Frequency-Enhanced Wavelet-based Transformer in Imitation Learning for Humanoid Robot

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Project Website: *https://humanoid-black-knight.github.io/*.

APPENDIX

A. Comparison of Parameters and FLOPs

Table A1 shows that, based on the ACT policy baseline and Backbone (ResNet18), the FE-EMA module reduces the computational complexity (FLOPs) compared to the EMA module. Where the Simulation Tasks (ACT baseline) are ***Cube Transfer*** and ***Bimanual Insertion***, respectively.

Table A1. Comparison of Parameters and FLOPs for One Epoch.

Method	Backbone	Simulation Tasks	
		#.Param.	FLOPs
Baseline (ACT)	ResNet18	60.7566 M	37570.51 M
EMA + ACT		60.7592 M	37616.59 M
FE-EMA + ACT (ours)		**60.7621 M**	**37596.91 M**

B. Training Details

We adopt the hyperparameters reported in the ACT Policy and Mobile ALOHA paper, with the sole modification of reducing the batch size from 8 to 4. The complete hyperparameter settings are summarized in **Table A2**. We deploy our policy with inference on a desktop with an NVIDIA RTX 3060 GPU.

Table A2. Hyperparameters of the FEWT (based on ACT Policy).

Hyperparameter	**FEWT**
Learning rate	1e-5
Batch size	4
# encoder layers	4
# decoder layers	7
Feedforward dimension	3200
Hidden dimension	512
# heads	8
Chunk size	100
KL weights	10

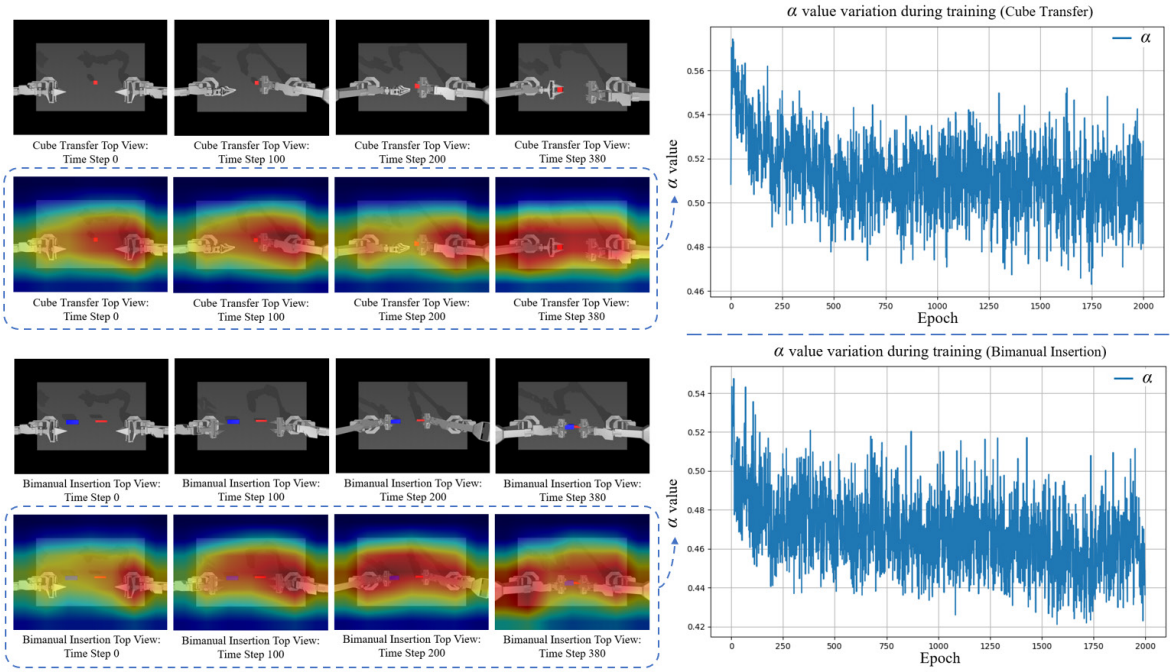

Fig. A1: Visualization of the dynamic weight α in the FE-EMA module (training phase, effect of 2000 epoch under different simulation tasks).

For the two simulation tasks, ***Cube Transfer*** and ***Bimanual Insertion***, the dynamic weight α is consistently maintained at approximately 0.5 during training (see **Fig. A1**). This suggests that the time-domain and frequency-domain feature weights are well balanced during model training. Dynamically fusing the time-domain and frequency-domain features allows effective capture of information across different scales.

C. The Construction of Humanoid Black Knight

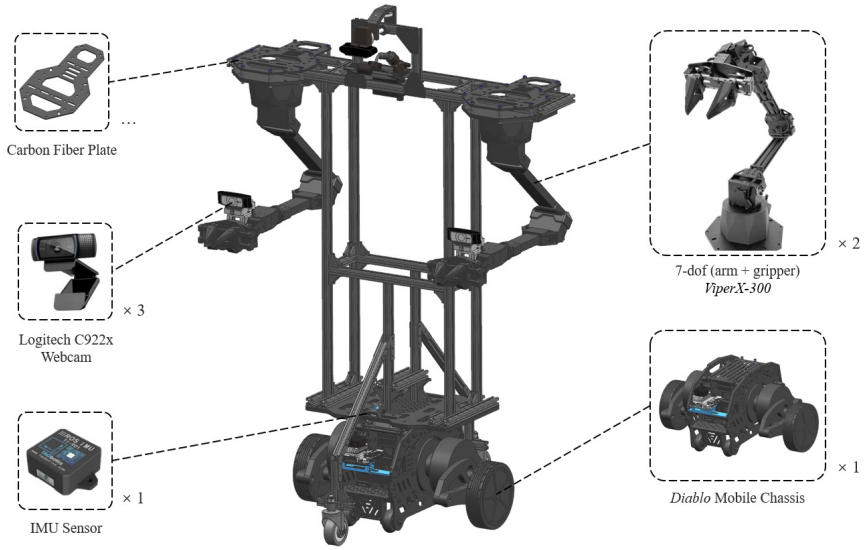

Fig. A2: The design of humanoid robot (*Humanoid Black Knight*, HBK).

The construction of *Humanoid Black Knight* (HBK) mainly consists of two 7-dof (arm + gripper) robotic arms (*ViperX-300*), a two-wheeled differential mobility chassis (*Diablo*), three RGB cameras (Logitech C922x webcams), and an inertial measurement unit (IMU sensor).