

Supplementary Material of Diff3DHPE: A Diffusion Model for 3D Human Pose Estimation

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1. Proof of Iteration Steps Required by DDIM

The reverse diffusion process proposed by DDIM [2] is:

$$\hat{\mathbf{y}}_{\tau_{i-1}} = \sqrt{\bar{\alpha}_{\tau_{i-1}}} \left(\frac{\hat{\mathbf{y}}_{\tau_i} - \sqrt{1 - \bar{\alpha}_{\tau_i}} \hat{\boldsymbol{\epsilon}}_{\tau_i}}{\sqrt{\bar{\alpha}_{\tau_i}}} \right) + \sqrt{1 - \bar{\alpha}_{\tau_{i-1}}} \hat{\boldsymbol{\epsilon}}_{\tau_{i-1}}, \quad (1)$$

$$\hat{\mathbf{y}}_0 = \frac{\hat{\mathbf{y}}_{\tau_1} - \sqrt{1 - \bar{\alpha}_{\tau_1}} \hat{\boldsymbol{\epsilon}}_{\tau_1}}{\sqrt{\bar{\alpha}_{\tau_1}}}, \quad (2)$$

where τ_i is sampled every $\lceil T/S \rceil$ steps from $\{t_1, t_2, \dots, t_T\}$, $\tau_1 < \tau_2 < \dots < \tau_S \in [1, T]$, $S < T$, $\hat{\mathbf{y}}_t$ is the estimated 3D coordinates at step t , $\hat{\mathbf{y}}_{\tau_S} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$, and $\bar{\alpha}_t$ is a predefined noise schedule. In this paper, we select *cos* schedule for $\bar{\alpha}_t$ proposed by [1]:

$$\bar{\alpha}_t = \frac{f(t)}{f(0)}, f(t) = \cos\left(\frac{t/T + s}{1+s} \cdot \frac{\pi}{2}\right)^2, s = 0.008. \quad (3)$$

We assume the 3D coordinate value of a human joint is between $[-1000, 1000]$ mm after centralizing the body. Then, we normalize the coordinate value to $[-1, 1]$, which is required by the diffusion model. Since $\boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$, we have 95% probability that $|\epsilon| < 2\sigma = 2$. σ is the standard deviation of $\boldsymbol{\epsilon}$. Therefore, we shall have

$$\frac{\sqrt{1 - \bar{\alpha}_{\tau_1}}}{\sqrt{\bar{\alpha}_{\tau_1}}} < 10^{-3} \cdot \frac{1}{|\epsilon|} = 5 \times 10^{-4} \quad (4)$$

in Eq. 2, which ensures impact introduced by noise value to the final prediction has 95% probability smaller than 1 mm. To achieve this, the minimum $\tau_1 = 1$. Then, we derive

$$\bar{\alpha}_1 = \frac{\cos\left(\frac{1/T+s}{1+s} \cdot \frac{\pi}{2}\right)^2}{\cos\left(\frac{s}{1+s} \cdot \frac{\pi}{2}\right)^2} > \frac{1}{1 + (5 \times 10^{-4})^2}, \quad (5)$$

$$\frac{\cos\left(\frac{1/T+s}{1+s} \cdot \frac{\pi}{2}\right)}{\cos\left(\frac{s}{1+s} \cdot \frac{\pi}{2}\right)} > \sqrt{\frac{1}{1 + (5 \times 10^{-4})^2}} \quad (6)$$

from Eq. 4. According to small-angle approximations, we can have

$$\frac{1 - \frac{(\frac{1/T+s}{1+s} \cdot \frac{\pi}{2})^2}{2}}{1 - \frac{(\frac{s}{1+s} \cdot \frac{\pi}{2})^2}{2}} > \sqrt{\frac{1}{1 + (5 \times 10^{-4})^2}}, \quad (7)$$

when $T \gg 1$ and $s = 0.008$. Thus, we obtain:

$$T > \frac{1}{\frac{2(1+s)}{\pi} \sqrt{2 - \sqrt{\frac{1}{1+(5 \times 10^{-4})^2}} (2 - (\frac{s}{1+s} \cdot \frac{\pi}{2})^2)} - s} \approx 1.55 \times 10^5, \quad (8)$$

which can meet the target.

2. Hyper-parameter settings

The hyper-parameter search space and the final choice in our experiments are listed in Table 1 and 2.

Table 1. Hyper-parameter search space. *lr*: learning rate. *StepEmb*: whether or not using step embedding. *S*: the number of reverse diffusion steps.

Param.	Search Space
<i>lr</i>	1E-4,4E-4,1E-3,4E-3
<i>StepEmb</i>	T, F
<i>S</i>	1,3,4,5,6,7,8,10,15,20,40,80,160,320

References

- [1] Alexander Quinn Nichol and Prafulla Dhariwal. Improved denoising diffusion probabilistic models. In *International Conference on Machine Learning*, pages 8162–8171. PMLR, 2021. 1
- [2] Jiaming Song, Chenlin Meng, and Stefano Ermon. Denoising diffusion implicit models. In *International Conference on Learning Representations*, 2021. 1

Table 2. Final hyper-parameters of each model. Diff3DHPE-M: Diff3DHPE with MixSTE backbone. Diff3DHPE-P: Diff3DHPE with PoseFormer backbone. DDIM-M: Diffusion model with DDIM reverse diffusion method and MixSTE backbone. *: we train the baselines with only L2 loss of 3D pose prediction error and normalize the training target 3D pose ground truth to $[-1, 1]$. F : the number of frames. bs : batch size. lr : learning rate. dim : embedding dimension. $depth$: the number of Transformer blocks. $StepEmb$: whether or not using step embedding. S : the number of reverse diffusion steps. dr : dropout rate. wd : weight decay. lrd : learning rate decay factor.

Model	Dataset	F	bs	lr	dim	$depth$	$StepEmb$	S	dr	wd	lrd
Diff3DHPE-P	H3.6M CPN	81	1024	4E-3	32	8	T	5	0.1	0.1	0.1
Diff3DHPE-P	H3.6M GT	81	1024	4E-3				5			
PoseFormer	H3.6M CPN	81	1024	1e-4			N/A	N/A			
PoseFormer	H3.6M GT	81	1024	1e-4							
Diff3DHPE-M	H3.6M CPN	81	64	4E-4	512	16	T	9			
Diff3DHPE-M	H3.6M CPN	243	24	4E-4				5			
Diff3DHPE-M	H3.6M GT	81	64	4E-4				5			
Diff3DHPE-M	H3.6M GT	243	24	4E-4				6			
Diff3DHPE-M w/o PDE	H3.6M CPN	81	64	1E-4				6			
Diff3DHPE-M w/o PDE	H3.6M CPN	243	24	1E-4				5			
DDIM-M	H3.6M CPN	81	64	4E-4			40				
DDIM-M	H3.6M CPN	243	24	4E-4				80			
MixSTE	H3.6M CPN	81	64	1E-4			N/A	N/A			
MixSTE	H3.6M CPN	243	24	1E-4							
MixSTE	H3.6M GT	81	64	1E-4							
MixSTE	H3.6M GT	243	24	1E-4							
Diff3DHPE-M	3DHP GT	27	64	4E-4	F	7					