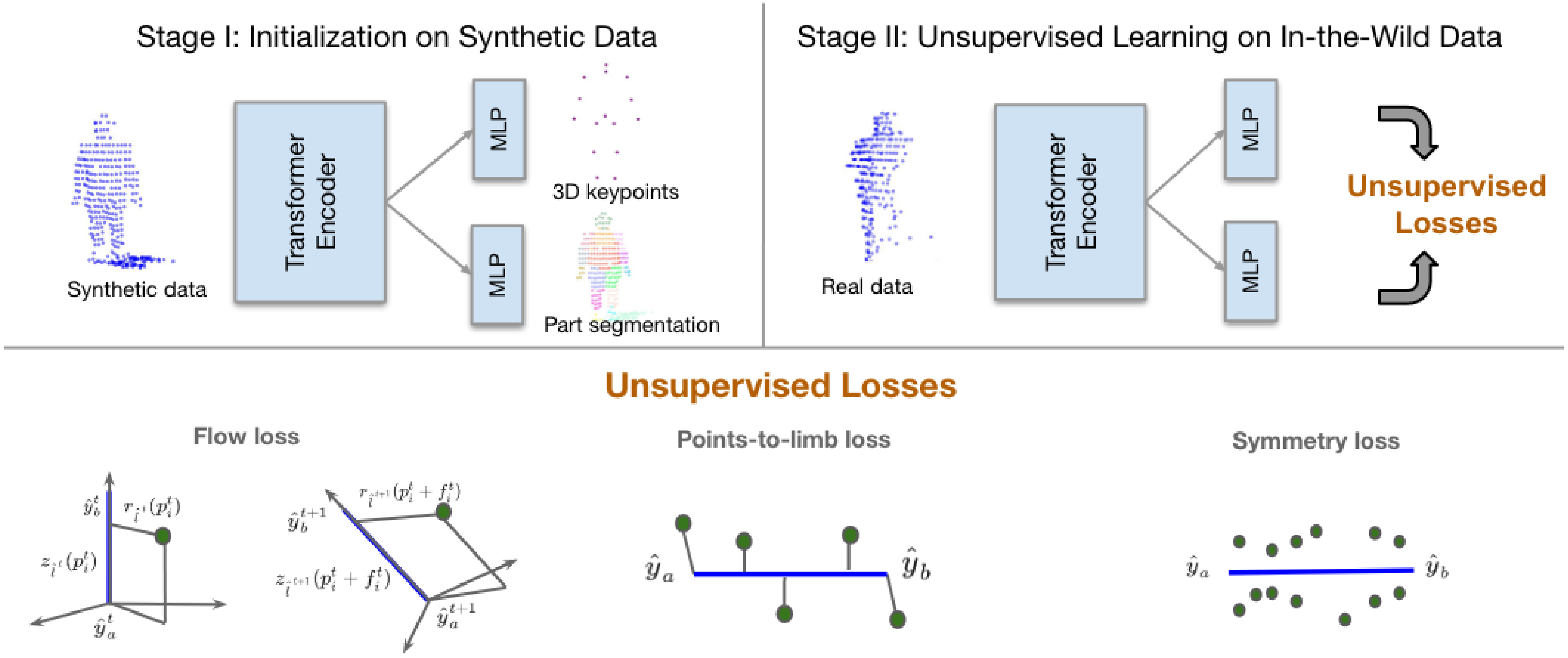

3D Human Keypoints Estimation from Point clouds in the Wild Without Human Labels

In CVPR 2023

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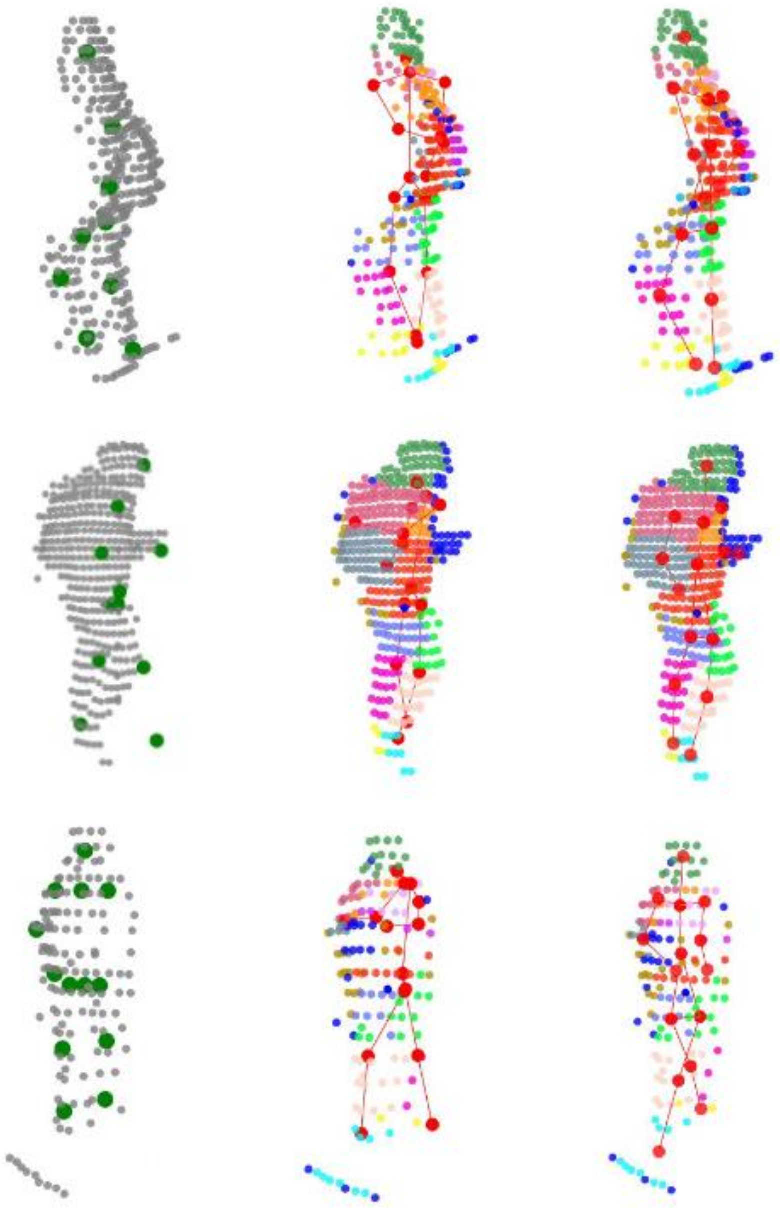
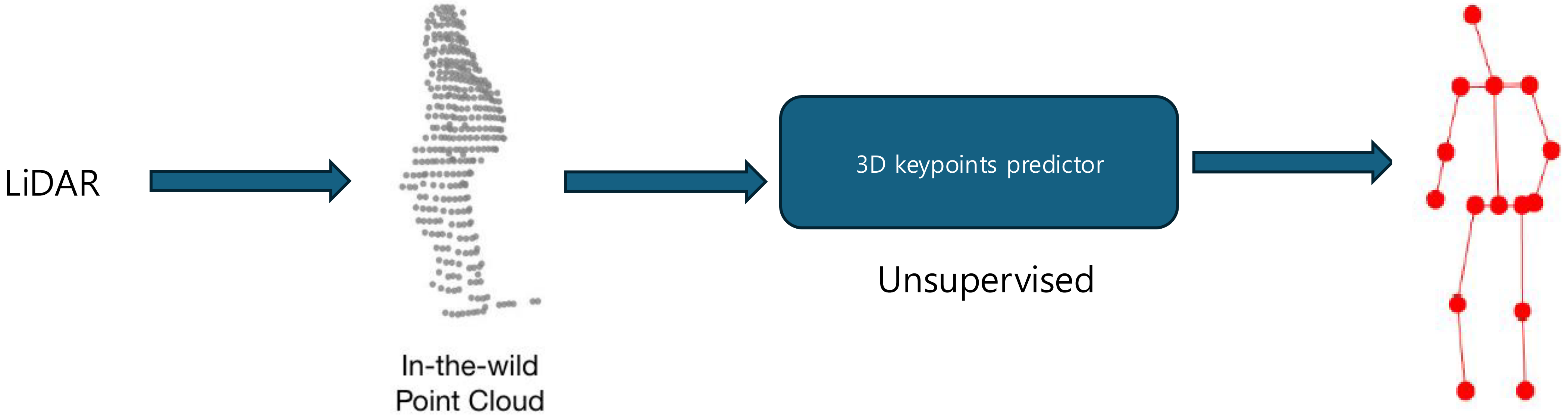


Goal

3D human keypoints estimation from point clouds in the Wild

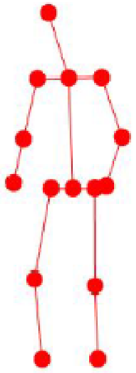


Prior works

Supervision

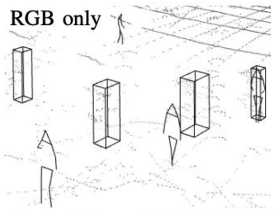
\+ Label

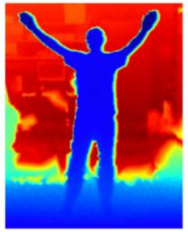
3D keypoints predictor



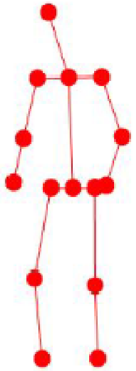
Prior work)
3d data + label : expensive
