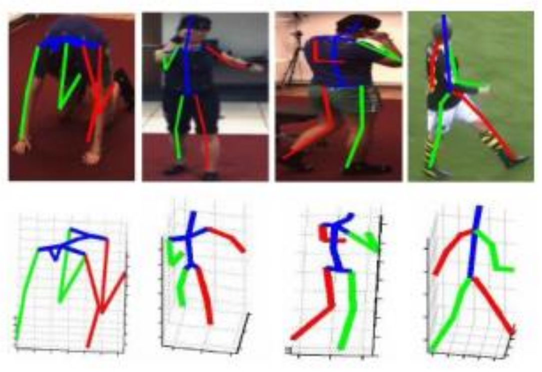
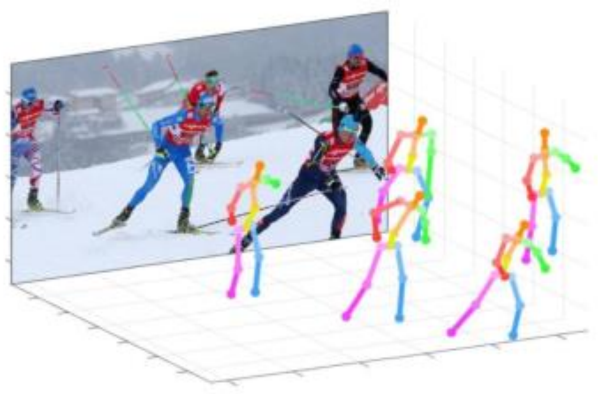
Unsupervised 3D Human Pose Estimation in Multi-view-multi-pose Video

Cheng Sun(Kyushu University), Diego Thomas(Kyushu University), Hiroshi Kawasaki (Kyushu University)

Introduction

- 3D human pose estimation aims to extract 3D poses of people from 2D images or videos.
- Methods can be divided into unsupervised methods and supervised methods.



