

Structural Action Transformer for 3D Dexterous Manipulation

Supplementary Material

001 1. Embodied Joint Codebook Mapping Table

002 As introduced in Section 3.3.2 of the main paper, the Em-
003 bodied Joint Codebook is central to our structural-centric
004 formulation, enabling the policy to handle morphological
005 heterogeneity. It resolves the ambiguity of our unordered,
006 variable-length action sequence $\mathbf{A}_t \in \mathbb{R}^{D_a \times T}$ by provid-
007 ing a unique, learnable embedding for each joint. Table 3
008 provides the mapping used in our experiments.

009 2. 3D Re-implementation of HPT and UniAct

010 To ensure a fair and rigorous comparison against our 3D-
011 native approach, we adapt the primary 2D-based baselines,
012 HPT [4] and UniAct [5], to accept 3D point cloud inputs.
013 This adaptation is crucial as these models, in their original
014 form, cannot process the 3D observation space used by SAT.
015 Results are presented in Table 1.

016 2.1. 3D-HPT

017 The HPT [4] framework is designed with a modality-
018 specific “stem” and a shared “trunk” transformer. The
019 original model employs 2D vision stems to process image-
020 based inputs. For our 3D baseline (referred to as 3D-HPT),
021 we replace the original 2D vision stem with a 3D-specific
022 stem. This new stem is architected similarly to our own ob-
023 servation tokenizer (Section 3.3.1), utilizing a hierarchical
024 PointNet-based encoder. It processes the raw point cloud
025 \mathcal{P}_t by performing Farthest Point Sampling (FPS) and K-
026 Nearest Neighbor (KNN) grouping to extract local geomet-
027 ric tokens, along with a global scene token. These 3D to-
028 kens are then projected to the required embedding dimen-
029 sion and fed into the original, unchanged HPT trunk. This
030 modification allows HPT to leverage 3D geometric informa-
031 tion while maintaining the integrity of its core architecture.

032 2.2. 3D-UniAct

033 The adaptation of UniAct [5] requires a different ap-
034 proach, as its architecture is deeply integrated with a Vision-
035 Language Model (VLM). The core VLM-based component,
036 which processes sequences of discretized tokens, is left un-
037 modified. Our intervention focuses on the visual tokenizer
038 and re-encoding stages. The original UniAct feeds visual
039 tokens, generated by a 2D tokenizer, into the VLM. Cruci-
040 ally, it also re-introduces raw visual features at later stages
041 to ground the policy’s output. We replace this second, “in-
042 the-loop” 2D feature encoder with a 3D PointNet encoder.
043 This 3D encoder takes the raw point cloud \mathcal{P}_t as input at
044 each relevant time step, processes it, and provides the neces-
045 sary 3D-grounded visual conditioning to the policy decoder.

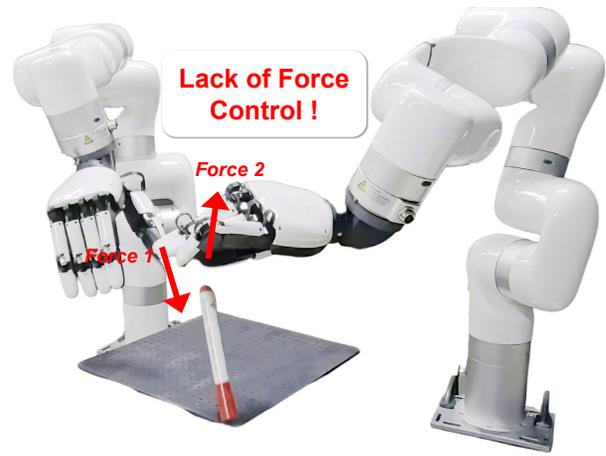


Figure 1. Failure case analysis.

This allows the model to operate on 3D data while retaining
its original reasoning and action-generation mechanism.

046 3. Visualization of Failure Cases 047 048

049 While our Structural Action Transformer (SAT) demon-
050 strates robust performance, it is not without limitations, par-
051 ticularly in scenarios involving complex contact dynamics.
052 Figure 1 illustrates representative failure case from our real-
053 world experiments. Our policy is not conditioned on haptic
054 or force-torque information. This becomes a critical bottle-
055 neck in tasks requiring precise force modulation. For exam-
056 ple, in the “Remove the pen cap” task, the policy might
057 successfully grasp the cap but fail to apply sufficient axial
058 force to overcome the friction, resulting in the fingers
059 slipping. These failures highlight a key avenue for future
060 work: integrating tactile and force-sensing modalities with
061 our structural-centric action representation.