focus on utilizing 2d weak data

weak Supervision : RGB, depth, etc…





3D keypoints predictor



This work)
un-labeled LiDAR data has a lot of useful information

- *M. Furst, S. T. P. Gupta, R. Schuster, O. Wasenmuller, and D. Stricker, "HPERL: 3D human pose estimation from RGB and LiDAR," IEEE, 2021*
- *J. Zheng, X. Shi, A. Gorban, J. Mao, Y. Song, C. R. Qi, T. Liu, V. Chari, A. Cornman, Y. Zhou, and others, "Multi-modal 3D human pose estimation with 2D weak supervision in autonomous driving," IEEE, 2022*

Propose : GC-KPL

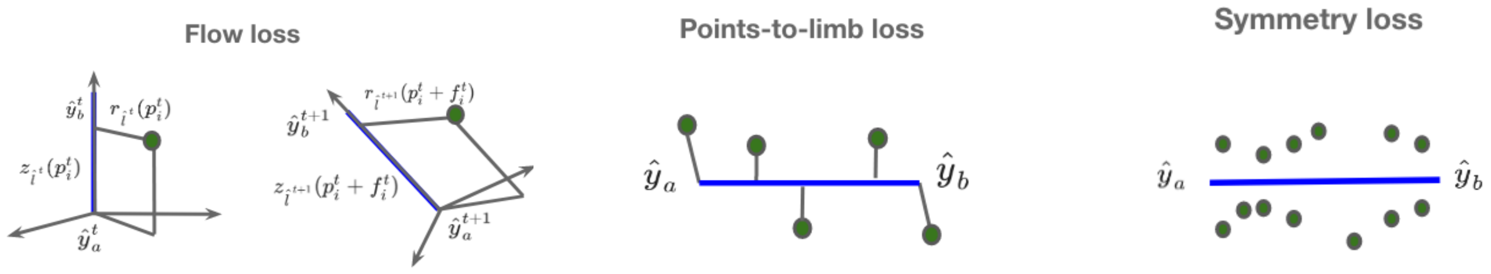
GC-KPL : Geometry Consistency inspired Key Point Leaning

