Not Afraid of the Dark

NIR-VIS Face Recognition via Cross-spectral Hallucination and Low-rank Embedding

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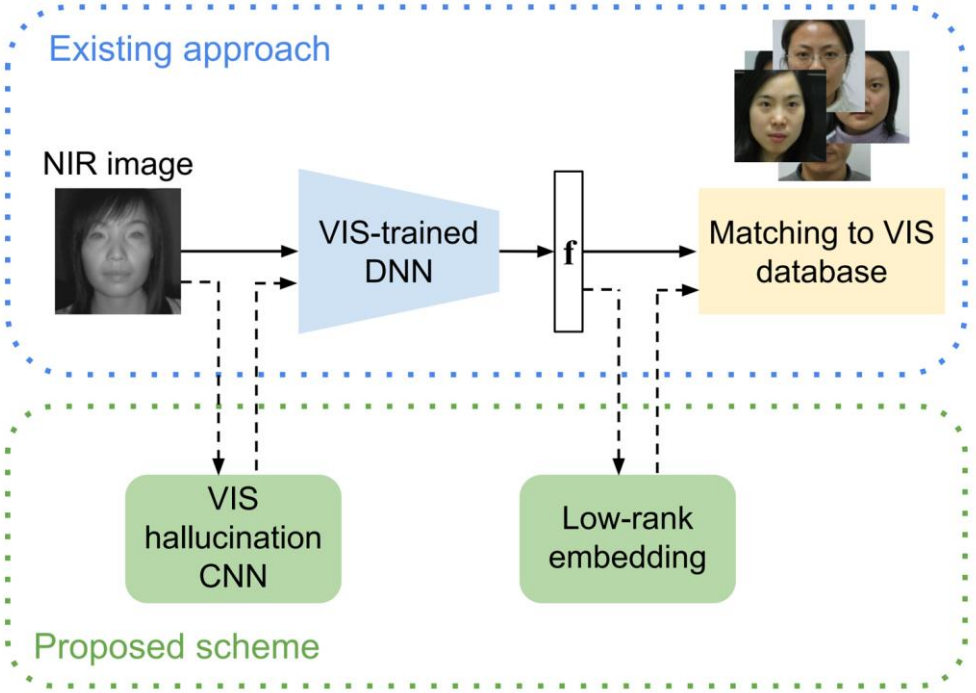
* Denotes equal contribution

Challenge

Apply deep learning for NIR-VIS face recognition:

- Limited near-infrared (NIR) training faces.
- Face galleries to be matched are mostly visible light (VIS).

Proposed Approach



No re-training of VIS-DNNs!

NIR-VIS Hallucination

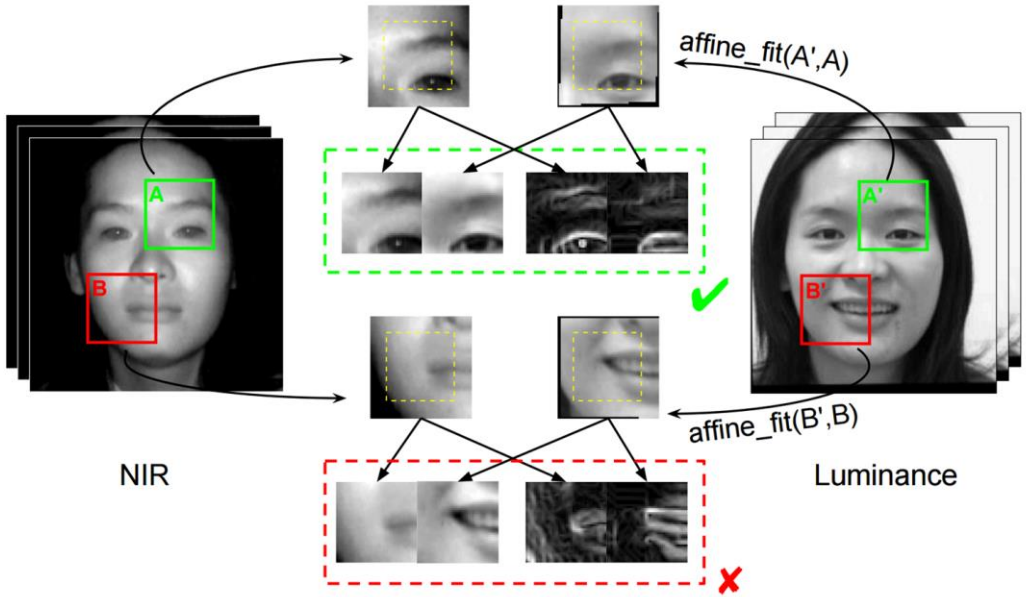
- Use a patch-based CNN to learn the mapping from NIR-VIS
- *Challenge:* No database of **aligned** NIR-VIS pairs
- *Approach:* Construct a database by mining aligned pairs from *CASIA NIR-VIS 2.0 Face Dataset*

