

# Pedestrian-Centric 3D Pre-collision Pose and Shape Estimation from Dashcam Perspective

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### **Motivation and Main Contribution**

# **Motivation and Main Contribution**



Daily human pose

#### Motivation

- Pedestrian pre-collision pose is a key factor in determining collision injury.
- Lack of real pedestrian collision pose dataset.
- Robustness of human pose estimation algorithm.



Pedestrian pre-collision pose



#### The contributions are as follows:

- **PVCP**, a **P**edestrian-**V**ehicle pre-**C**ollision **P**ose dataset.
- PPSE, a Pedestrian Pre-collision Pose and Shape Estimation network.
- Both data and algorithmic support for active safety protection for pedestrians.

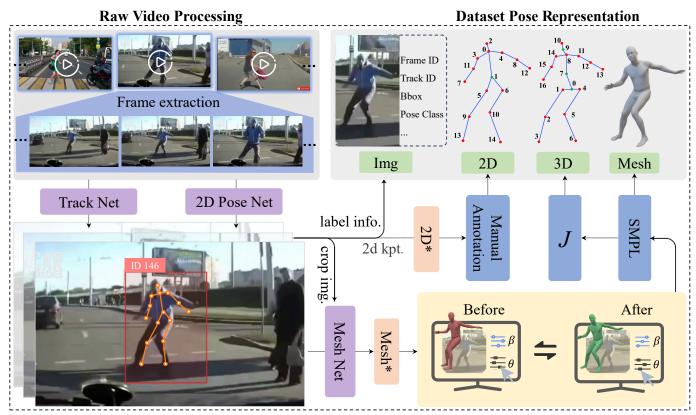




# **PVCP Dataset Pipeline**

# **PVCP** Dataset Pipeline

- Semi-automatic data set annotation process.
- Dashcam Perspective of a real pedestrian-vehicle collision.
- Algorithm initialization annotation and manual annotation tool correction.
- Multiple representation data annotation results (Bbox, ID,2D kpt, 3D kpt and mesh).





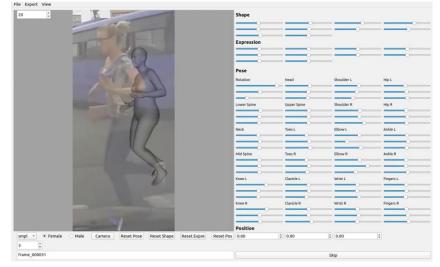


Diagram of the SMPL Annotation Tool



**2D Initialization Result** 

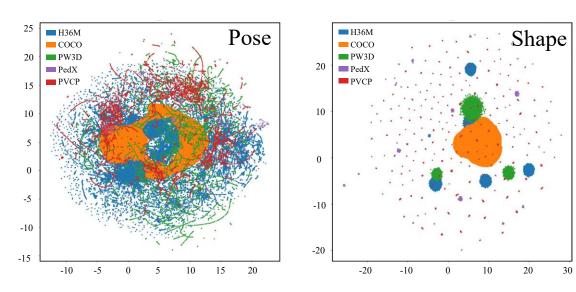
**SMPL Annotation Tool** 

### **PVCP** Dataset Pipeline

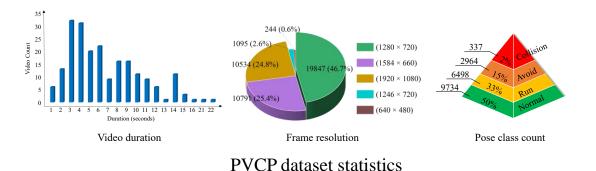


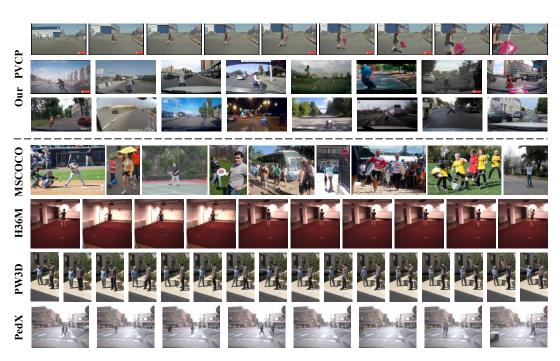
Table 1: Comparison of datasets on *Accident Warning*, *Traffic Scene* and *Pedestrian Pose*. 'V' represents the vehicle perspective, 'M' represents the monitoring perspective, 'D' represents a dynamic background and 'S' represents a static background.

