GLPose: Global-Local Attention Network with Feature Interpolation Regularization for Head Pose Estimation of People Wearing Facial Masks

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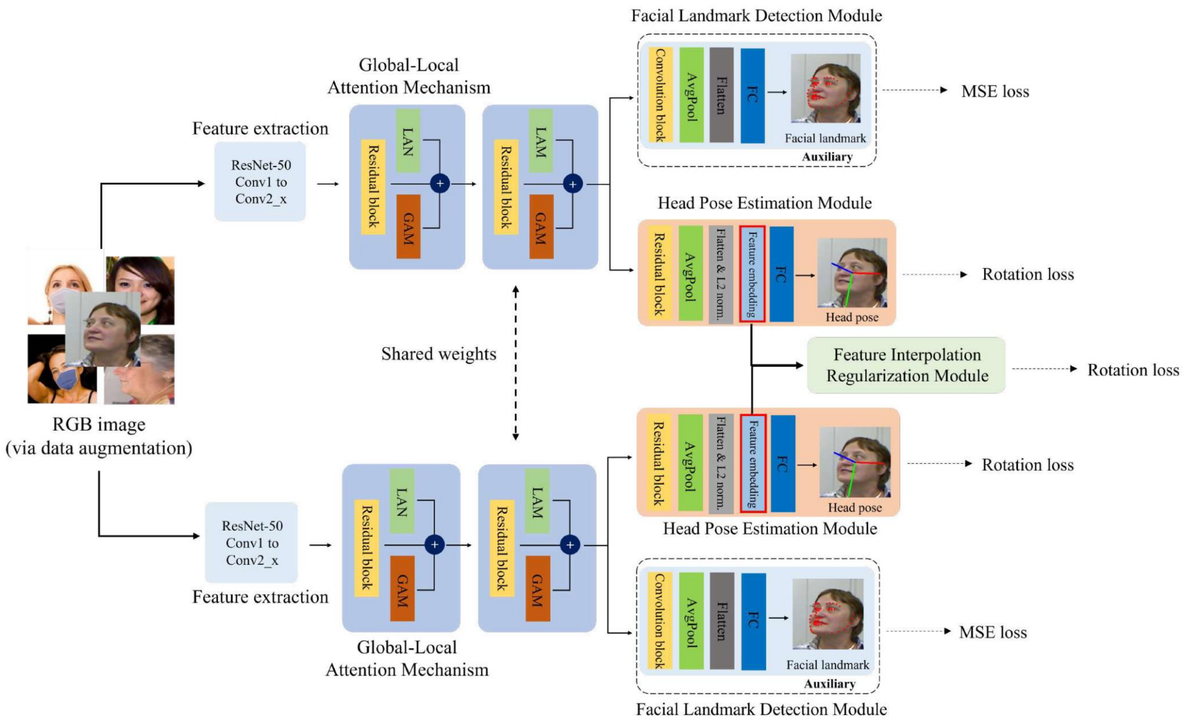
Motivation and Objective

- The public datasets for head pose estimation have fewer cases of facial mask occlusion.
  - Generate the synthesized facial masks on original datasets as a way of the data augmentation.
- Hardly to discriminate the valuable information from feature maps, especially under facial mask situations.
  - Develop a deep learning model with attention mechanisms and auxiliary task supervision to make features more discriminative to estimate head pose.
- The performance for head pose estimation might degrade when the head orientations are not seen before.
  - Design the regularization module to optimize the feature space for head pose estimation to increase the robustness.

Methodology

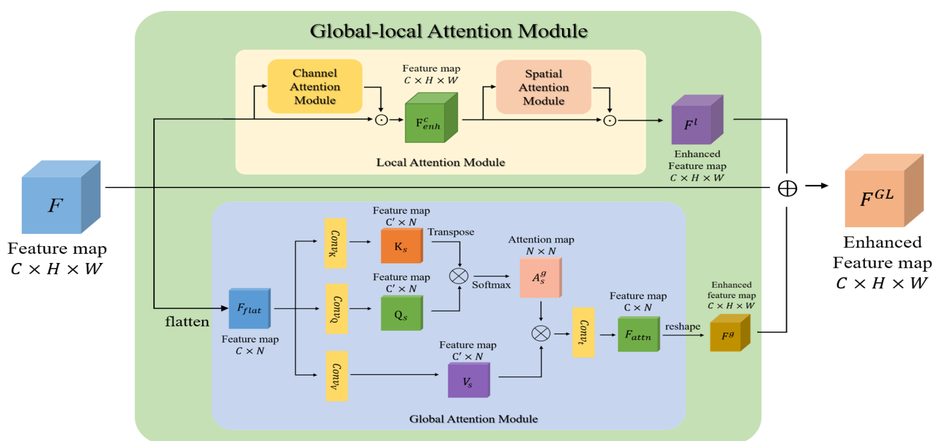
Architecture Overview

- The proposed GLPose integrates the global-local attention mechanisms in the backbone network. The facial landmark detection module as an auxiliary task for predicting the 2D facial landmarks and the head pose prediction module as a main task for predicting head poses. The feature embeddings from two HPE branches are fed into the feature interpolation regularization module (FIRM).
- The FIRM and the facial landmark detection module can be removed in the reference stage and thus will not affect the inference time.



