Incorporating Test-Time Optimization into Training with Dual Networks for Human Mesh Recovery

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Introduction

Motivation

Q1

There is a gap between the training and testing optimizations objectives.

Q2

Pretrained model is not specially tailored for the test-time optimization.

Contribution

- We propose a novel dual-network HMR framework with test-time optimization involved into the training procedure, which improves the effectiveness of the test-time optimizations.
- We ensure the test-time objectives identical to the training objectives, further facilitating the joint-training of the test-time and training-time optimizations.
- Extensive experiments validate that our results outperform those of previous approaches both quantitatively and qualitatively.

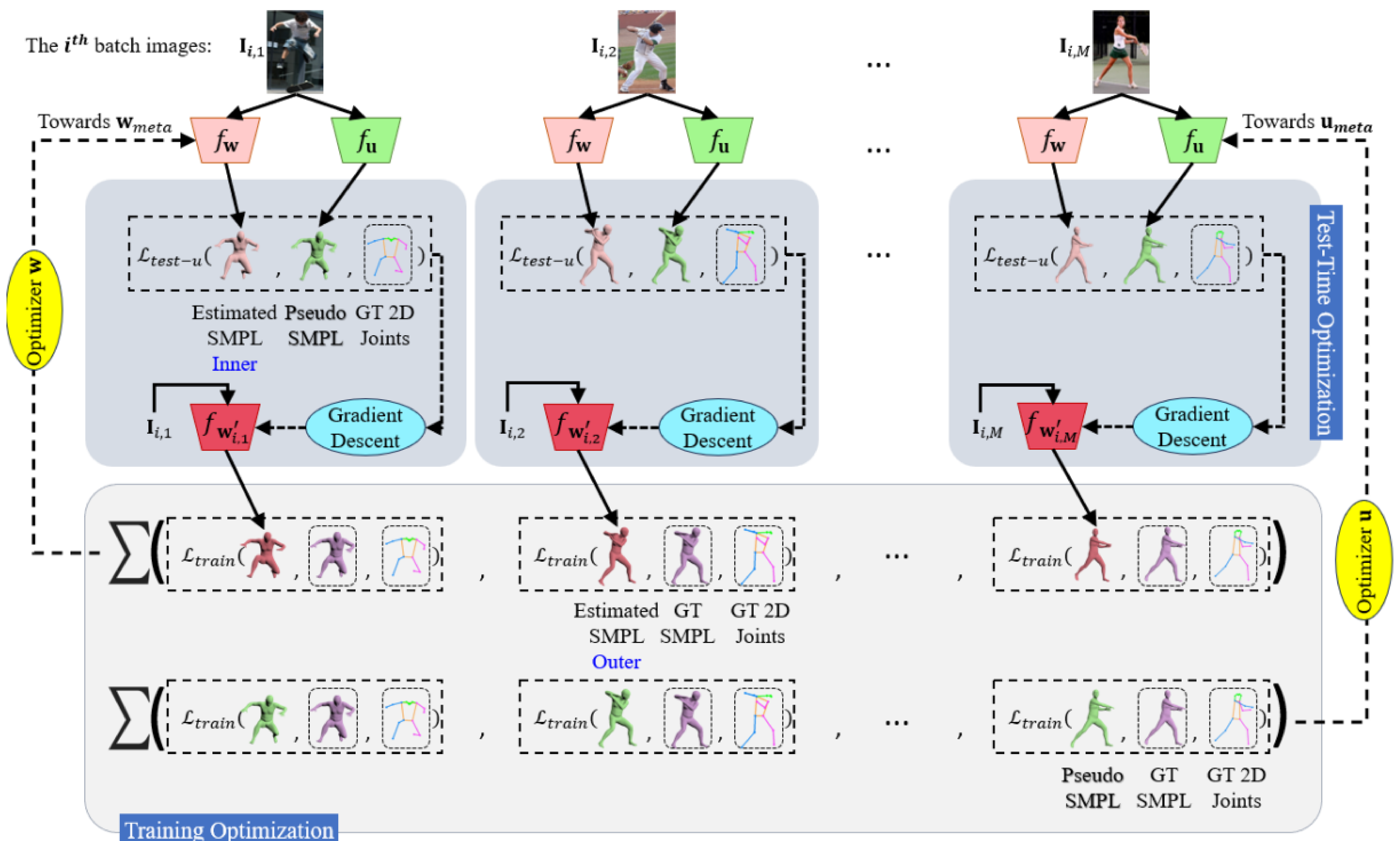
More Information

Github

Paper

Method

Overall Pipeline



Step1

Auxiliary network $f_{\mathbf{u}}$ produces pseudo labels and unifies the training and test-time optimization objectives:

$$\hat{\Theta}^u_{i,j} = f_{\mathbf{u}}(\mathbf{I}_{i,j}) \qquad \mathbf{w}'_{i,j} = \mathbf{w} - \alpha \nabla_{\mathbf{w}} \mathcal{L}_{test-u}(f_{\mathbf{w}}(\mathbf{I}_{i,j}), \hat{\Theta}^u_{i,j}, \hat{\mathbf{J}}_{i,j})$$

Step2

Inspired by optimization-based meta-learning, we perform a step of test-time optimization before conducting training optimization. This results in a meta-model, whose meta-parameters are friendly to test-time optimization.