Туре	Dataset	Year	Perspective	Background	Detection	Track	Depth	Pose	Shape	Class	Frame
	DAD(22)	2016	v	D	√(2D Bbox)	~	×	×	×	×	>62k
	ShanghaiTech 46	2017	Μ	S	√(Mask)	$\checkmark$	×	×	×	×	>300k
Accident Warning	A3D(23)	2019	V	D	√(2D Bbox)	$\checkmark$	×	×	×	×	>128k
	DADA(47	2019	V	D	√(3D Bbox)	×	×	×	×	×	>650k
	CCD(24)	2020	V	D	√(2D Bbox)	$\checkmark$	×	×	×	×	>75k
	KITTI(19	2012	v	D	√(3D Bbox)	~	~	×	×	×	>30K
	Cityscapes 48	2015	V	D	√(Mask)	×	×	×	×	×	>5k
Traffic Scene	CityPersons(49)	2016	V	D	√(2D Bbox)	×	×	×	×	×	>5k
	MOT(50)	2012-2017	V/M	D/S	√(2D Bbox)	$\checkmark$	×	×	×	×	-
	Nuscenes 18	2019	v	D	√(3D Bbox)	$\checkmark$	$\checkmark$	×	×	×	>35k
	MSCOCO(20)	2014-2017	Daily scene	S	√(2D Bbox)	×	×	√(2D)	×	×	>1000k
	Human3.6M(16)	2014	M	S	√(2D Bbox)	$\checkmark$	$\checkmark$	√(2D/3D)	×	×	>500k
Pedestrian Pose	PW3D(21)	2018	hand-held camera	D	×	$\checkmark$	×	√(3D)	×	×	>50k
	Accident Video	2020	V/M	D/S	×	$\checkmark$	×	×	×	-	
	PedX(14)	2018	Μ	S	√(Mask)	$\checkmark$	$\checkmark$	√(2D/3D)	$\checkmark$	×	>10k
Ours	PVCP	2024	V(Dashcam)	D/S	√(2D Bbox)	~	~	√(2D/3D)	~	√	>40k



Pose and Shape parameters distribution





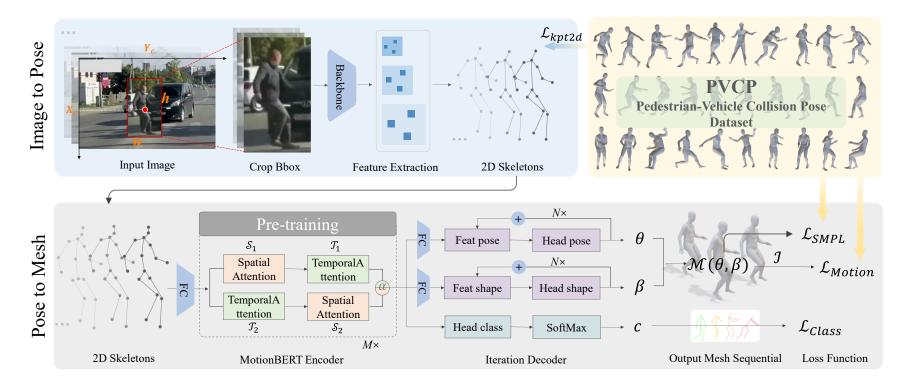
Visualization comparison of PVCP with other pose datasets



#### **PPSE Network Architecture**

# **PPSE Network Architecture**





#### ITP (Image to Pose)

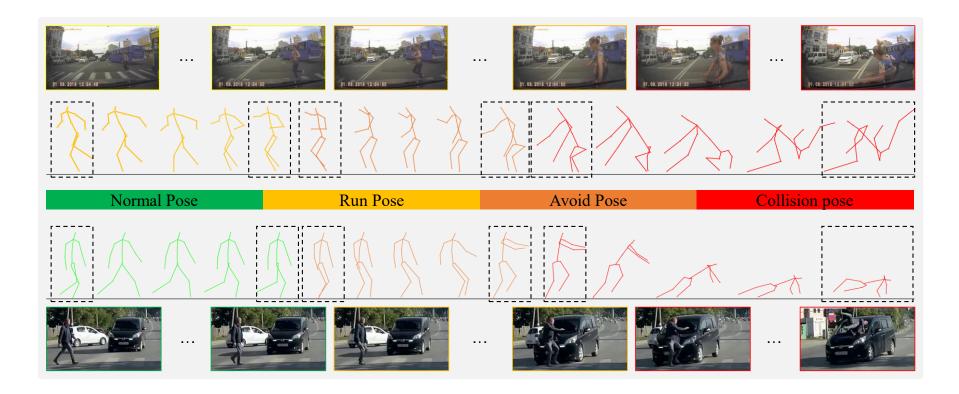
- *Input*: Accident frames and pre-selected pedestrian collision targets *Bbox*.
- *Output*: Pedestrian 2D pre-collision pose  $P_{2d} \in \mathbb{R}^{15 \times 2}$ .

