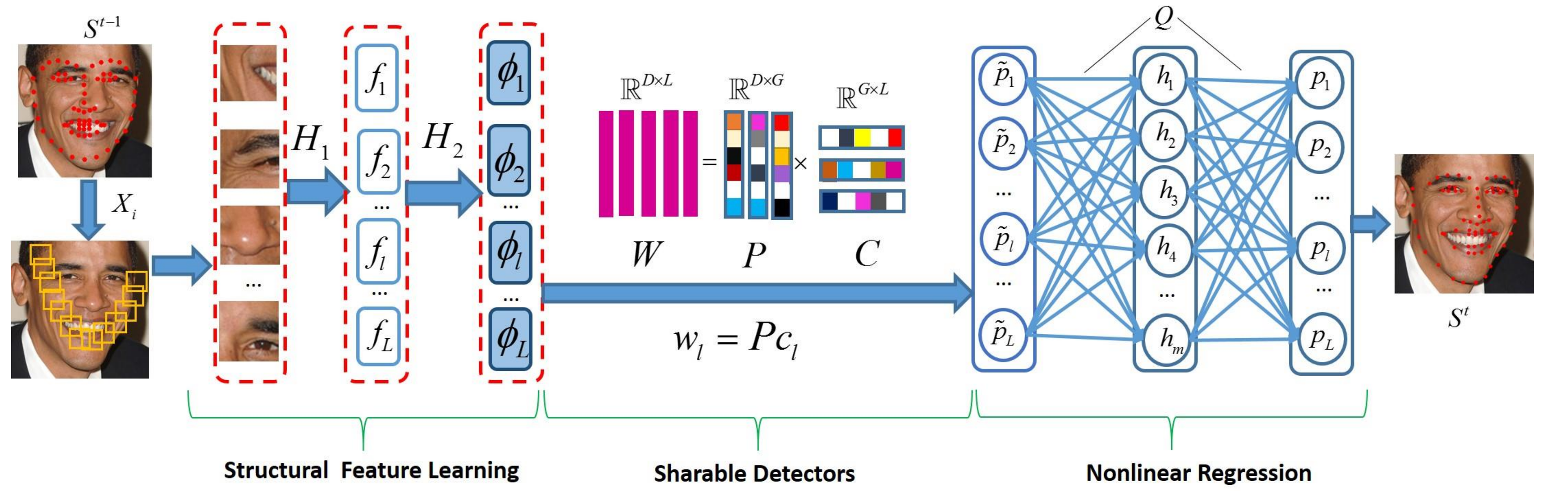
Main Contributions

- Propose a deep sharable and structural detectors approach for face alignment, which aims to capture the shape-sensitive local features while exploiting the local spatial correlation.
- Develop a group-aware deep feature learning method to address the missing labels issue incurred in most face aging datasets.
- Propose a ordinal deep feature learning method to model the order information for ages, in parallel to learning robust face descriptors.