Patch Mining

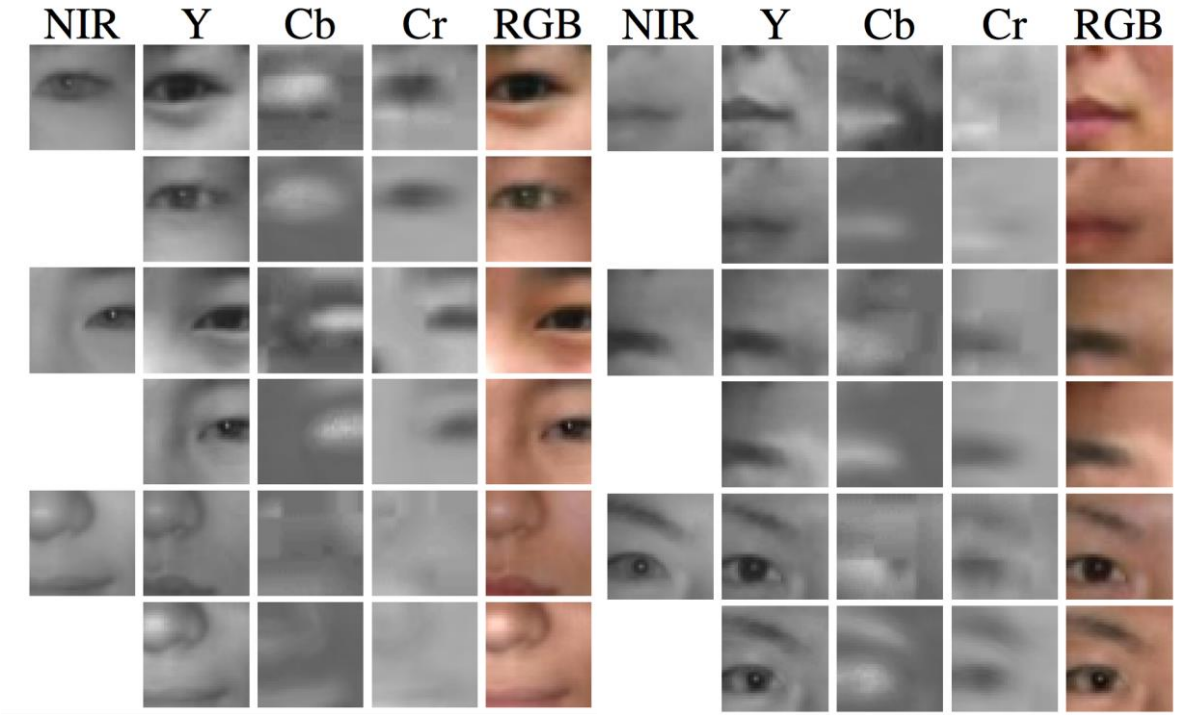
Over pairs of NIR/Luminance images, extract pairs of patches that are highly correlated after an affine transforms.

