Self-Correctable and Adaptable Inference for Generalizable Human Pose Estimation

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Highlights

- We demonstrate that it is theoretically possible to learn a feedback-correction network to refine the prediction results of a well-trained network, outperforming the SOTA and SCIO by 1.4%, which is quite significant.

- We have introduced a correction network which is able to correct the prediction error for the test sample guided by the self-referential feedback error. This error was generated by a learned fitness feedback network. We found that this self-referential error is highly correlated with the actual network prediction error.

- Using the self-referential error, we introduced a new loss function to perform quick adaptation and optimization of the correction network during the inference stage.

- We apply the proposed self-correctable and adaptable inference method to human pose estimation and have achieved remarkable performance gain and significant improvement of generalization capability of the pose estimation network.

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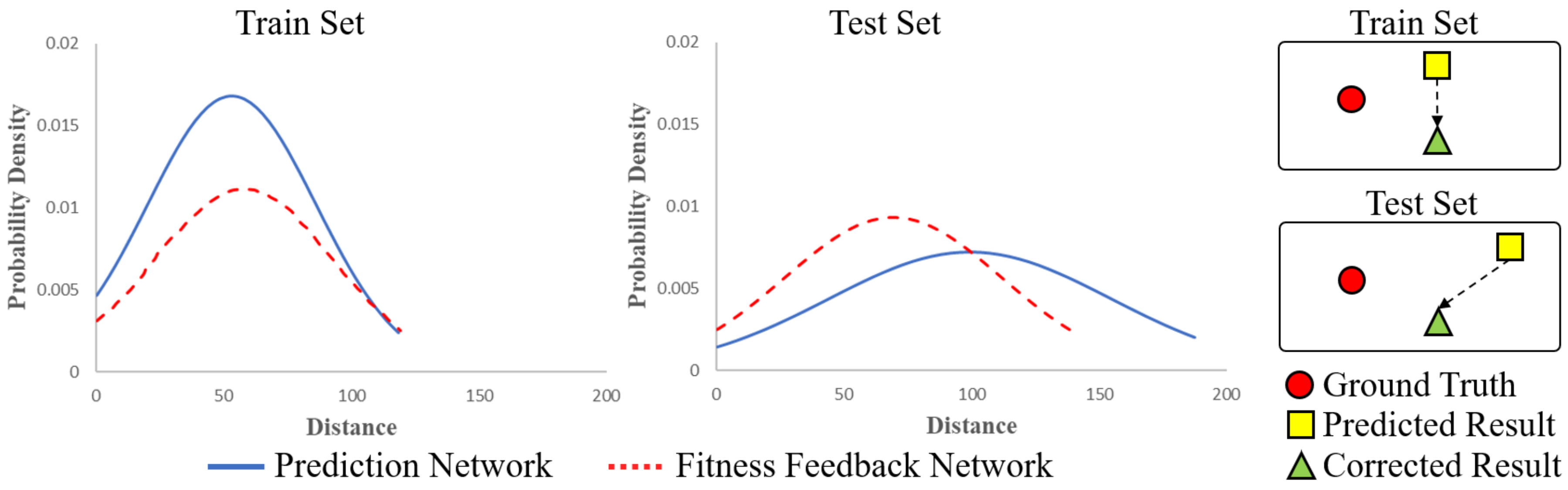
Problem Definition