Assumptions

- human skeletons are roughly centered rigid body parts
- surface points : “location + movement” -> skeleton “movement”

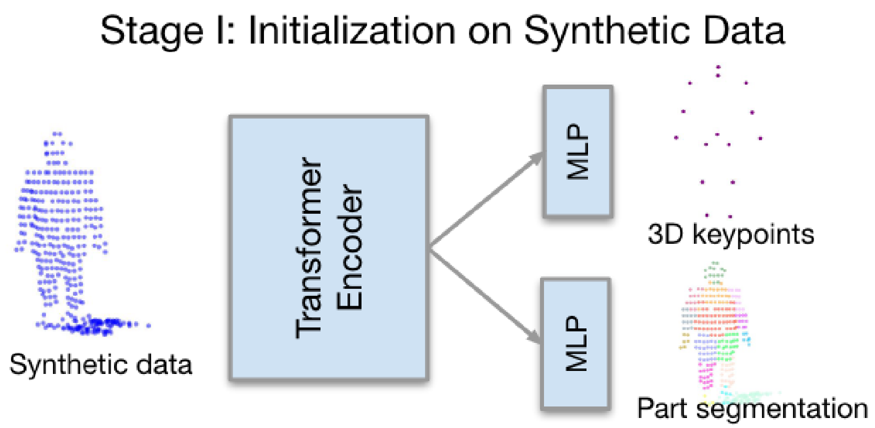
propose

- novel unsupervised losses term
  - Flow Loss
  - Points-to-Limb Loss
  - Symmetry Loss



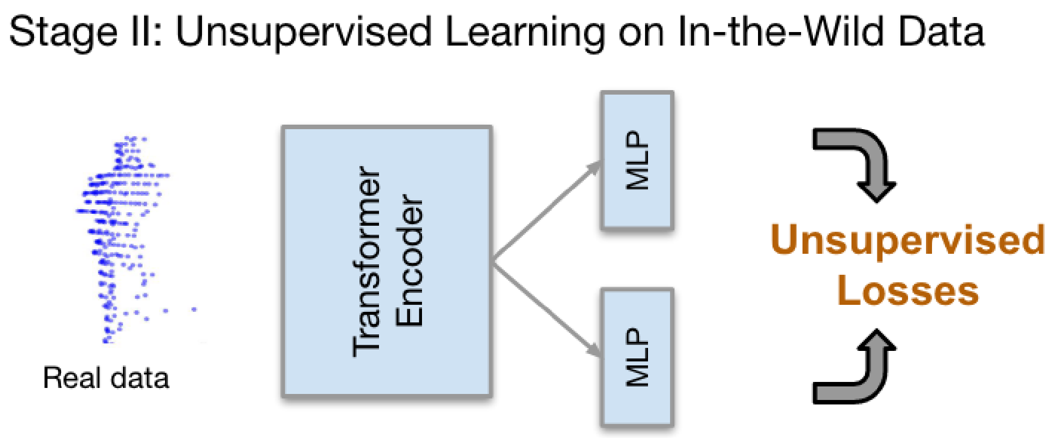
Process - Overall

Stage I – Warm Up



- transformer-based regression model : keypoints
- semantic segmentation model : localizing body parts on a synthetic data
- synthetic data : constructed from randomly posed **SMPL human body model**

Stage II – refine the network



- Using unsupervised Losses
- Flow Loss
- Points-to-limb Loss
- Symmetry Loss

Process – Stage I : Input & Output

Input : Point Clouds
Output : {3D keypoints, Part segmentation}

$$\mathbf{P} \in \mathbb{R}^{N\times 3} \rightarrow \hat{\mathbf{Y}} \in \mathbb{R}^{(J+1)\times 3}$$

$$\mathbf{P} \in \mathbb{R}^{N\times 3} \rightarrow \hat{\mathbf{W}} \in \mathbb{R}^{N\times (J+1)}$$

$$\{\hat{\mathbf{Y}}, \hat{\mathbf{W}}\} = f(\mathbf{P})$$

$$\forall i \in [N], \sum_{j=1}^{J+1} \hat{\mathbf{W}}_{i,j} = 1$$

$\hat{Y}$: 3D Locations of keyPoints
$\widehat{W}$: probability of each point i(body parts || background)

<Keypoints : L2 Loss>

$$\mathcal{L}_{kp} = \|\hat{\mathbf{Y}} - \mathbf{Y}\|_2$$

<segmentation : Cross-Entropy Loss>

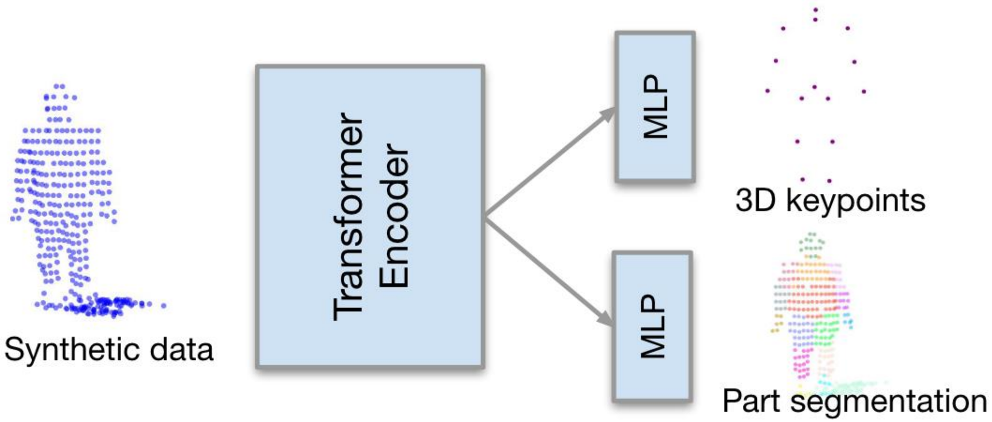
$$\mathcal{L}_{seg} = -\sum_{i=1}^{N}\sum_{j=1}^{J+1} \mathbf{W}_{i,j} \log(\hat{\mathbf{W}}_{i,j})$$