$$\mathbf{w}_{meta}, \mathbf{u}_{meta} = \arg\min_{\mathbf{w},\mathbf{u}} \sum_{i=1}^{B}\sum_{j=1}^{M} (\mathcal{L}^1_{train}(f_{\mathbf{w}'_{i,j}}(\mathbf{I}_{i,j}), \hat{\Theta}_{i,j}, \hat{\mathbf{J}}_{i,j}) + \mathcal{L}^2_{train}(f_{\mathbf{u}}(\mathbf{I}_{i,j}), \hat{\Theta}_{i,j}, \hat{\mathbf{J}}_{i,j}))$$

Step3

Armed with meta-learning and dual networks, we perform several test-time optimization steps starting from the meta-parameters, ultimately achieving higher HMR accuracy compared to starting from a standard pretrained regression model.

Experiments

Quantitative Comparison

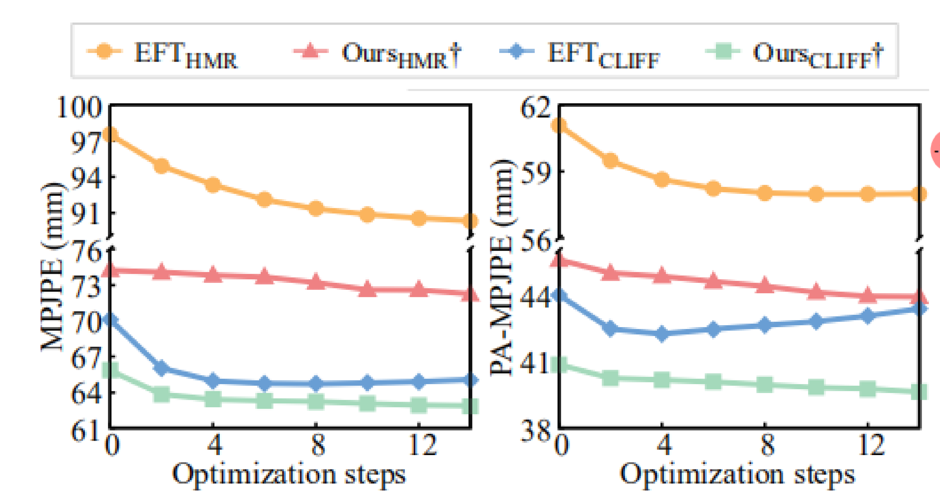
Method	3DPW			Human3.6M	
	MPJPE↓	PA-MPJPE↓	PVE↓	MPJPE↓	PA-MPJPE↓
CLIFF [31]'22	69.0	43.0	81.2	47.1	32.7
LearnSample [58]'22	70.5	43.3	82.7	45.9	33.5
ProPose [11]'23	68.3	40.6	79.4	45.7	**29.1**
POTTER [65]'23	75.0	44.8	87.4	56.5	35.1
DeFormer [59]'23	72.9	44.3	82.6	44.8	31.6
EFT [20]'21	85.1	52.2	98.7	63.2	43.8
NIKI [29]'23	71.3	40.6	86.6	-	-
ReFit [55]'23	65.8	41.0	-	48.4	32.2
PLIKS [47]'23	66.9	42.8	82.6	49.3	34.7
$\text{Ours}_{\text{CLIFF}}\dagger$(OpenPose 2D)	62.9	39.7	80.1	43.9	30.3
$\text{Ours}_{\text{CLIFF}}*$(RSN 2D)	**62.4**	**39.5**	**78.1**	**42.0**	**29.1**

Qualitative Comparison

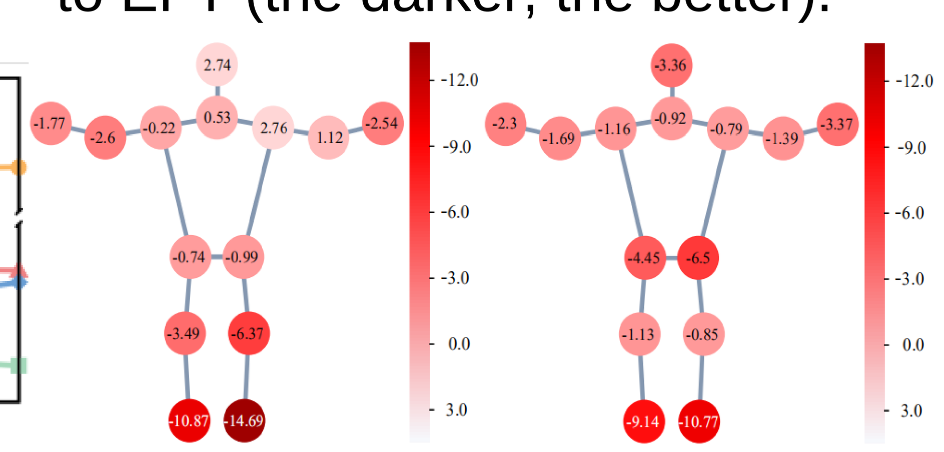
Input CLIFF Ours† Ours∗ Novel view Input Refit Ours† Ours∗ Novel view

Discussion

Influence of optimization steps



Per-joint error analysis compared to EFT (the darker, the better).



Acknowledgements

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