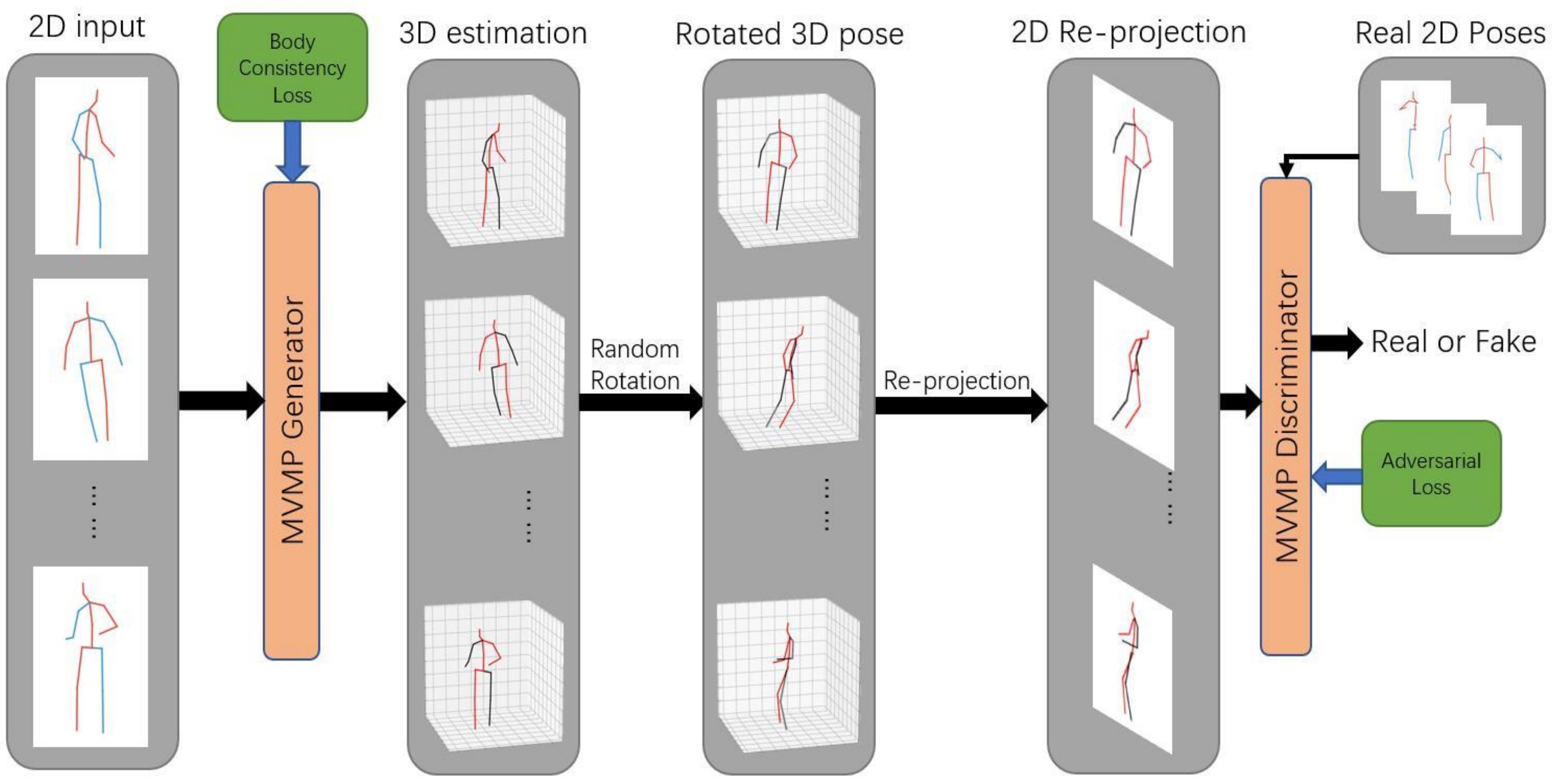


- Supervised methods: Accurate, need large-scale 3D datasets
- Unsupervised methods: Not very accurate, but can take advantage of large amount of in-the-wild 2D data

3D data:
- Needs expensive equipment such as motion capture systems
- Needs careful calibration and elaborate setup with multiple sensors and bodysuits
- Impractical to use outside

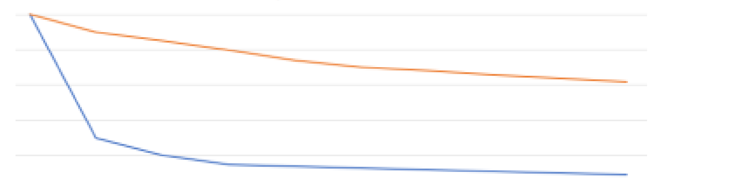
2D data:
- Easy and cheap to obtain, such as videos on YouTube

Proposed Strategies



Replacing GAN with WGAN

- The balancing problem in GAN.



Discriminator's loss(blue) converges much faster than Generator's loss(orange)

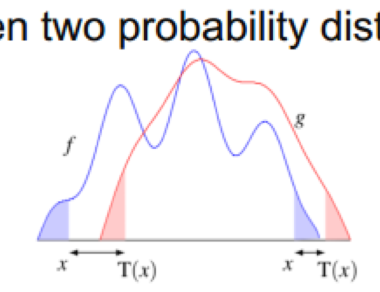
- Original GAN's loss:

$$L = E_{x \sim P_{data}}[\log D(x)] + E_{x \sim P_G}[\log(1 - D(x))]$$

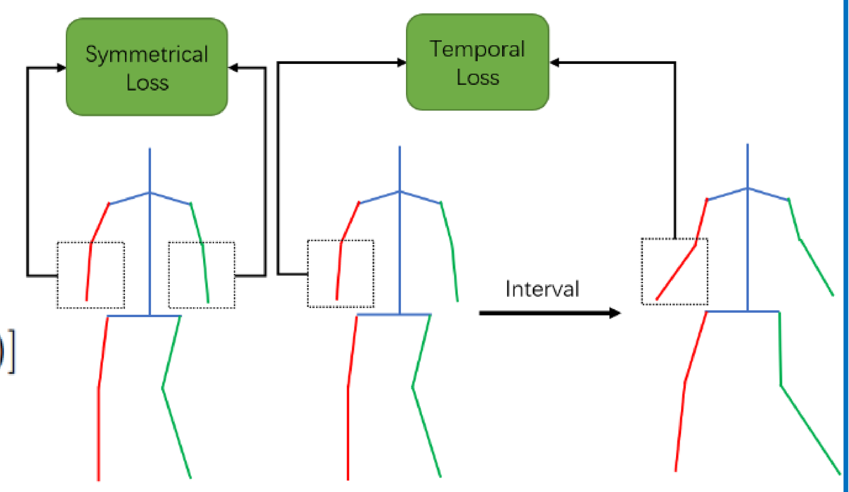
- WGAN's loss:

$$L = E_{x \sim P_{data}}[f_w(x)] - E_{x \sim P_G}[f_w(x)]$$

- Wasserstein Distance measures distance between two probability distributions:



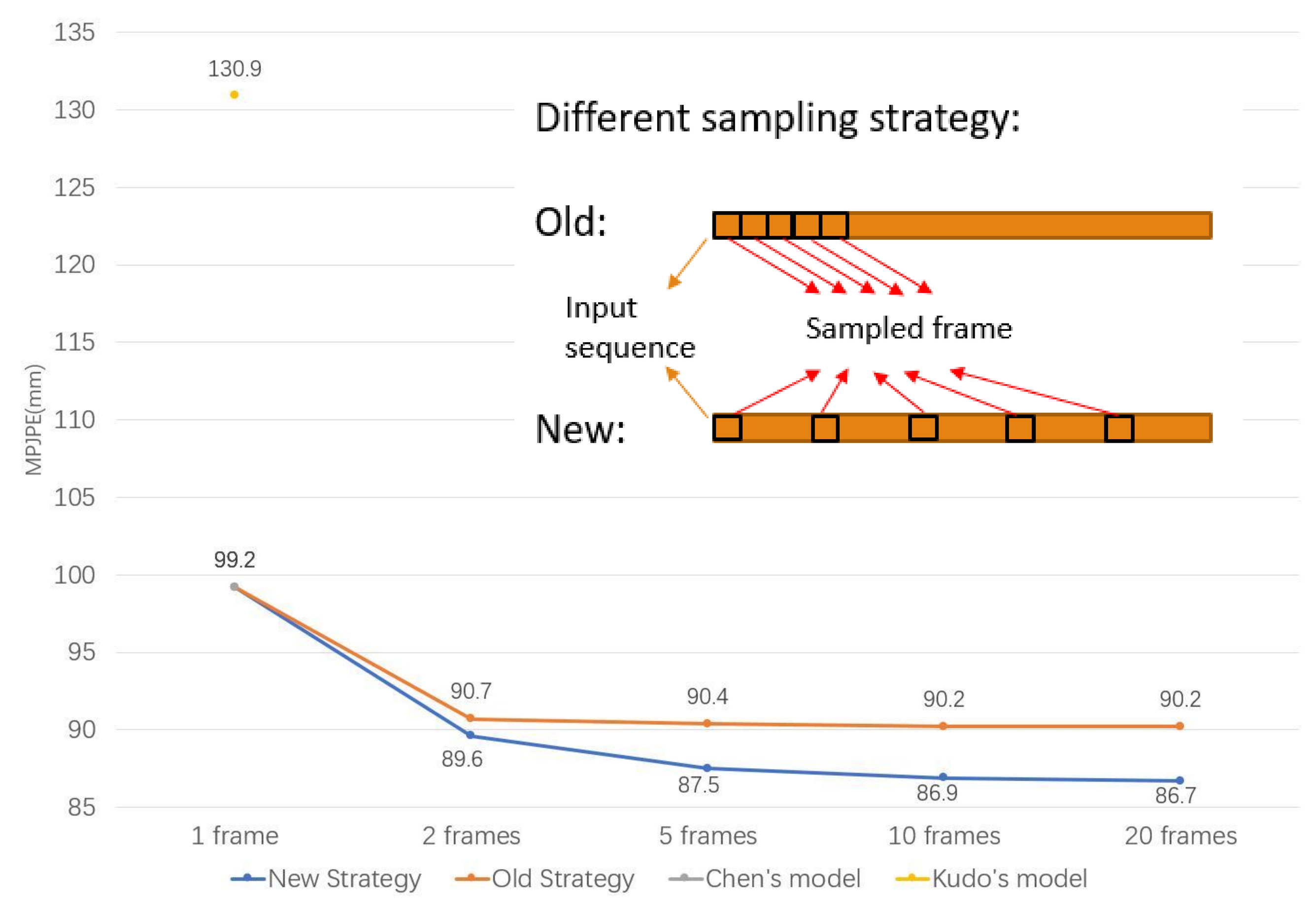
Body consistency constraints



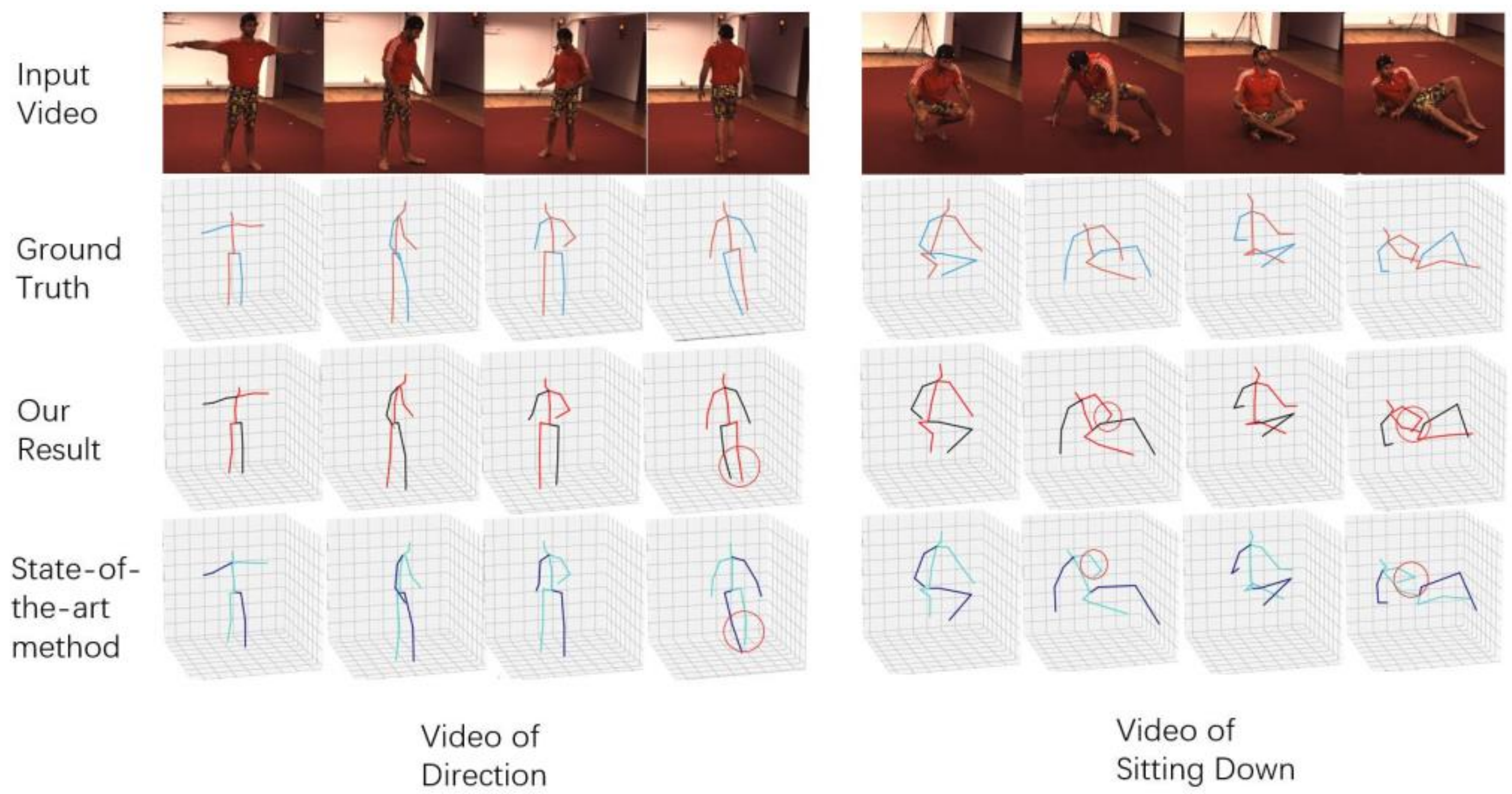
- Referring to bone lengths in our model.
- Corresponding body parts should share same bone lengths in a single frame.
- Same body part should maintain same bone length in different frames.