<Minimize>

$$\mathcal{L}_{syn} = \lambda_{kp}\mathcal{L}_{\mathrm{kp}} + \lambda_{seg}\mathcal{L}_{\mathrm{seg}}$$

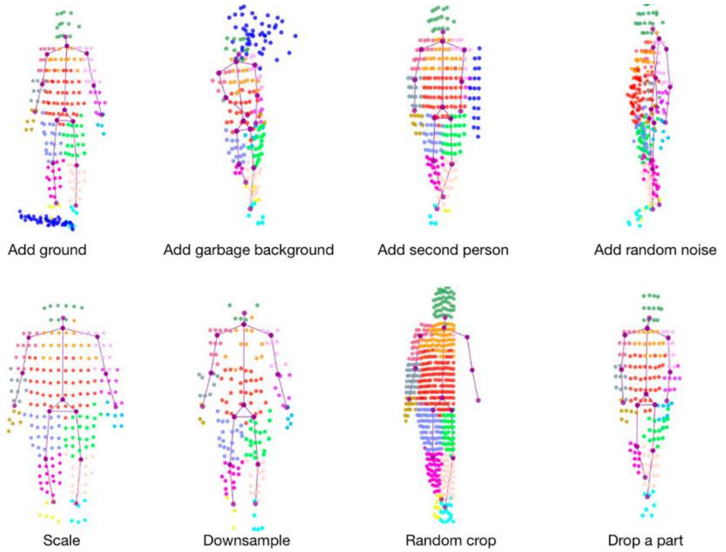
Process – Stage I

3D human keypoints estimation from points clouds in the wild



L2 -> regression

Cross Entropy -> classification

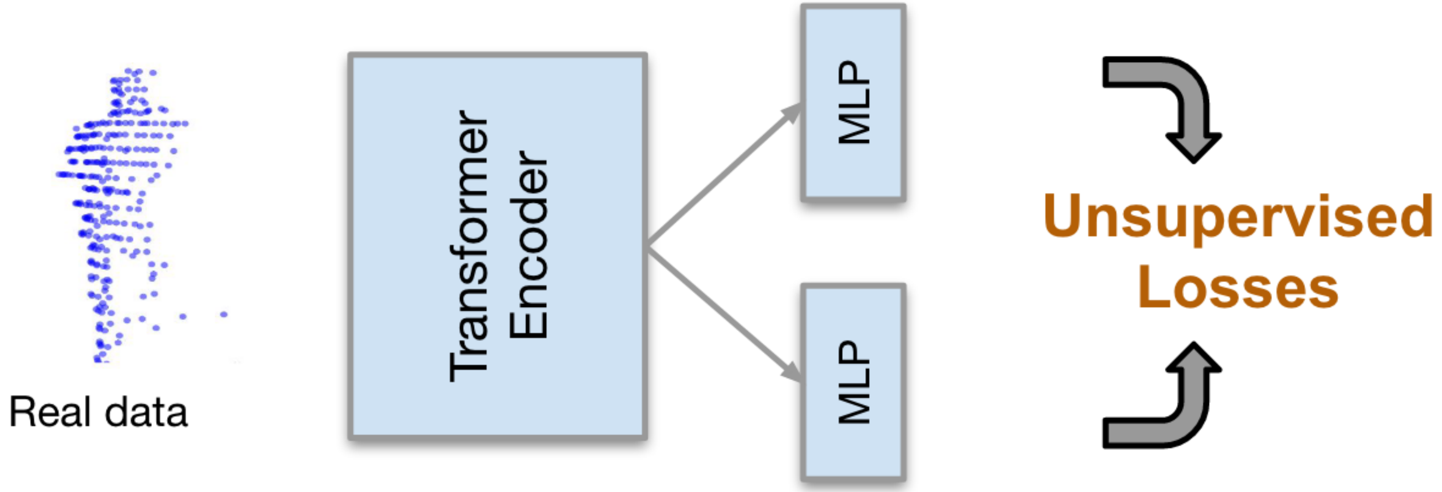


<augmentation>

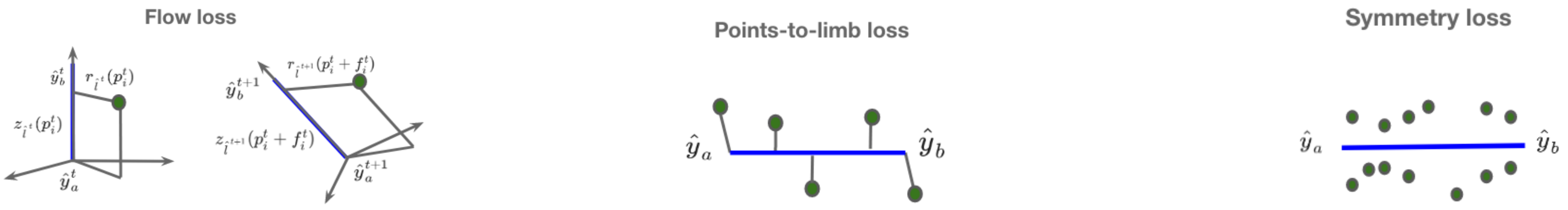
- Add ground
- Add garbage background
- Add random noise
- Scale
- Downsample
- Random crop
- Drop a part

