

A Unified Framework for Human-centric Point Cloud Video Understanding

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Motivation	Prior Knowledge Extraction	Experiment
global & Action Recognition	 Build HBSeg and HMFlow networks and 	
-level T Pand-Duar Sports	synthetic datasets to provide fine-grained	$\begin{array}{c c c c c c }\hline mAcc & MPJPE(mm) \downarrow \\\hline \hline PointNet & 47.3 & LiDARCap(PC) & 69.4 \\\hline \end{array}$
geometry Fitness Sit	geometric structure and motion information.	1000000000000000000000000000000000000
part s		PointMLP 58.1 UniPVU-Human(PC) 58.8
-level 3D Pose Estimation	(a) Prior Knowledge Extraction	$\begin{array}{c c c c c c c c c c c c c c c c c c c $
		$\frac{1000}{1000} \frac{1000}{1000} $
point -level motion flow		$\begin{array}{c c c c c c c c }\hline\hline PointMAE^{\dagger} & 58.0 \\\hline MaST-Pre^{\dagger} & 54.1 \\\hline \end{array} \ \ \textbf{T} \ \ \textbf{3D} \ \ \textbf{Pose Estimation in LIP}$
	HBSeg: Extract body	$\underline{\text{UniPVU-Human}} \underline{\textbf{61.8}} \leftarrow \text{Action Recognition in HuCenLife}$
Considering that human has specific	PC structure semantic.	Self-learning Mask Hierarchical Feature
characteristics, including the		part division spatial temporal global token motion flow mAcc
structural semantics of human body		X X X X 53.4
and the dynamics of human motions,		X X X 56.1
we propose a unified framework to		× ✓ × ✓ ✓ 58
make full use of the prior knowledge	• HMFlow : Explore fine-	X X X X 54.1
and explore the inherent features in	<i>F</i> grained motion infomation	
the data itself for generalized human-	Semantic-guided ST Representation Self-learning	$\begin{array}{c c c c c c c c c c c c c c c c c c c $
centric point cloud video	(b) Semantic-guided Spatio-temporal Representation Self-learning	$\begin{array}{c c c c c c c c c c c c c c c c c c c $
understanding.	Spatial Masking T_M Loss	\checkmark \checkmark \checkmark \checkmark \checkmark 59.3
	Spatio	✓ ✓ ✓ ✓ × 61.3
Contributions	$\begin{array}{c c} Layer \\ \hline Temporal Masking \\ \hline T_V \\ \hline Temporal Masking \\ \hline Tempora \\ \hline Temporal Masking \\ \hline Temporal Masking \\ \hline Temporal Mask$	
 We propose the first framework 	• Based on structure semantics of human bodies, the	 Ablation Studies of Network Design
for human-centric point cloud video	model mines essential geometric and motion features	proportion of fine-tuning dataset
understanding for various tasks.	from human point cloud video data itself by masking	$\begin{array}{c c c c c c c c c c c c c c c c c c c $
 Containing semantic-guided 	and predicting body part patches.	MaST-Pre [25] 39.8(-14.3) 42(-12.1) 48.8(-5.3) 54.1
spatio-temporal representation self-	Hierarchical Feature Enhanced Fine-tuning	UniPVU-Human* 44.9(-10.9) 46.4(-9.4) 49.5(-6.3) 55.8
learning and hierarchical feature	Action	UniPVU-Human 51(-10.8) 53.8(-8) 57.3(-4.5) 61.8
enhanced fine-tuning, our method	Global Feature	Effectiveness of Our Self-learning Mechanism in
takes advantage of prior knowledge	$= \blacksquare \blacksquare \blacksquare \bullet $	Semi-supervised Settings
of humans for human-centric	Part Feature	
representation learning.	Point Feature (c) Hierarchical Feature Enhanced Fine-tuning	

Our project:

https://github.com/viteng-xu/CVPR2024-UniPVU-Human

• Our method achieves state-ofthe-art performance on datasets for various human-centric tasks.

Integrate global, part, and point level point cloud features to pre-trained STEncoder, therefore fully leveraging prior knowledge for effective and robust human-centric representation learning.