2. Facial Age Estimation Framework

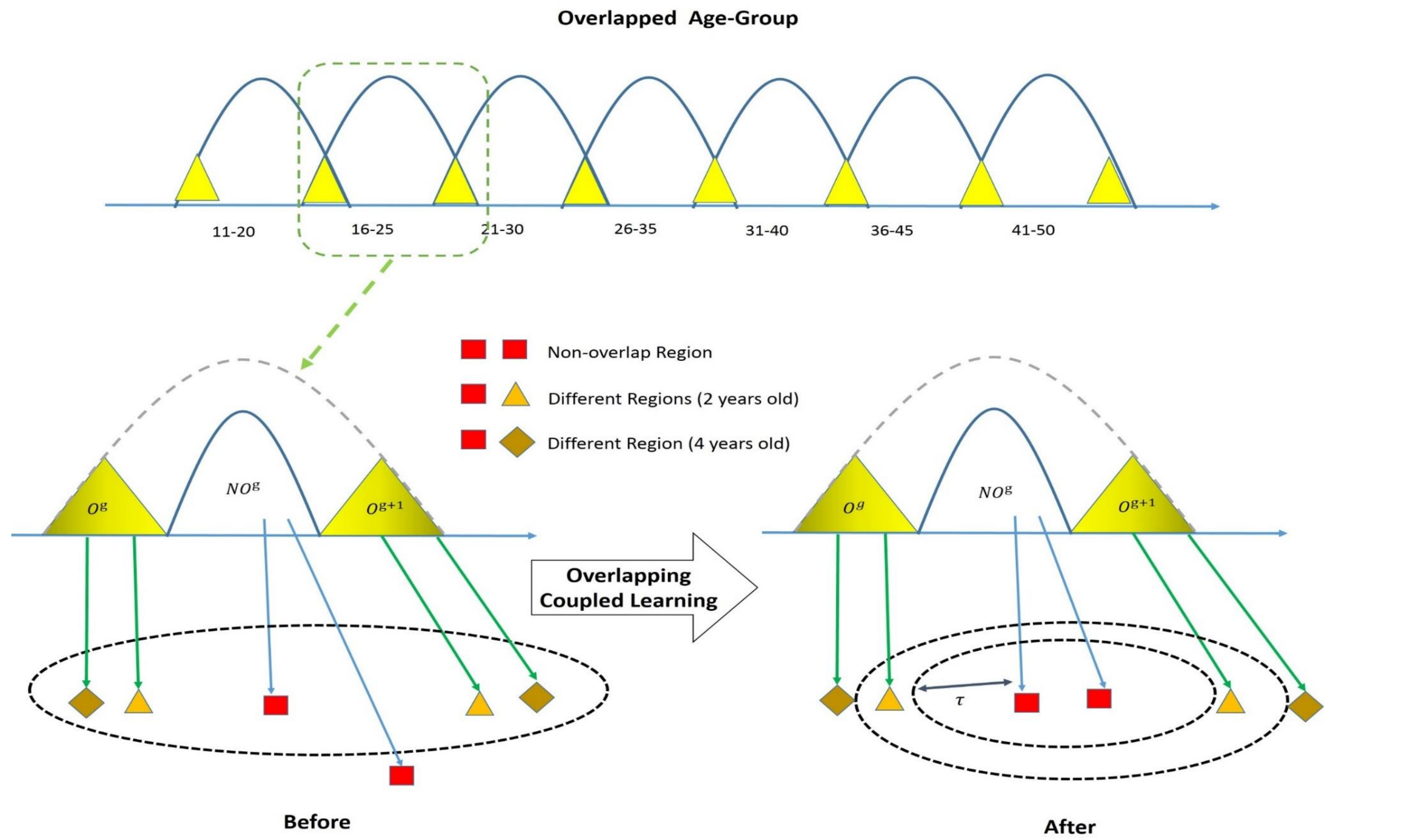
- Face Alignment: we localize seven facial landmarks in order to align the detected face image to the center of the bounding box.
- Age Estimation: we feed testing faces to the trained deep network and then compute the exact age values by a learned age ranker.

3. Face Alignment[1]



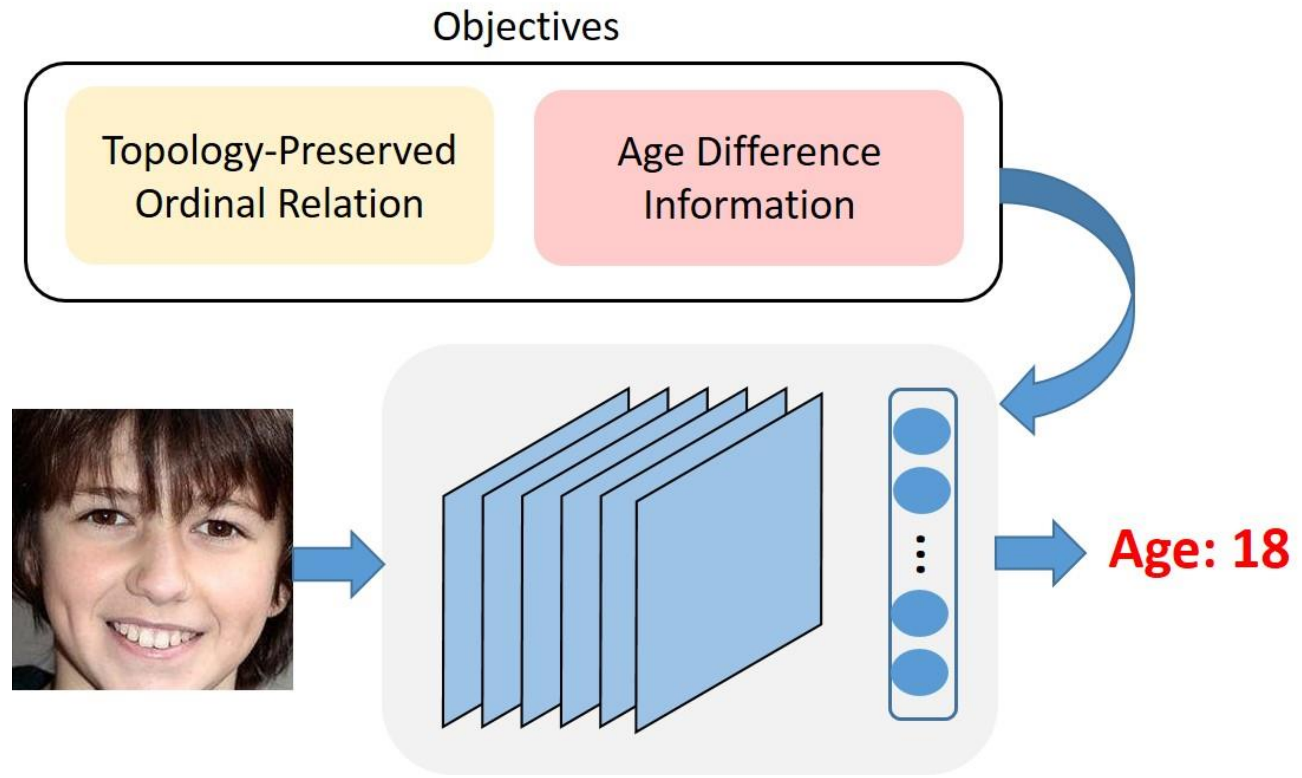
- Structural Feature Learning: model the correlation of neighbouring landmarks to cover semantic details, i.e., eyes, nose or mouth corners.
- Sharable Detectors: remove the noises from spatially overlapped patches.
- Nonlinear Regression: infer occluded part by non-occluded facial part.