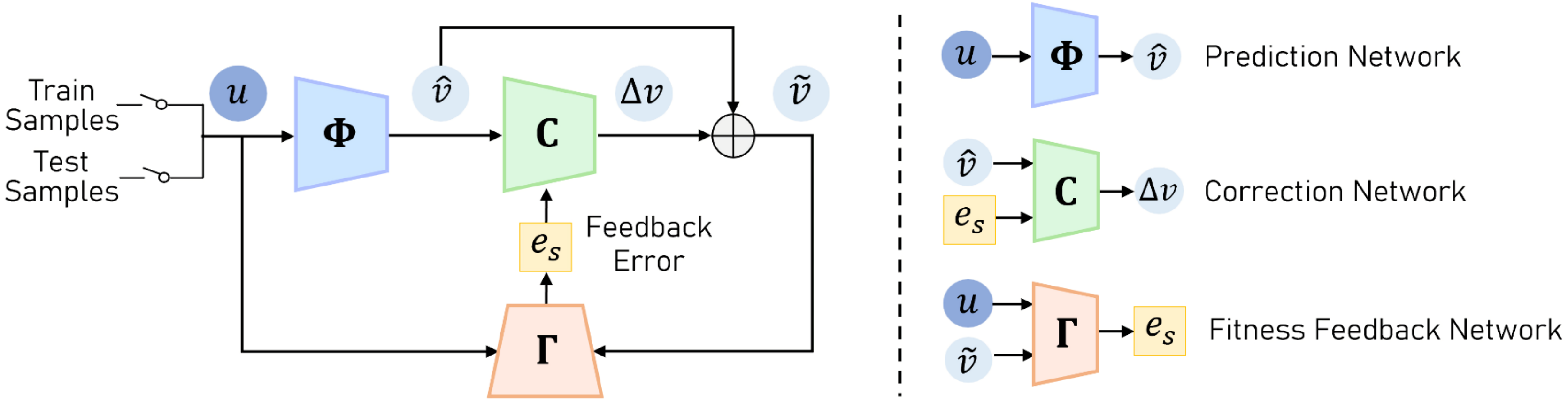
Goal: Human pose estimation aims to correctly detect and localize keypoints, i.e., human body joints or parts.

- How can we tell if the prediction is accurate or not during testing and how to characterize the prediction error?
- How to correct the prediction error based on the specific characteristics of the test sample?



Main Idea

- We propose the construction of a novel Feedback Fitness Network (FFN) that possesses the capability to assess the accuracy of predictions without prior knowledge of the ground truth.
- By leveraging the FFN, we extract self-referential errors that exhibit a strong correlation with actual errors. These errors serve as valuable indicators for training a prediction-correction network, enabling dynamic adjustment of predictions during inference.
- Furthermore, we utilize the self-referential errors in conjunction with the FFN to construct a self-supervised loss function, which facilitates rapid adaptation and optimization of network models during inference, particularly on test samples.



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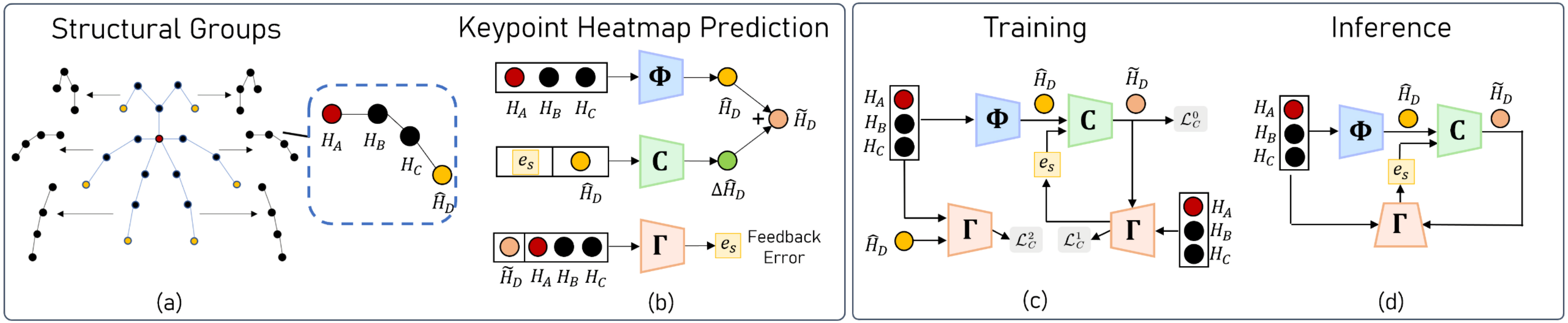
Method

- Partitioned the body keypoints into 6 structural groups according to their biological parts, and each structural group is further partitioned into two subsets: distal keypoints and proximal keypoints.

- Developed a prediction-FFN network that effectively extracts self-referential errors and facilitates learning of a correction network under the guidance of these errors.

- During the inference phase, the self-referential error is leveraged to dynamically update the correction network by incorporating information from new samples.



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Experimental Results

➤ Comparison with the state-of-the-art methods on COCO test-dev.