#### PTM (Pose to Mesh)

- *Input*: Pedestrian 2D pre-collision pose sequence  $P_{2d}^L \in \mathbb{R}^{T \times J \times C}$ .
- *Output*: Pedestrian 3D mesh pre-collision pose sequence  $\mathcal{M}(\theta, \beta) \in \mathbb{R}^{T \times N \times C}$ .

## **PPSE Network Architecture**





Pre-trained model

 $F^{i} = \alpha_{ST}^{i} \circ \mathcal{T}_{1}^{i}(\mathcal{S}_{1}^{i}(F^{i-1})) + \alpha_{TS}^{i} \circ \mathcal{S}_{2}^{i}(\mathcal{T}_{2}^{i}(F^{i-1}))$  $\alpha_{ST}^{i}, \alpha_{TS}^{i} = softmax(\mathcal{W}_{f}(\mathcal{T}_{1}^{i}(\mathcal{S}_{1}^{i}(F^{i-1})) \oplus \mathcal{S}_{2}^{i}(\mathcal{T}_{2}^{i}(F^{i-1}))))$ 

Iterative regression

 $\theta^{k} = W_{\theta}^{k}(F_{\theta}) + \theta^{k-1}$  $\beta^{k} = W_{\beta}^{k}(F_{\beta}) + \beta^{k-1}$  $c = softmax(W_{c}(F_{c}))$ 

Introduce pose category loss

 $\mathcal{L}_{Class} = \lambda_{c} \mathcal{L}_{Cross \ Entropy}(\hat{C}, C)$  $\mathcal{L} = \mathcal{L}_{PTM} + \mathcal{L}_{PTM}$  $= \mathcal{L}_{2} + \mathcal{L}_{SMPL} + \mathcal{L}_{Motion} + \mathcal{L}_{Class}$ 





#### **Evaluation Metric**

- (Procrustes-Aligned) Mean Per-Vertex Error
- (Procrustes-Aligned) Mean Per Joint Position Error
- *X*\_*14j* (14 common keypoints, Red keypoints)
- $X_{17j}$  (Representation of the Human3.6M)

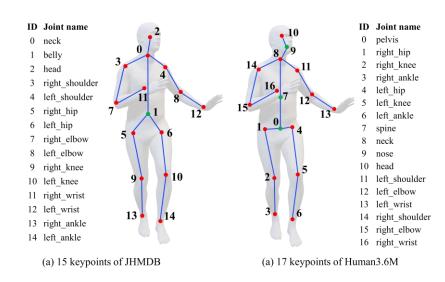


Table 2: Effects of Dataset and Pre-training. Top use detected 2D pose sequences. Bottom use GT 2D pose sequences.

Input	Train Set	testset	Pose class	MPVE	PAMPVE	MPJPE_14j	PAMPJPE_14j	MPJPE_17j	PAMPJPE_17j
			Normal	315.94	160.25	272.18	130.72	246.42	121.30
			Run	318.29	189.84	274.78	160.35	246.95	145.07
	PVCP	PVCP	Avoid	305.01	159.19	260.31	121.42	232.56	113.21
			Collision	347.53	171.82	311.88	145.64	281.35	139.46
			All	315.64	168.11	271.91	137.75	245.35	126.92
			Normal	347.10	190.17	312.21	154.85	285.62	145.55
			Run	309.19	183.27	277.01	152.19	251.53	141.11
2D Det	Pretrain	PVCP	Avoid	330.18	189.69	293.76	155.54	264.89	144.38
			Collision	334.14	164.32	301.52	133.26	275.28	128.19
			All	335.11	188.09	300.80	154.06	274.27	144.12
			Normal	294.73	170.10	253.80	137.39	232.74	128.24
	Pretrain		Run	253.16	149.99	219.06	124.01	200.19	115.27
	+	PVCP	Avoid	286.85	159.69	246.94	124.86	222.02	114.96
	PVCP		Collision	250.58	161.25	222.47	127.37	200.38	120.47
			All	282.50	163.58	243.59	132.43	222.70	123.33
	PVCP	PVCP	Normal	304.65	167.56	260.68	138.49	233.70	126.83
			Run	296.75	192.00	254.58	163.80	226.49	146.66
			Avoid	277.51	157.48	234.30	123.02	206.55	113.44
			Collision	354.76	178.22	319.56	154.95	287.38	146.83
			All	300.04	173.09	256.69	143.73	229.30	130.85
		PVCP	Normal	175.24	111.72	152.10	87.68	138.87	82.11
	Pretrain		Run	153.45	107.26	131.93	84.02	118.99	77.76
2D GT			Avoid	143.32	93.61	122.91	73.45	111.33	68.89
			Collision	151.18	91.20	133.60	77.66	124.71	71.06
			All	165.90	108.48	143.52	85.14	130.56	79.48
-		PVCP	Normal	156.06	103.16	132.74	80.59	120.35	74.92
	Pretrain + PVCP		Run	129.49	89.31	109.93	70.91	100.19	65.70
			Avoid	127.04	85.36	108.30	65.35	96.74	60.44
			Collision	135.89	89.71	127.11	70.86	112.50	64.94
			All	145.77	97.50	124.04	76.34	112.43	70.87