Process – Stage II

3D human keypoints estimation from points clouds in the wild



points clouds -> set of points {x, y, z}



Losses

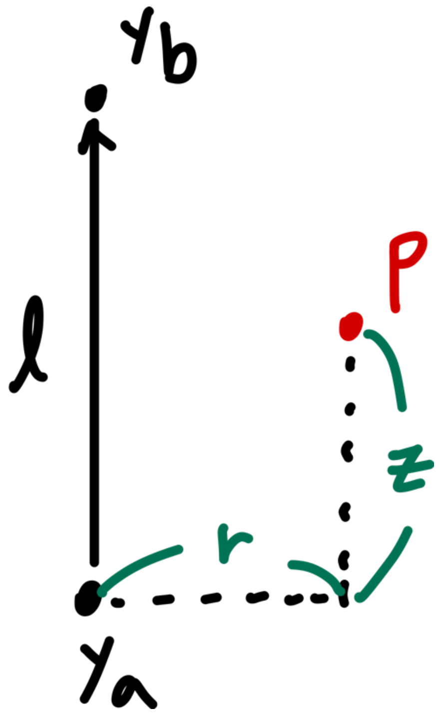
- L : human skeleton composed of limbs
- y_a : parent keypoint
- y_b : child keypoint

$$l = (y_a, y_b) \in L$$: Limb

$$\mathbf{z}(p, \hat{l}) = \frac{(p - \hat{y}_a) \cdot (\hat{y}_b - \hat{y}_a)}{||\hat{y}_b - \hat{y}_a||_2}$$: axial

$$\mathbf{r}(p, \hat{l}) = ||p - \hat{y}_a - \mathbf{z}(\hat{y}_b - \hat{y}_a, \hat{l})||_2$$: radial

$\hat{\mathbf{W}}_{ia}$: The probability of each point I belonging to body part a



points → each limbs' local cylindrical coordinate

Losses – Flow Loss

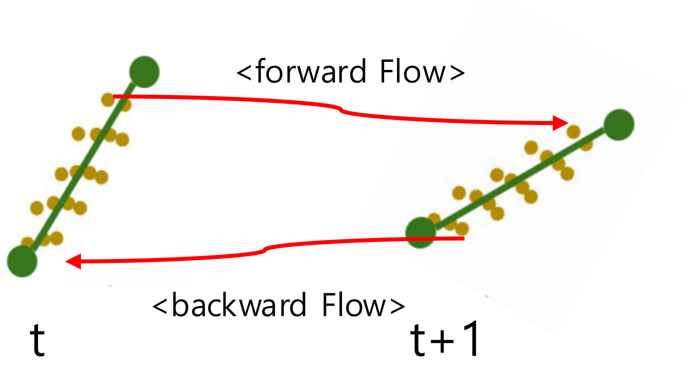
- For considering the predictions from two consecutive frames
- For consistency of the radial and altitude components of all points with respect to scene flow

<Forward Flow>

$$\mathcal{L}_{ff} = \frac{1}{N}\sum_i \hat{\mathbf{W}}_{ia}^t \cdot (|\mathbf{r}_{\hat{l}^{t+1}}(p_i^t + f_i^t) - \mathbf{r}_{\hat{l}^t}(p_i^t)| + |\mathbf{z}_{\hat{l}^{t+1}}(p_i^t + f_i^t) - \mathbf{z}_{\hat{l}^t}(p_i^t)|)$$

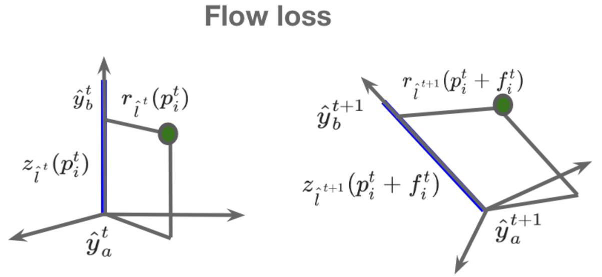
<backward Flow>

$$\mathcal{L}_{bf} = \frac{1}{N}\sum_i \hat{\mathbf{W}}_{ia}^{t+1} \cdot (|\mathbf{r}_{\hat{l}^t}(p_i^{t+1} + b_i^{t+1}) - \mathbf{r}_{\hat{l}^{t+1}}(p_i^{t+1})| + |\mathbf{z}_{\hat{l}^t}(p_i^{t+1} + b_i^{t+1}) - \mathbf{z}_{\hat{l}^{t+1}}(p_i^{t+1})|)$$



<Flow loss = Forward + backward>

$$\mathcal{L}_{flow} = \frac{1}{|L|}\sum_{\hat{l}^t} \frac{\mathcal{L}_{ff} + \mathcal{L}_{bf}}{2}$$



(a) After moving, **points** stay in the same place (despite rotation around axis) within each **limb's** local cylindrical coordinate system.

