



Unsupervised Learning of Landmarks based on Inter-Intra Subject Consistencies

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Code Available: https://github.com/Weijian-li/unsupervised_inter_intra_landmark

DEA.





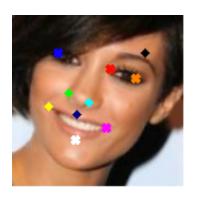


Facial Landmark Localization









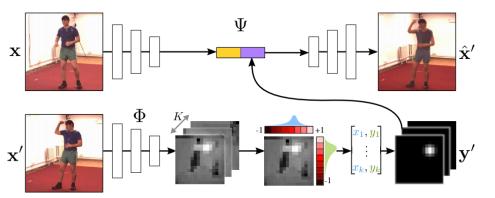
supervised learning

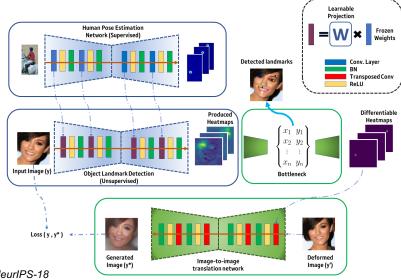
unsupervised learning

Left: Li et al., Structured Landmark Detection via Topology-Adapting Deep Graph Learning, *ECCV-20* Right: Sanchez et al., Object Landmark Discovery Through Unsupervised Adaptation, *NeurIPS-19*



Unsupervised Landmark Localization





Left: Jakab et al., Unsupervised learning of object landmarks through conditional image generation, *NeurIPS-18* Right: Sanchez et al., Object Landmark Discovery Through Unsupervised Adaptation, *NeurIPS-19*



Motivation

- Current approaches leverage reconstructing paired images for landmark learning
- Ensure position consistency across different subjects
 - Inject auxiliary landmarks
- Enrich position consistency for the same subject
 - Construct cycle-alike structure





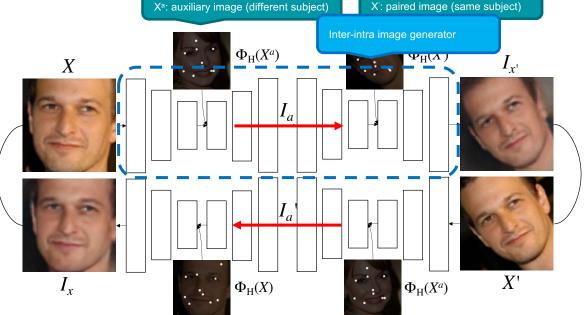




Method

Φ: Landmark Detector

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$$u_{k} = \frac{\sum_{i} exp(\beta S_{k}(i))i}{\sum_{i} exp(\beta S_{k}(i))} \Phi_{H}(x;k) = exp(-\frac{1}{2\sigma^{2}} \|u - u_{k}\|^{2})$$

Inter-intra image generator

$$\mathcal{I}_a = \Psi(\mathcal{F}_s, \Phi_H(x^a)) = \Psi(\Phi_E(x), \Phi_H(x^a))$$
$$\mathcal{I} = \Psi(\mathcal{F}_t, \Phi_H(x^t)) = \Psi(\Phi_E(\mathcal{I}_a), \Phi_H(x^t))$$

Method



- Training
 - Reconstruction Loss
 - Perceptual Loss

$$\mathcal{L}_{R}(\mathcal{I}, \mathcal{I}_{gt}) = \left\| \mathcal{I} - \mathcal{I}_{gt}
ight\|^{2}$$

$$\mathcal{L}_P(\mathcal{I}, \mathcal{I}_{gt}) = \sum_l \left\| VGG^l(\mathcal{I}) - VGG^l(\mathcal{I}_{gt}) \right\|^2$$

$$\mathcal{L} = \mathcal{L}_R(\mathcal{I}_x, x) + \mathcal{L}_R(\mathcal{I}_{x\prime}, x\prime) + \mathcal{L}_P(\mathcal{I}_x, x) + \mathcal{L}_P(\mathcal{I}_{x\prime}, x\prime)$$

Results





Results

TABLE I: Normalized MSE evaluations on the public MAFL and AFLW dataset. Baseline*: our re-implementation of [12].

Method	K	MAFL	AFLW			
Supervised						
TCDCN [25]	•	7.95	7.65			
RAR [26]		-	7.23			
MTCNN [27]		5.39	6.90			
Unsupervised						
Thewlis [28]	-	5.83	8.80			
Shu [18]	-	5.45	-			
Sahasrabudhe [29]	-	6.01	-			
Wiles [17]	-	3.44	-			
Thewlis [10]	10	7.95	-			
Sanchez [12]	10	3.99	6.69			
Zhang [14]	10	3.46	7.01			
Jakab [11]	10	3.19	6.86			
Zhang [14]	30	3.15	6.58			
Jakab [11]	30	2.58	6.31			
Thewlis [13]	50	2.86	6.54			
Jakab [11]	50	2.54	6.33			
Baseline*	10	3.41	6.59			
w. Inter-Subject	10	3.10	6.24			
w. Cycle	10	3.12	6.28			
Ours-All	10	3.08	6.20			
Ours-All	30	2.89	6.08			
Ours-All	50	2.85	6.04			

TABLE II: Normalized MSE evaluations on the MAFL test-set for varying number (N) of supervised samples from MAFL training set used for learning the regressor. We use K=10 intermediate landmarks.

N	Thewlis K=30 [10]	Sanchez K=10 [12]	Jakab K=30 [11]	Ours K=10
1	10.82	18.70	12.89	9.03
5	9.25	8.77	8.16	7.50
10	8.49	7.13	7.19	7.09
100	-	4.53	4.29	3.71
500		4.13	2.83	3.23
1000		4.16	2.73	3.17
5000		4.05	2.60	3.09
All	7.15	3.99	2.58	3.08









Discussion

- Semantically consistent but geometrically not
 - Include spatial constraints







Thank You! Contact: weijian.li@rochester.edu

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