We obtain a dataset of ~1 Million **aligned** NIR-VIS patches of 40x40 pixels

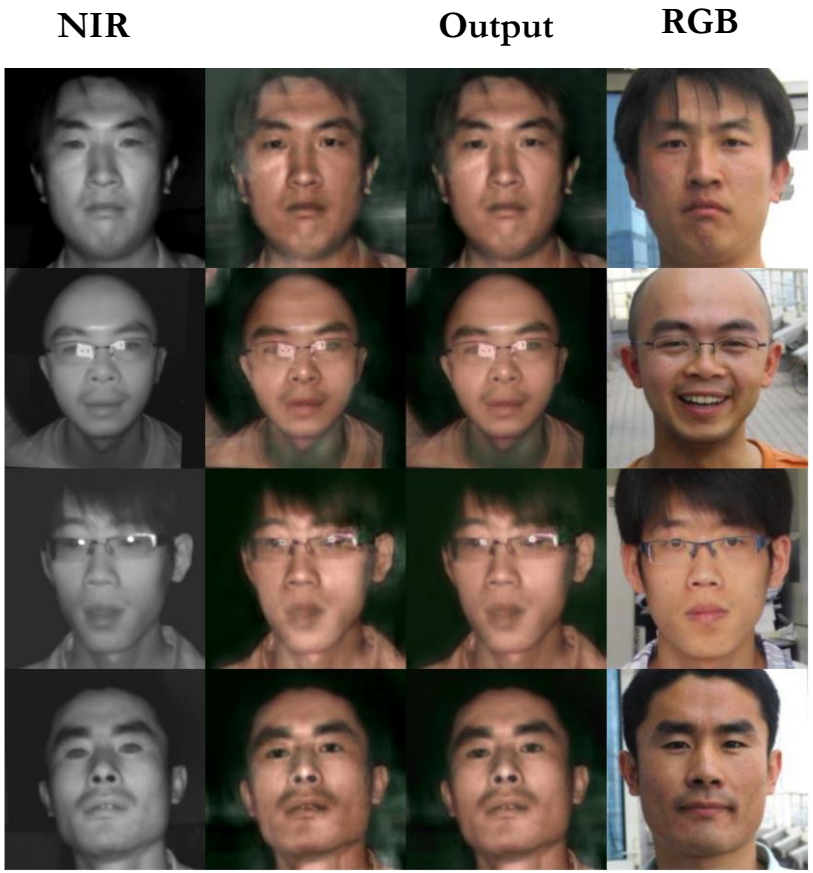
Using this dataset we train a NIR-VIS hallucination CNN



NIR-VIS Hallucination Results - Patches



NIR-VIS Hallucination Results - Images



Cross-modal Low-rank Embedding

Apply low-rank embedding to the output features of the VIS-DNN:

Group together features of the same subjects across modalities

Separate features of different subjects across modalities

$$\sum_{c=1}^{C} ||\mathbf{TY}_c||_* - ||\mathbf{TY}||_*$$

Qiang Qiu, Guillermo Sapiro, "Learning Transformations for Clustering and Classification", Journal of Machine Learning Research (JMLR), 16(Feb):187−225, 2015.

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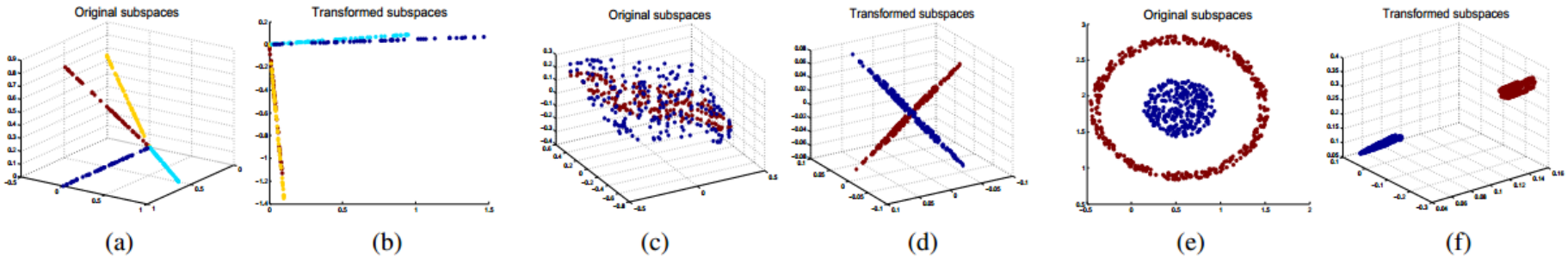