Pretrain Iter MPVE Class Loss Pose class PAMPVE MPJPE\_14j PAMPJPE\_14j MPJPE\_17j PAMPJPE\_17j Input All 282.50 163.58 243.59 132.43 222.70 123.33  $\checkmark$ 3 All 266.20 146.88 225.38 116.99 204.98 108.63 2D Det All 259.05 143.52 220.39 115.47 200.16 107.03  $\checkmark$  $\checkmark$ 3 All 257.75 144.19 218.61 114.50 198.16 105.86 145.77 124.04 76.34 70.87 All 97.50 112.43 69.89 145.75 96.69 123.16 75.13 111.90 3 All 2D GT 67.58 All 141.28 92.78 120.16 72.43 108.90  $\checkmark$ 3  $\checkmark$ All 140.43 96.43 118.80 75.13 107.47 69.56

Table 3: Component of system. Top use detected 2D pose sequences. Bottom use GT 2D pose sequences.

Table 4: Comparison of 2D GT input in different iterations number.

Iter	Pose class	MPVE	PAMPVE	MPJPE_14j	PAMPJPE_14j	MPJPE_17j	PAMPJPE_17j
2	All	141.95	97.43	120.04	75.45	108.63	69.85
3	All	140.43	96.43	118.80	75.13	107.47	69.56
4	All	139.96	96.92	118.46	75.19	107.16	69.62
5	All	140.01	$\overline{97.10}$	118.54	75.40	107.27	69.83
6	All	140.41	97.42	118.89	75.70	107.68	70.14

Table 5: Comparison of state-of-the-art methods on the PVCP testset. <sup>†</sup> denotes that the training weights provided by the official are used, and \* denotes the model weights trained together with the PVCP trainset.

Paradigm	Method	Pose class	MPVE	PAMPVE	MPJPE_14j	PAMPJPE_14j	MPJPE_17j	PAMPJPE_17j
	<sup>†</sup> VIBE(66)	Normal	856.87	234.47	731.90	217.35	_	_
		Run	856.10	232.67	732.33	226.45	-	_
		Avoid	777.92	227.16	664.25	216.72	-	_
		Collision	950.47	212.21	869.86	202.01	-	-
One Stage		All	849.09	233.08	725.92	219.55	-	-
One Stage	<sup>†</sup> PARE( <mark>67</mark> )	Normal	225.99	147.04	193.62	114.35	-	_
		Run	235.99	180.98	193.40	137.08	-	_
		Avoid	210.02	143.88	176.76	109.10	-	-
		Collision	247.18	167.62	225.96	132.89	-	-
		All	226.98	155.72	191.97	<u>119.85</u>	-	-
	<sup>†</sup> Pose2Mesh <mark>(68)</mark>	Normal	247.24	148.87	222.34	122.42	-	_
		Run	255.26	181.16	222.33	145.14	-	-
		Avoid	217.97	141.43	191.38	112.35	-	_
		Collision	231.65	174.44	210.44	145.54	-	-
		All	245.88	156.69	218.71	127.41	-	_
	*MotionBERT(12)	Normal	294.73	170.10	253.80	137.39	232.74	128.24
		Run	253.16	149.99	219.06	124.01	200.19	115.27
Two Stage		Avoid	286.85	159.69	246.94	124.86	222.02	114.96
		Collision	250.58	161.25	222.47	127.37	200.38	120.47
		All	282.50	163.58	243.59	132.43	222.70	123.33
	*PPSET(Ours)	Normal	272.79	149.02	230.49	117.47	209.99	109.04
		Run	226.22	133.45	193.75	109.50	174.47	100.73
		Avoid	251.60	143.52	212.75	109.75	190.00	100.09
		Collision	217.68	134.95	201.15	113.10	174.57	105.94
		All	257.75	144.19	<u>218.61</u>	114.50	198.16	105.86







#### **Limitations and Future Work**

# **Limitations and Future Work**



#### Integrity of the dataset

✓ Due to the difficulty of collecting the dataset, the dataset is *small in size* and lacks real *camera parameters*, *vehicle speed* information, *global position* and *direction* of pedestrians.

#### **Real-time performance of the model**

 ✓ Our method is not real-time at present, because our input is *Image* and *pre-selected Bbox sequence* of collision pedestrian targets. Thanks for your listening.



#### Pedestrian-Centric 3D Pre-collision Pose and Shape Estimation

from Dashcam Perspective



https://github.com/wmj142326/PVCP





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