Method	Backbone	Size	AP	AP^{50}	AP^{75}	AP^{M}	AP^{L}	AR
CFN [14]	-	-	72.6	86.1	69.7	**78.3**	64.1	-
CPN(ensemble) [4]	ResNet-Incep.	384×288	73.0	91.7	80.9	69.5	78.1	79.0
CSM+SCARB [28]	R152	384×288	74.3	91.8	81.9	70.7	80.2	80.5
CSANet [42]	R152	384×288	74.5	91.7	82.1	71.2	80.2	80.7
HRNet [30]	HR48	384×288	75.5	92.5	83.3	71.9	81.5	80.5
MSPN [21]	MSPN	384×288	76.1	93.4	83.8	72.3	81.5	81.6
PoseFix [25]	HR48+R152	384×288	76.7	92.6	84.1	73.1	82.6	81.5
DARK [43]	HR48	384×288	76.2	92.5	83.6	72.5	82.4	81.1
UDP [13]	HR48	384×288	76.5	92.7	84.0	73.0	82.4	<u>81.6</u>
Graph-PCNN [35]	HR48	384×288	76.8	92.6	84.3	73.3	82.7	<u>81.6</u>
SCIO [15]	HR48	384×288	<u>79.2</u>	<u>93.5</u>	<u>85.8</u>	74.1	<u>84.2</u>	<u>81.6</u>
SCAI (Ours)	HR48	384×288	**80.6**	**94.8**	**87.0**	<u>78.1</u>	**84.8**	**83.1**
Performance Gain			**+1.4**	**+1.3**	**+1.2**	**-0.2**	**+0.6**	**+1.5**

Experimental Results

- Comparison with the state-of-the-art methods on CrowdPose test-dev.

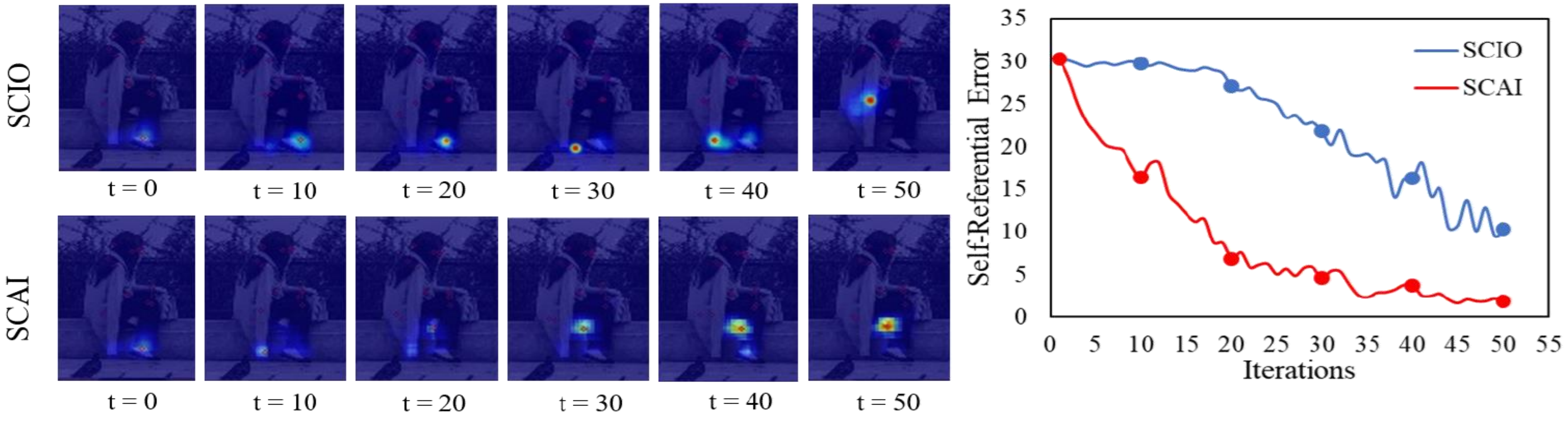
Method	Backbone	AP	AP^{med}
Mask-RCNN [12]	ResNet101	60.3	-
AlphaPose [8]	-	61.0	61.4
OccNet [10]	ResNet50	65.5	66.6
JC-SPPE [20]	ResNet101	66.0	66.3
HigherHRNet [5]	HR48	67.6	-
MIPNet [16]	HR48	70.0	71.1
SCIO [15]	HR48	71.5	72.2
SCAI (Ours)	HR48	**72.4**	**73.2**
Performance Gain		**+0.9**	**+1.0**

- Comparison with state-of-the-art of three baselines on COCO test-dev.