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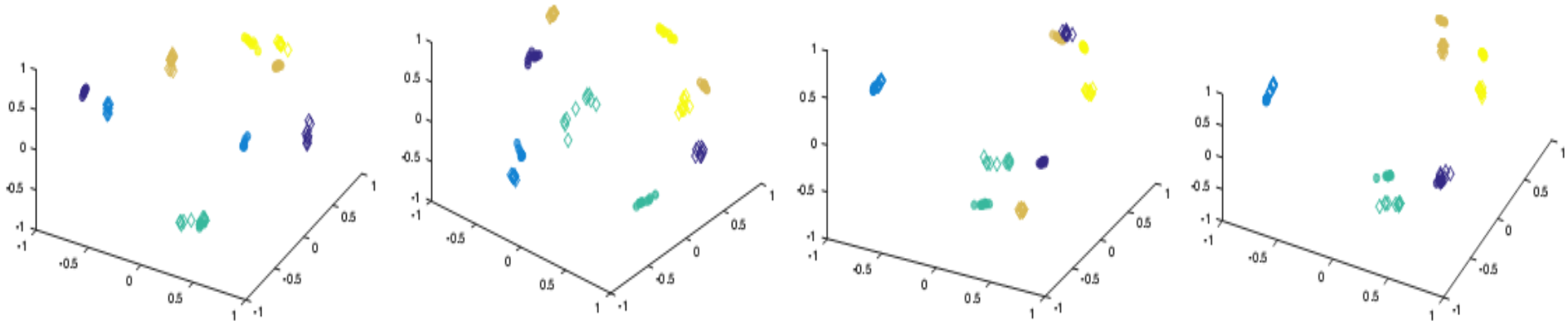
Cross-modal Low-rank Embedding



(a) No embedding (b) Pairwise embedding (c) Triplet embedding (d) Low-rank embedding

5 subjects. Filled circle: VIS samples. Empty diamond: NIR samples.

Results

	Accuracy (%)
Jin et al. [15]	75.70 ± 2.50
Juefei-Xu et al. [16]	78.46 ± 1.67
Lu et al. [25]	81.80 ± 2.30
Saxena et al. [30]	85.90 ± 0.90
Yi et al. [37]	86.16 ± 0.98
Liu et al. [24]	**95.74 ± 0.52**
VGG-S	57.53 ± 2.31
VGG-face	66.97 ± 1.62
COTS	79.29 ± 1.54
VGG-S + Triplet	67.13 ± 3.01
VGG-face + Triplet	75.96 ± 2.90
COTS + Triplet	84.91 ± 3.32
VGG-S + Low-rank	82.07 ± 1.27
VGG-face + Low-rank	80.69 ± 1.02
COTS + Low-rank	*89.59 ± 0.89*

Results on CASIA NIR-VIS 2.0 dataset (not cross-modal hallucination). [24] performs DNN fine-tuning.

	Accuracy (%)
VGG-S	75.04
VGG-S + Hallucination	80.65
VGG-S + Low-rank	89.88
VGG-S + Hallucination + Low-rank	95.72
VGG-face	72.54
VGG-face + Hallucination	83.10
VGG-face + Low-rank	82.26
VGG-face + Hallucination + Low-rank	91.01
COTS	83.84
COTS + Hallucination	93.02
COTS + Low-rank	91.83
COTS + Hallucination + Low-rank	**96.41**

Results on CASIA NIR-VIS 2.0
NIR-VIS hallucination and low-rank embedding separately improve recognition of a black-box DNN, and more so when used in combination

Conclusions

Adapted pre-trained state-of-the-art VIS DNN to generate discriminative features for both VIS and NIR faces, *without retraining the DNN*

Cross-spectral hallucination performs a conversion of the NIR image into the VIS spectrum

Low-rank embedding restores low-rank structure for cross-spectral features

Significant improvement in cross-spectral face recognition with the proposed approach

New direction in the intersection of transfer learning and joint embedding