Learning Progressive Joint Propagation for Human Motion Prediction Supplementary

In this supplementary document, we provide materials not included in the main paper due to space constraints. Firstly, we provide more details about the DCT/IDCT process in Section 1. Secondly, we show the detailed architecture of our proposed network in Section 2. Lastly, detailed quantitative results are elaborated in Section 3.

1 Details of DCT/IDCT process

Following [3], we employ DCT to encode the temporal trajectories into the frequency domain. A key benefit is that, by discarding the high-frequencies, the DCT can provide a more compact representation to captures the smoothness of human motion. Specifically, given the trajectory $\tilde{\mathbf{x}}_j = (\mathbf{x}_{j,1}, \mathbf{x}_{j,2}, ... \mathbf{x}_{j,t})$, where j denotes the index of joint, the corresponding l^{th} DCT coefficient can be computed as:

$$C_{j,l} = \sqrt{\frac{2}{T}} \sum_{t=1}^{T} x_{j,t} \sqrt{\frac{1}{1+\delta_{l,1}}} \cos(\frac{\pi}{2T})(2t-1)(l-1)$$
 (1)

where $\sigma_{m,n}$ denotes the Kronecker delta function:

$$\delta_{m,n} = \begin{cases} 1 & \text{if } m = n \\ 0 & \text{if } m \neq n \end{cases} \tag{2}$$

Similarly, the final output can be transformed to temporal domain via the Inverse Discrete Cosine Transform (IDCT).

$$x_{j,t} = \sqrt{\frac{2}{T}} \sum_{l=1}^{T} C_{j,l} \sqrt{\frac{1}{1+\delta_{l,1}}} cos(\frac{\pi}{2T}) (2t-1)(l-1)$$
 (3)

2 Network Architecture

Figure 1 illustrates the detailed architectures of our proposed network, including the transformer-encoder (left), dictionary (left), and the progressive decoder (right). Note that all operations (i.e. Linear, Feed Forward, Attention) are deployed for each joint with shared parameters. For more details of the progressive decoder and dictionary module, please kindly refer to Section 3.4 and 3.5 in our main paper.

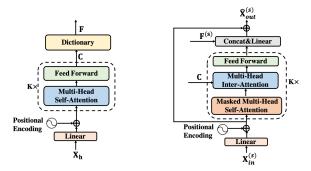


Fig. 1. Detailed architecture of our proposed network. Left: Encoder and Dictionary. \mathbf{X}_h denotes the encoded historical trajectories of each joint. \mathbf{C} is the generated context feature and \mathbf{F} is the future dynamics summarized from the learned dictionary. Right: Progressive decoder at stage s. $\mathbf{X}_{in}^{(s)}$, $\hat{\mathbf{X}}_{out}^{(s)}$ are the input and corresponding output of the progressive decoder at stage s. $\mathbf{F}^{(s)}$ is the future dynamics used in stage s. More details of the progressive decoding process can be found in Section 3.4 in our main paper.

3 More Quantitative Results

3.1 Comparison with the State-of-the-art Methods

As mentioned in Section 4.3, we provide the full table of our proposed method compared with the state-of-the-art approaches [4, 3, 2, 5, 1] on Human 3.6M dataset. As can be seen in Table 1 and Table 2, our results outperforms other methods on both MAE and MPJPE protocols.

Table 1. Short-term prediction results in Mean Angle Error (MAE) on Human3.6M for all actions. The best result is marked in bold.

	Walking Ea						Eating Smoking						Discussion					Directions				Greeting			
milliseconds	80	160		400	80			400	80		320	400	80		320		80			400	80		320	400	
zero-velocity [4]	0.39	0.68	0.99	1.15	0.27	0.48	0.73	0.86	0.26	0.48	0.97	0.95	0.31	0.67	0.94	1.04	0.39	0.59	0.79	0.89	0.54	0.89	1.30	1.49	
Residual sup. [4]	0.28	0.49	0.72	0.81	0.23	0.39	0.62	0.76	0.33	0.61	1.05	1.15	0.31	0.68	1.01	1.09	0.26	0.47	0.72	0.84	0.75	1.17	1.74	1.83	
convSeq2Seq [2]	0.33	0.54	0.68	0.73	0.22	0.36	0.58	0.71	0.26	0.49	0.96	0.92	0.32	0.67	0.94	1.01	0.39	0.60	0.80	0.91	0.51	0.82	1.21	1.38	
AGED w/o adv [1]	0.28	0.42	0.66	0.73	0.22	0.35	0.61	0.74	0.30	0.55	0.98	0.99	0.30	0.63	0.97	1.06	0.26	0.46	0.71	0.81	0.61	0.95	1.44	1.61	
AGED w/ adv [1]	0.22	0.36	0.55	0.67	0.17	0.28	0.51	0.64	0.27	0.43	0.82	0.84	0.27	0.56	0.76	0.83	0.23	0.39	0.63	0.69	0.56	0.81	1.30	1.46	
Imitation [5]	0.21	0.34	0.53	0.59	0.17	0.30	0.52	0.65	0.23	0.44	0.87	0.85	0.23	0.56	0.82	0.91	0.27	0.46	0.81	0.89	0.43	0.75	1.17	1.33	
GNN [3]															0.77										
ours	0.17	0.30	0.51	0.55	0.16	0.29	0.50	0.61	0.21	0.40	0.85	0.78	0.19	0.54	0.89	0.94	0.22	0.39	0.62	0.69	0.34	0.58	0.94	1.12	
	Phoning					Posing				Purchase			Sitting				Sitting Down				Taking Photo				
milliseconds	80			400				400							320								320		
zero-velocity [4]															1.02										
Residual sup. [4]															1.49										
convSeq2Seq [2]															1.02										
AGED w/o adv [1]																									
															1.05										
Imitation [5]															0.87										
GNN [3]															0.80										
ours	0.46			1.37									0.27		0.78	0.96	0.27	0.54	0.88	0.97	0.13	0.33	0.60	0.74	
	Waiting					Walking Dog					Toge				erage										
milliseconds	80		320									400			320										
zero-velocity [4]															1.07										
Residual sup. [4]															1.02										
convSeq2Seq [2]															1.01										
AGED w/o adv [1]																									
AGED w/ adv [1]															0.85										
Imitation [5]															0.90										
GNN [3]															0.83		1								
ours	0.21	0.48	0.86	1.08	0.40	0.75	1.05	1.23	0.14	0.32	0.52	0.55	0.25	0.49	0.83	0.94									