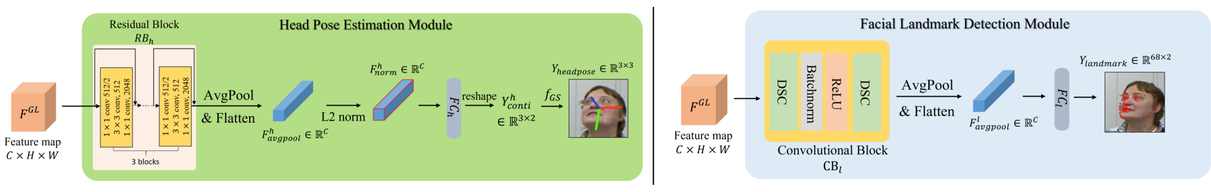
Global-Local Attention Module

- To discriminate the valuable features effectively, we design global-local attention module, which consists of the global attention module and local attention module.
- We apply CBAM[1] as our local attention module, which introduce channel attention and spatial attention into the model. And inspired by the Vision Transformer[2], self-attention is applied as our global attention module to extract the features of larger areas over the feature maps to obtain global information.



Facial Landmark Detection & Head Pose Estimation Module

- To help the model learn additional and discriminative features, we design a landmark detection branch as the auxiliary task supervision. The output of this module is landmark locations $Y_{landmark} \in \mathbb{R}^{68\times2}$, where DSC refer to depthwise separable convolution. The HPE branch predicts the rotation matrix $Y_{headpose} \in \mathbb{R}^{3\times3}$, which is transformed from Y^h_{conti} using the transformation function f_{GS}.



Feature Interpolation Regularization Module

- In order to optimize the feature embedding for the head pose estimation model for further improvement, we design the feature interpolation regularization module during training.
  1. Take $F^h_{norm1}, F^h_{norm2} \in \mathbb{R}^{C\times1\times1}$ from two HPE branches as input
  2. $F^h_3 = (F^h_{norm1} + F^h_{norm2})/2$
  3. $F^h_{norm3} = F^h_3 / ||F^h_3||_2$
  4. $Y_{headpose3} = f_{Gs}(FC_h(F^h_{norm3}))$

Loss Function

- Geodesic distance loss: $Geo(\mathrm{R}^p_i, \mathrm{R}^g_i) = \cos^{-1}\left(\frac{tr(\mathrm{R}^p_i \mathrm{R}^g_i)-1}{2}\right)$
- Facial landmark prediction loss: $MSE(P^p_i, P^g_i) = \sum_{k=1}^{L} \left|\left|p^p_{ik} - p^g_{ik}\right|\right|_2$

For i^{th} input image, where
R^p_i: the model prediction of the rotation matrix
R^p_i: the ground truth of the rotation matrix
$tr(\cdot)$: the trace of the rotation matrix

For i^{th} input image, where
P^p_i: the model prediction of landmark locations
P^g_i: the ground truth of landmark locations
L : Number of landmarks

- Overall loss: $L_{total} = \frac{1}{N}\left(\sum_{i=1}^{N}\left[Geo(\mathrm{R}^{p1}_i, \mathrm{R}^{g1}_i) + \alpha \cdot MSE(P^{p1}_i, P^{g1}_i)\right]\right) + \frac{1}{N}\left(\sum_{j=1}^{N}\left[Geo\left(\mathrm{R}^{p2}_j, \mathrm{R}^{g2}_j\right) + \alpha \cdot MSE\left(P^{p2}_j, P^{g2}_j\right)\right]\right) + \frac{1}{N}\sum_{k=1}^{N}\beta \cdot Geo(R^{p3}_k, R^{g3}_k)$

Experiments

Comparisons on AFLW2000 and BIWI datasets

Method	AFLW2000				BIWI			
	Yaw	Pitch	Roll	MAE	Yaw	Pitch	Roll	MAE
HopeNet[1]	6.47	6.56	5.44	6.16	5.17	6.98	3.39	5.18
FSA-Net[2]	4.50	6.08	4.64	5.07	4.27	4.96	2.76	4.00
TriNet[3]	4.20	5.77	4.04	4.67	3.04	4.76	4.11	3.97
OsGG-Net[4]	3.96	5.71	3.51	4.39	**3.26**	4.85	3.38	3.83
WHENet[5]	5.11	6.24	4.92	5.42	3.99	4.39	3.06	3.81
6DRepNet[6]	3.63	4.91	3.37	3.97	**3.24**	4.48	**2.68**	**3.47**
Our	**3.33**	**4.71**	**3.16**	**3.73**	4.23	**3.54**	2.78	3.51
Our*	**3.35**	**4.58**	**3.11**	**3.68**	4.18	**3.45**	**2.67**	**3.43**

* indicates using the synthesis data during training

Ablation Study

Module			BIWI				AFLW2000			
GLAM	Multi-Task	Feature Interpolation	Yaw	Pitch	Roll	MAE	Yaw	Pitch	Roll	MAE
			4.34	4.06	2.77	3.72	3.76	4.98	3.23	3.99
√			4.17	3.64	2.77	3.52	3.63	4.87	3.22	3.90
	√		4.19	3.63	2.74	3.52	3.75	4.95	3.24	3.98
		√	4.24	3.53	2.74	3.50	3.41	4.83	3.21	3.81
√	√		**4.05**	3.60	**2.60**	**3.41**	3.50	4.86	3.23	3.86
√	√	√	4.18	**3.45**	2.67	3.43	**3.35**	**4.58**	**3.11**	**3.68**

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