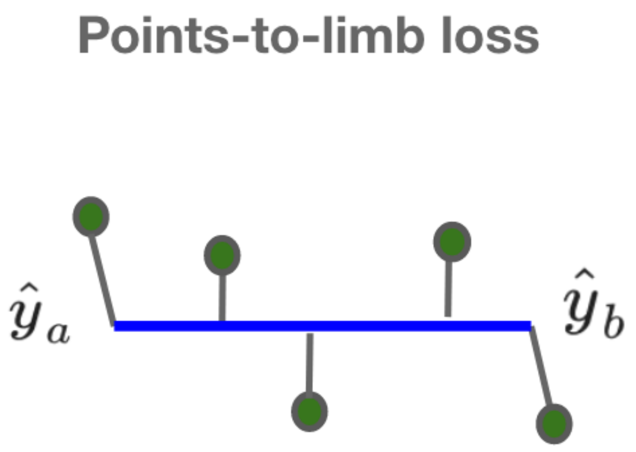
Losses – Points-to-Limb Loss

$$\mathcal{L}_{p2l}^{\hat{l}} = \frac{1}{N}\sum_{i}\hat{\mathbf{W}}_{ia}\mathbf{d}(p_i, \hat{l})$$

d : L2 distance function(point <-> limb)

<Points-to-Limb loss = Sum over all points>

$$\mathcal{L}_{\mathrm{p2l}} = \frac{1}{|L|}\sum_{\hat{l}}\mathcal{L}_{\mathrm{p2l}}^{\hat{l}}$$



(b) Minimize **points**-to-**limb** distance to encourage the limb to stay *within* the body.

- To minimize the distance of the points to the corresponding limb

Losses – Symmetry Loss

$$\mathcal{L}^{\hat{l}}_{sym} = \frac{1}{N}\sum_i \hat{\mathbf{W}}_{ia}(\mathbf{r}_{\hat{l}}(p_i) - \bar{\mathbf{r}}_{\hat{l}}(p_i))^2$$

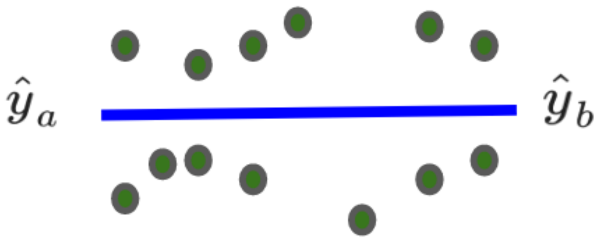
$\bar{\mathbf{r}}_{\hat{l}}$: weighted mean of radial values of points

$$\bar{\mathbf{r}}_{\hat{l}}(p_i) = \frac{\sum_j K_h(\mathbf{z}_{\hat{l}}(p_i), \mathbf{z}_{\hat{l}}(p_j))(\hat{\mathbf{W}}_{i*} \cdot \hat{\mathbf{W}}_{j*})\mathbf{r}_{\hat{l}}(p_j)}{\sum_j K_h(\mathbf{z}_{\hat{l}}(p_i), \mathbf{z}_{\hat{l}}(p_j))(\hat{\mathbf{W}}_{i*} \cdot \hat{\mathbf{W}}_{j*})}$$

K_h : Gaussian kernel with bandwith h

$$K_h(x,y) = e^{-(\frac{x-y}{h})^2}$$

Symmetry loss



(c) **Points** are symmetrical around **limb.** (i.e. points with similar height z have similar radius r)

<Symmetry loss = Sum over all points>

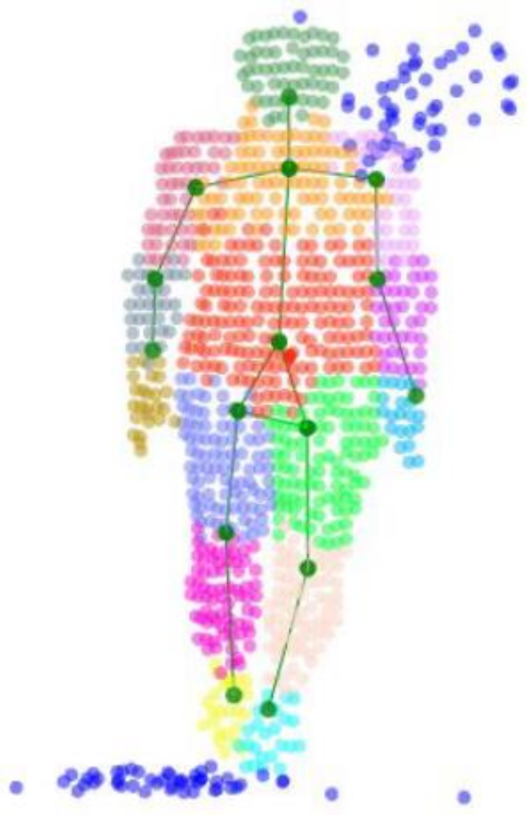
$$\mathcal{L}_{sym} = \frac{1}{|L|}\sum_{l \in L} \mathcal{L}^{l}_{sym}$$

- to encourage that all points around the limb are roughly symmetrical around it

Losses – Joint-to-Part Loss(Optional)

- To encourage each joint to be close to the center of the points on that part

$$\mathcal{L}_{j2p}^{j} = \left\| \hat{y}_j - \frac{\sum_i \hat{\mathbf{W}}_{ij} p_i}{\sum_i \hat{\mathbf{W}}_{ij}} \right\|_2$$