4. Group-Aware Deep Feature Learning[2]



- Group-aware Relationship: 1) inter-group variances are maximized, 2) intra-group variances are minimized.
- Overlap-aware Smoothness: face samples within overlaps should be smoothly weighted according to the age value gaps.

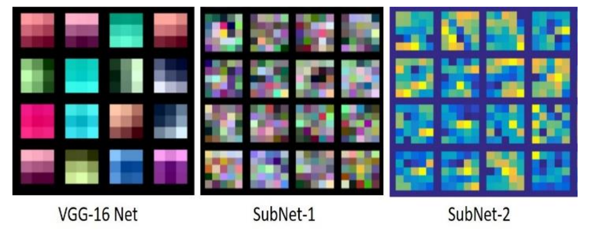
5. Ordinal Deep Feature Learning[3]



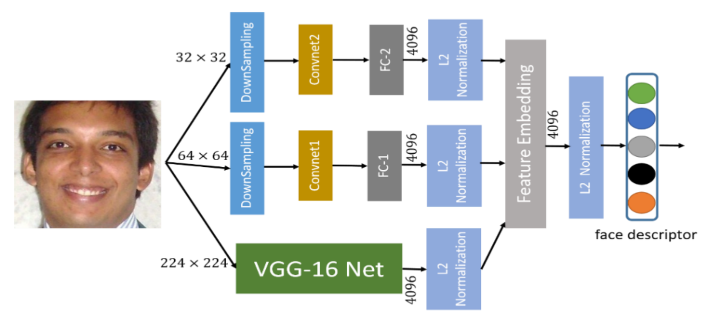
- Topology-Preserved Ordinal Relation: the topology-aware ordinal relation of face samples is preserved in the learned feature space.
- Age Difference Information: the age difference information is exploited in a ranking-preserving manner

6. Experimental Results

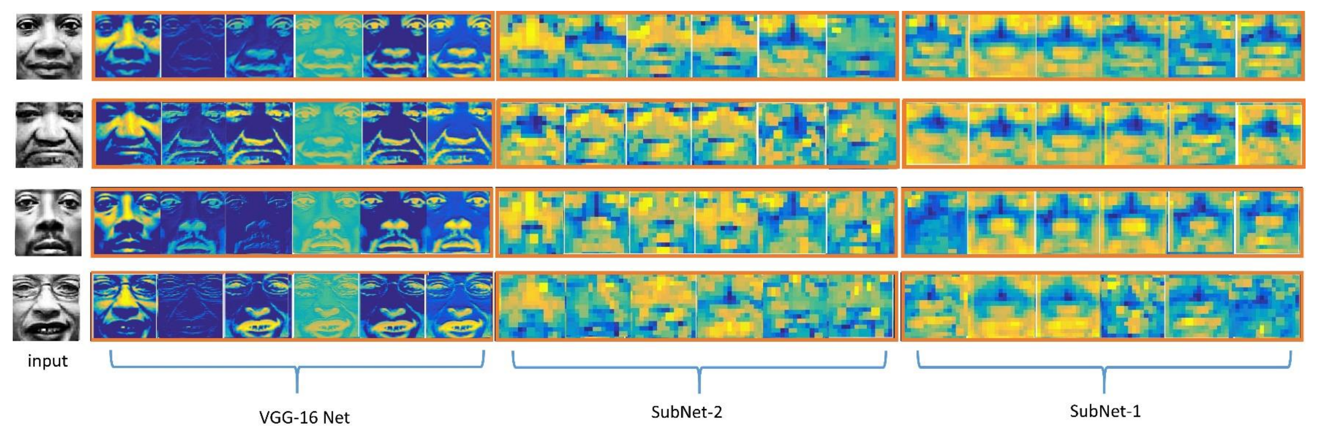
Learned Filters:



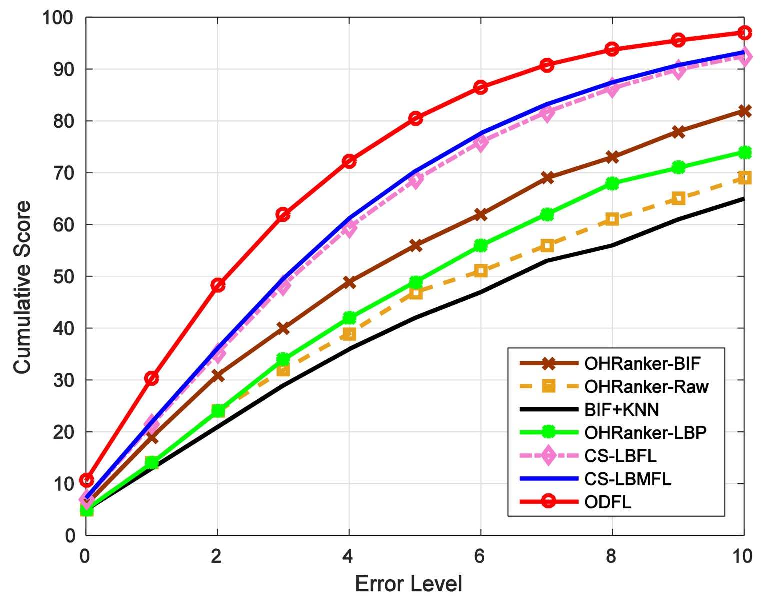
Network Architecture:



Response Maps:



Method	MAE
BIF+KNN	9.64
AGES [1]	8.83
Raw+OHRanker	7.34
LBP+OHRanker	6.88
BIF+OHRanker	6.49
MTWGP [18]	6.28
LDL [20]	5.69
CPNN [20]	5.67
CA-SVR [44]	4.87
BIF+OLPP [45]	4.20
CS-LBFL [11]	4.52
CS-LBMFL [11]	4.37
DeepRank [33]	3.57
DeepRank+ [33]	3.49
OR-CNN [16]	3.27
ODFL	**3.12**



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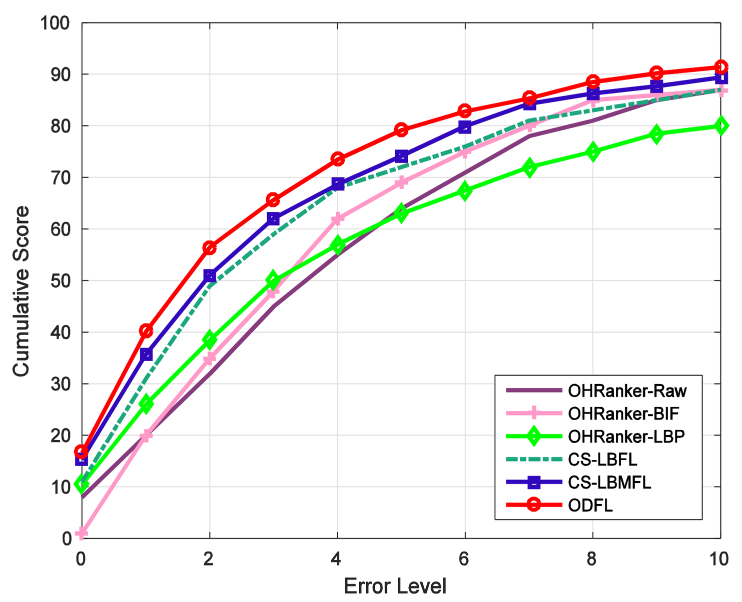
Method	MAE
BIF+KNN	8.24
Raw+OHRanker	6.25
LBP+OHRanker	4.92
BIF+OHRanker	4.48
RUN [48]	5.78
AGES [1]	6.77
MTWGP [18]	4.83
PLO [6]	4.82
LDL [20]	5.77
CPNN [20]	4.76
CA-SVR [44]	4.67
CS-LBFL [11]	4.43
CS-LBMFL [11]	4.36
ODFL	**3.89**



FG-NET

References

[1] Hao Liu*, Jiwen Lu, Jianjiang Feng, Jie Zhou: Learning Deep Sharable and Structural Detectors for Face Alignment. In IEEE Transactions on Image Processing (**TIP**) 26(4): 1666-1678 (2017).

[2] Hao Liu*, Jiwen Lu, Jianjiang Feng, Jie Zhou: Group-aware deep feature learning for facial age estimation. In Elsevier Pattern Recognition (**PR**) 66: 82-94 (2017)

[3] Hao Liu*, Jiwen Lu, Jianjiang Feng, Jie Zhou. Ordinal Deep Feature Learning for Facial Age Estimation. In IEEE Conference on Automatic Face and Gesture (**FG** 2017).