062 4. Ablation on Action Horizon Length 063

064 In the main paper (Sec 4.3), we demonstrate that our Struc-
065 tural Action Transformer (SAT) is robust to the compression
066 of the temporal trajectory, *i.e.*, projecting the T -dimensional
067 feature vector to a lower-dimensional embedding d_{feat} .
068 Here, we provide a complementary ablation study on the
069 original action horizon length T itself.

070 We pre-train and fine-tune our SAT model with varying
071 horizon lengths T , keeping other parameters consistent with
072 our best model from the main paper. The average success
073 rate on Adroit [3] is reported in Table 2. We observe that in-
creasing the horizon shows a marginal decrease. The addi-

Method	Modality	Adroit (3) [3]	DexArt (4) [1]	Bi-DexHands (4) [2]	Average Success
3D-HPT [4]	3D	0.50±0.02	0.55±0.05	0.49±0.04	0.51±0.04
3D-UniAct [5]	3D	0.50±0.01	0.55±0.03	0.49±0.07	0.51±0.05
SAT (Ours)	3D	0.75±0.02	0.73±0.03	0.67±0.05	0.71±0.04

Table 1. Quantitative comparison of our method against 3D re-implementation of HPT [4] and UniAct [5] on 11 dexterous manipulation tasks from the Adroit [3], DexArt [1], and Bi-DexHands [2] simulation benchmarks.

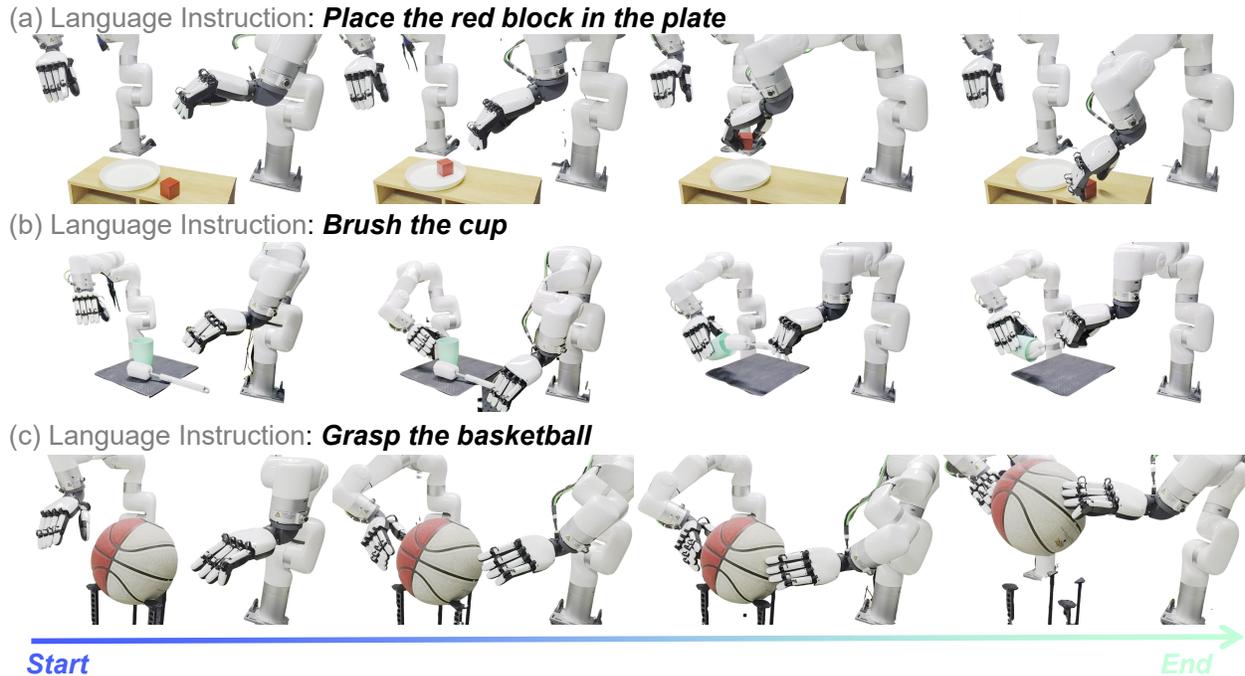


Figure 2. Qualitative rollouts of real-world tasks.

Horizon Length T	Average Success on Adroit (3)
8	0.51±0.03
16	0.54±0.02
32	0.47±0.03
64	0.43±0.04

Table 2. Ablation on action horizon length T .

074 tional temporal steps appear to introduce redundancy rather than new, useful long-term information. This result validates our structural-centric approach and its inherent capacity for temporal compression. It justifies that appropriate T provides a rich enough signal for compression without incurring the cost of processing unnecessary, redundant data.