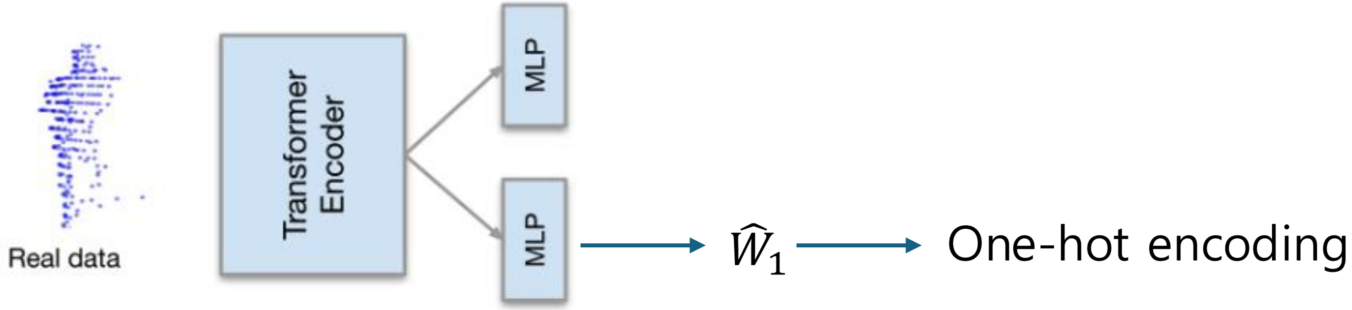


<Joint-to-part loss = Sum over all Joints>

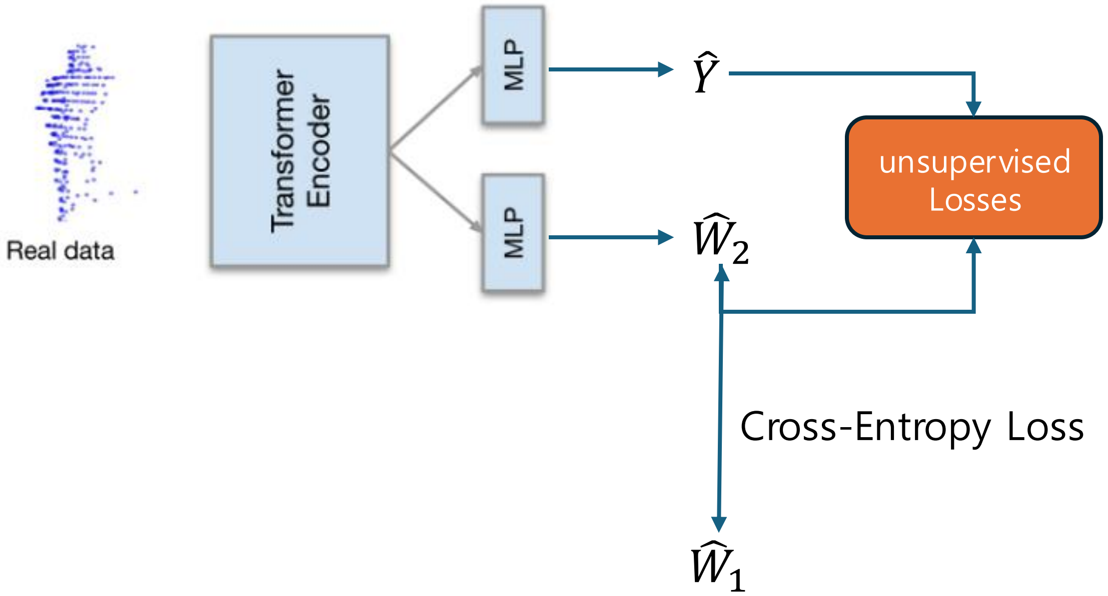
$$\mathcal{L}_{j2p} = \frac{1}{J} \sum_j \mathcal{L}_{j2p}^{j}$$

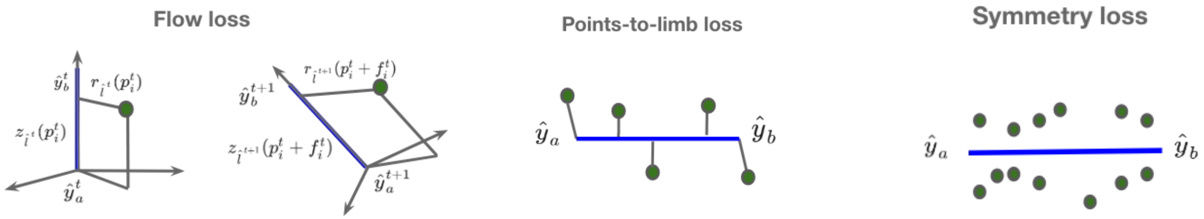
Losses – segmentation Loss && Training objective