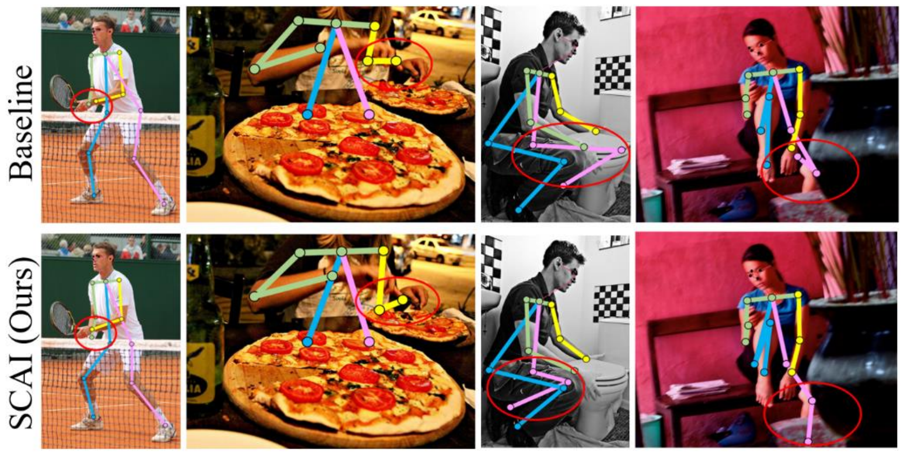
Method	Backbone	AP	AP^M	AR
SimpleBaseline	R152	73.7	70.3	79.0
+ **SCAI**	R152	**78.8**	**75.5**	**82.5**
Performance Gain		**+5.1**	**+5.2**	**+3.5**
HRNet	HR32	74.9	71.3	80.1
+ **SCAI**	HR32	**79.9**	**76.8**	**82.5**
Performance Gain		**+5.0**	**+5.5**	**+2.4**
HRNet	HR48	75.5	71.9	80.5
+ **SCAI**	HR48	**80.6**	**78.1**	**83.1**
Performance Gain		**+5.1**	**+6.2**	**+2.6**

Experimental Results

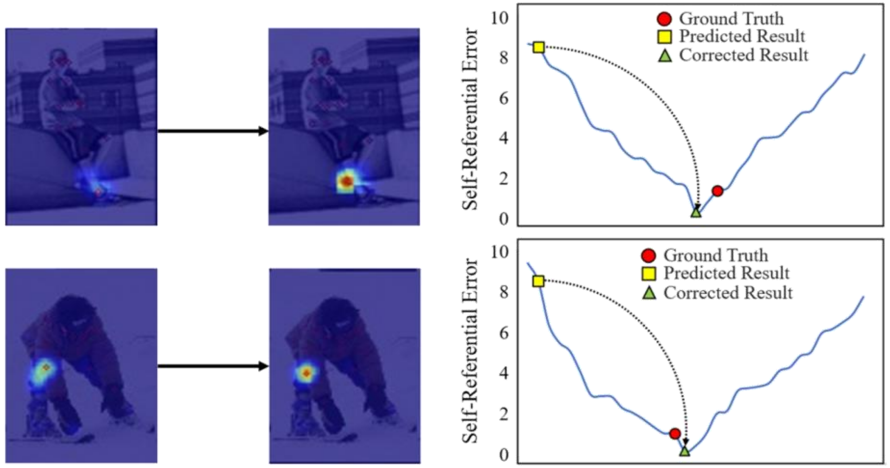
- Comparison between the local search and the correction from SCIO and SCAI.



- Refinement of predicted keypoints.