Table 2. Short-term prediction results in Mean Per Joint Position Error (MPJPE) on Human3.6M for all actions. The best result is marked in bold. A 3D suffix to a method indicates that the method was directly trained on 3D joint positions. Otherwise, the results were obtained by converting the joint angle to 3D positions. The best result is marked in bold.

	Walking					Eating				Smoking				Discussion				Directions					Greeting		
milliseconds	80	160	320	400	80	160	320	400	80	160	320	400	80	160	320	400	80	160	320	400	80	160	320	400	
Residual sup. [4]	21.7	38.1	58.9	68.8	15.1	28.6	54.8	67.4	20.8	39.0	66.1	76.1	26.2	51.2	85.8	94.6	27.9	44.8	63.5	78.2	29.3	56.0	110.2	125.6	
Residual sup. 3D [4]	23.8	40.4	62.9	70.9	17.6	34.7	71.9	87.7	19.7	36.6	61.8	73.9	31.7	61.3	96.0	103.5	36.5	56.4	81.5	97.3	37.9	74.1	1390	158.8	
convSeq2Seq [2]					13.3		48.6				39.3				68.4					72.4				122.8	
convSeq2Seq 3D [2]	17.1	31.2	53.8	61.5	13.7	25.9	52.5	63.3							67.7					73.4	24.5	46.2	90.0	103.1	
GNN [3]	11.1	19.0	32.0	39.1	9.2	19.5	40.3	48.9					11.3	23.7	41.9	46.6	11.2	23.2	52.7	64.1	14.2	27.7	67.1	82.9	
GNN 3D [3]	8.9			33.4	8.8	18.9	39.4	47.2			25.3				39.6										
Ours	9.6	18.0	33.1	39.1	9.1	19.5	40.2	48.8				29.7			43.4										
Ours 3D	7.9			34.5	8.4	18.1	37.4	45.3	6.8	13.2	24.1	27.5	8.3		43.9	48.0	11.1	22.7	48.0	58.4	13.2	28.0	64.5	77.9	
	Phoning				Posing			Purchase			Sitting				Sitting Down				Taking Photo						
milliseconds	80	160		400	80	160	320	400	80	160	320	400		160		400			320			160		400	
Residual sup. [4]					30.5			144.7													21.2				
Residual sup. 3D [4]																									
convSeq2Seq [2]				75.4				106.1																	
				61.3				105.6																	
GNN [3]			45.2		11.1		69.4								55.9								38.5		
GNN 3D [3]	11.5	20.2	37.9	43.2	9.4	23.9	66.2								50.6						6.8	15.2	38.2	49.6	
Ours	12.8	24.1	43.6	51.6	8.4	25.3	68.9	88.7	20.2	43.5	66.2	74.9	10.6	24.8	50.4	59.1	11.5	25.3	53.9	69.2	7.1	14.8	39.2	48.9	
Ours 3D	10.8	19.6	37.6	46.8	8.3	22.8	65.6	81.8	18.5	38.1	61.8	69.6	9.5	23.9	49.8	61.8	11.2	29.9	59.8	68.4	6.3	14.5	38.8	49.4	
	Waiting					Walking Dog				Walking Together				Average											
milliseconds	80	160		400	80	160	320	400			320	400			320	400									
Residual sup. [4]								156.9							88.9										
Residual sup. 3D [4]	29.5	60.5	119.9	140.6	60.5	101.9	160.8	188.3	23.5	45.0	71.3	82.8	30.8	57.0	99.8	115.5									
convSeq2Seq [2]								156.3							75.9										
convSeq2Seq 3D [2]			72.9					138.7																	
GNN [3]								126.8																	
GNN 3D [3]	9.5		57.5					122.7																	
Ours	9.2							127.2									i								
Ours 3D	8.4	21.5	53.9	69.8	22.9	50.4	100.8	119.8	8.7	18.3	34.2	44.1	10.7	23.8	50.0	60.2									

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