Before Stage II



Stage II : Start Training

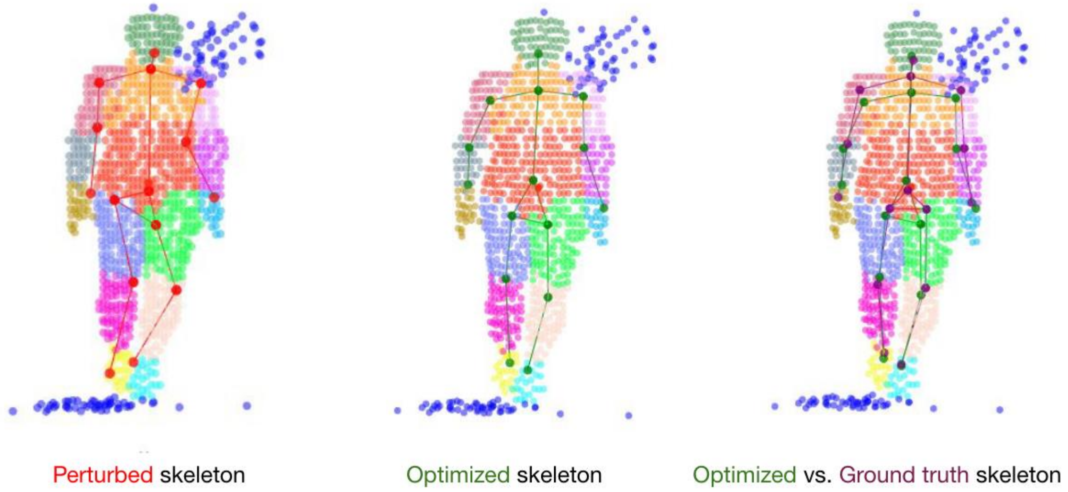


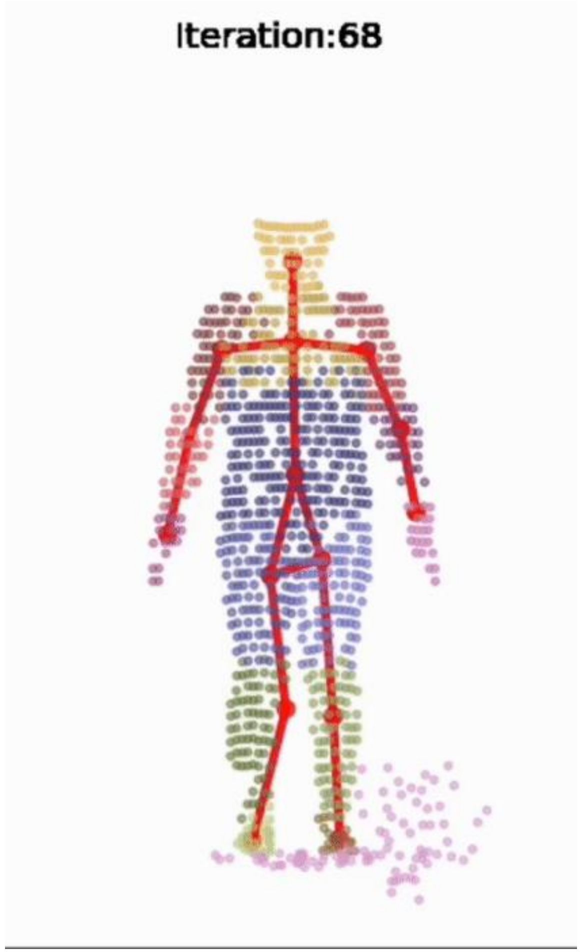


$$\mathcal{L} = \lambda_{flow}\mathcal{L}_{flow} + \lambda_{\text{p2l}}\mathcal{L}_{\text{p2l}} + \lambda_{sym}\mathcal{L}_{sym} + \lambda_{\text{j2p}}\mathcal{L}_{\text{j2p}} + \lambda_{\text{seg}}\mathcal{L}_{\text{seg}}$$

unsupervised Loss

Evaluation





hyper-parameter

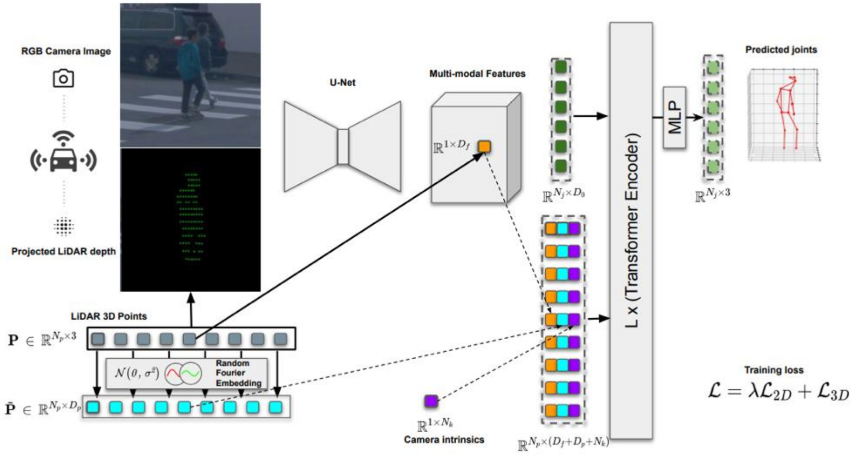
- $\lambda_{kp} = 0.5$
- $\lambda_{seg} = 1$
- $\lambda_{flow} = 0.02$
- $\lambda_{p2l} = 0.01$
- $\lambda_{sym} = 0.5$
- $\lambda_{j2p} = 2$
- $\lambda_{seg} = 0.5$

the result of applying the losses

$$\mathcal{L} = \lambda_{flow}\mathcal{L}_{flow} + \lambda_{\mathrm{p2l}}\mathcal{L}_{\mathrm{p2l}} + \lambda_{sym}\mathcal{L}_{sym} + \lambda_{\mathrm{j2p}}\mathcal{L}_{\mathrm{j2p}} + \lambda_{\mathrm{seg}}\mathcal{L}_{\mathrm{seg}}$$

Evaluation

Method	Backbone	Stage I supervised	1% training set MPJPE cm. (gain)	10% training set MPJPE cm. (gain)	100% training set MPJPE cm. (gain)
HUM3DIL [29]	Randomly initialized		19.57	16.36	12.21
GC-KPL	Pre-trained on synthetic only	✔	18.52 (-1.05)	15.10 (-1.26)	11.27 (-0.94)
	Pre-trained on 5,000 WOD-train	✔	17.87 (-1.70)	14.51 (-1.85)	10.73 (-1.48)
	Pre-trained on 200,000 WOD-train		17.80 (-1.77)	14.30 (-2.06)	10.60 (-1.61)
	Pre-trained on 200,000 WOD-train	✔	**17.20** (**-2.37**)	**13.40** (**-2.96**)	**10.10** (**-2.11**)



HUM3DIL : Image + LiDAR

Training data	$\text{MPJPE}_{\text{matched}}$ (↓)
Synthetic only	17.70
5,000 WOD-train	14.64
200,000 WOD-train	13.92

Table 2. Unsupervised learning (Stage II) results.

-A. Zanfir, M. Zanfir, A. Gorban, J. Ji, Y. Zhou, D. Anguelov, and C. Sminchisescu, "Hum3dil: Semi-supervised multi-modal 3D human pose estimation for autonomous driving" CoRL 2022