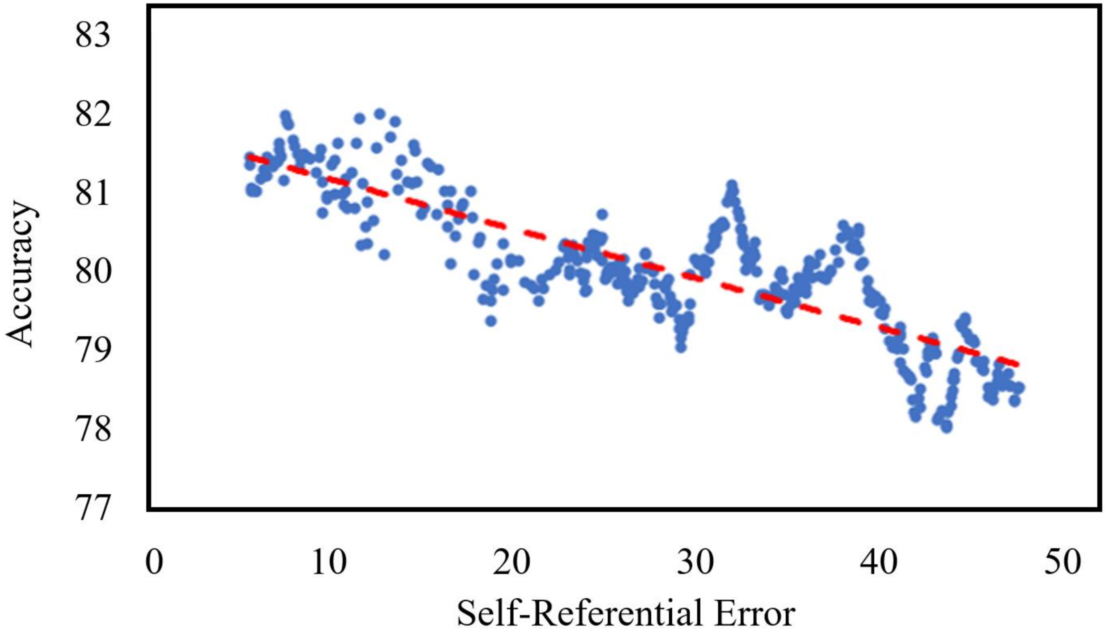


- Two examples of corrected keypoints.

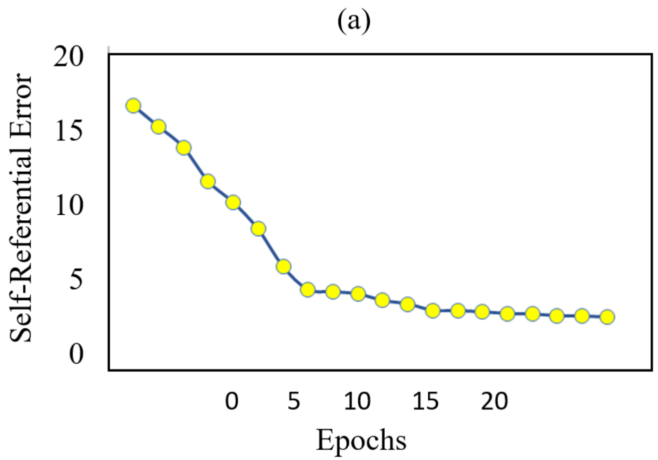


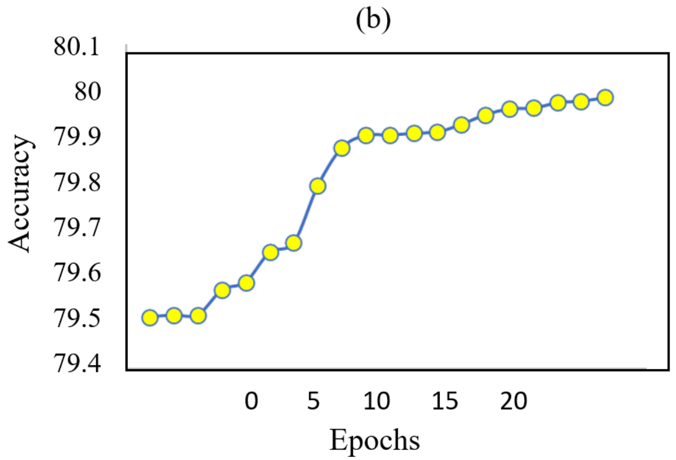
Experimental Results

- Strong correlation between self-referential error and network prediction accuracy.



- (a) is the loss training during inference, (b) is the test result corresponding to each epoch.





Conclusion

- We demonstrate that it is possible to learn a feedback-correction network to refine the prediction results of a well-trained network.
- We propose SCAI, a learning-based feedback-control method for prediction to address the generalization challenge.
- We apply the SCAI method to human pose estimation and achieve SOTA performance, improves the current best method by up to 1.4%.