Quantitative Results

Method	Dir.	Disc.	Eat	Greet	Phone	Photo	Pose	Purch.	Sit	SitD.	Smoke	Wait	WalkD.	Walk	WalkT.	Avg
supervised																
Martinez *et al.* [1]	51.8	56.2	58.1	59.0	69.5	78.4	55.2	58.1	74.0	94.6	62.3	59.1	65.1	49.5	52.4	62.9
Iskakov *et al.* [28]	19.9	20.0	18.9	18.5	20.5	19.4	18.4	22.1	22.5	28.7	21.2	20.8	19.7	22.1	20.2	20.8
self-supervised																
Kocabas *et al.* [29]	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	60.6
semi-supervised																
Pavllo *et al.* [3]	45.2	46.7	43.3	45.6	48.1	55.1	44.6	44.3	57.3	65.8	47.1	44.0	49.0	32.8	33.9	46.8
weakly-supervised																
Wandt *et al.* [30]	77.5	85.2	82.7	93.8	93.9	101.0	82.9	102.6	100.5	125.8	88.0	84.8	72.6	78.8	79.0	89.9
Yang *et al.* [2]	51.5	58.9	50.4	57.0	62.1	65.4	49.8	52.7	69.2	85.2	57.4	58.4	43.6	60.1	47.7	58.6
unsupervised																
Kudo *et al.* [4]	125.0	137.9	107.2	130.8	115.1	127.3	147.7	128.7	134.7	139.8	114.5	147.1	130.8	125.6	151.1	130.9
Chen *et al.* [5]	97.1	99.4	83.2	93.8	100.3	115.4	95.2	96.9	111.4	112.7	94.1	104.1	101.5	86.3	96.5	99.2
Ours(2-frame)	89.9	92.4	78.5	91.8	93.0	97.1	88.7	86.4	97.1	101.0	89.2	98.3	90.3	71.5	79.0	89.6
Ours(5-frame)	88.0	89.6	75.0	91.3	90.9	93.5	86.8	81.5	93.7	100.3	88.0	97.2	87.6	70.8	78.4	87.5
Ours(10-frame)	87.4	89.1	74.7	90.2	90.5	93.3	86.2	80.1	93.5	99.7	87.8	96.4	87.2	70.3	77.6	86.9
Ours(20-frame)	**87.1**	**88.7**	**74.6**	**90.0**	**90.3**	**93.4**	**85.7**	**80.2**	**93.1**	**99.9**	**87.4**	**96.3**	**87.2**	**70.0**	**77.1**	**86.7**



Qualitative Results



Conclusion

- We propose our model which is extended from single-frame GAN approach to process multi-view-multi-pose(MVMP) 3D human pose estimation in videos. Our contributions include:
  - Replace original adversarial loss with Wasserstein loss.
  - Implement a loose body consistency constraint relying on the symmetry within a single frame and body consistency over different frames.
  - Compare the strategy of sampling adjacent frames and the strategy of sampling frames with as big as possible intervals.
- With all the strategies our model outperforms state-of-the-art unsupervised method.