080 4.1. Additional Qualitative Results

081 We provide additional qualitative rollouts for the real-world tasks that could not be included in the main paper due to

space constraints. Figure 2 shows rollouts for the ‘Brush the cup’, ‘Grasp basketball’, and ‘Place block in plate’ real-world tasks. These visualizations highlight the policy’s ability to handle complex bimanual coordination and contact-rich interactions, successfully transferring the priors learned from simulation and human data to our real-world setup.

089 5. Real-World Demonstration Video

090 We have included a supplementary video file that shows our real-world experiments. The video demonstrates the performance of our SAT policy on the bimanual setup for tasks described in the main paper.

094 References

- [1] Chen Bao, Helin Xu, Yuzhe Qin, and Xiaolong Wang. Dexart: Benchmarking generalizable dexterous manipulation with articulated objects. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 21190–21200, 2023. 2

Table 3. Embodied Joint Codebook mapping for manipulators used in pre-training and evaluation. The indices for Functional Category and Rotation Axis are shared across all embodiments, forming the basis for cross-embodiment skill transfer. (To be continued ...)

Embodiment	Joint Name	Embodiment ID (e)	Functional Category (f)	Rotation Axis (r)
Shadow Dexterous Hand	T-CMC	1	1 (CMC)	1 (Flexion/Extension)
	T-CMC	1	1 (CMC)	2 (Abduction/Adduction)
	T-CMC	1	1 (CMC)	3 (Rotation)
	T-MCP	1	2 (MCP)	1 (Flexion/Extension)
	T-IP	1	3 (PIP)	1 (Flexion/Extension)
	IF-CMC	1	1 (CMC)	1 (Flexion/Extension)
	IF-CMC	1	1 (CMC)	2 (Abduction/Adduction)
	IF-CMC	1	1 (CMC)	3 (Rotation)
	IF-MCP	1	2 (MCP)	1 (Flexion/Extension)
	IF-MCP	1	2 (MCP)	2 (Abduction/Adduction)
	IF-MCP	1	2 (MCP)	3 (Rotation)
	IF-PIP	1	3 (PIP)	1 (Flexion/Extension)
	IF-DIP	1	4 (DIP)	1 (Flexion/Extension)
	MF-CMC	1	1 (CMC)	1 (Flexion/Extension)
	MF-CMC	1	1 (CMC)	2 (Abduction/Adduction)
	MF-CMC	1	1 (CMC)	3 (Rotation)
	MF-MCP	1	2 (MCP)	1 (Flexion/Extension)
	MF-MCP	1	2 (MCP)	2 (Abduction/Adduction)
	MF-MCP	1	2 (MCP)	3 (Rotation)
	MF-PIP	1	3 (PIP)	1 (Flexion/Extension)
	MF-DIP	1	4 (DIP)	1 (Flexion/Extension)
	RF-CMC	1	1 (CMC)	1 (Flexion/Extension)
	RF-CMC	1	1 (CMC)	2 (Abduction/Adduction)
	RF-CMC	1	1 (CMC)	3 (Rotation)
RF-MCP	1	2 (MCP)	1 (Flexion/Extension)	

- 100 [2] Yuanpei Chen, Yiran Geng, Fangwei Zhong, Jiaming Ji,
101 Jiechuang Jiang, Zongqing Lu, Hao Dong, and Yaodong
102 Yang. Bi-dexhands: Towards human-level bimanual dexter-
103 ous manipulation. *IEEE Transactions on Pattern Analysis and*
104 *Machine Intelligence*, 46(5):2804–2818, 2023. 2
- 105 [3] Aravind Rajeswaran, Vikash Kumar, Abhishek Gupta, Giu-
106 lia Vezzani, John Schulman, Emanuel Todorov, and Sergey
107 Levine. Learning complex dexterous manipulation with deep
108 reinforcement learning and demonstrations. *arXiv preprint*
109 *arXiv:1709.10087*, 2017. 1, 2
- 110 [4] Lirui Wang, Xinlei Chen, Jialiang Zhao, and Kaiming He.
111 Scaling proprioceptive-visual learning with heterogeneous
112 pre-trained transformers. *Proceedings of the Advances in Neu-
113 ral Information Processing Systems (NeurIPS)*, 37:124420–
114 124450, 2024. 1, 2
- 115 [5] Jinliang Zheng, Jianxiong Li, Dongxiu Liu, Yinan Zheng,
116 Zhihao Wang, Zhonghong Ou, Yu Liu, Jingjing Liu, Ya-
117 Qin Zhang, and Xianyuan Zhan. Universal actions for en-
118 hanced embodied foundation models. In *Proceedings of*
119 *the IEEE/CVF Conference on Computer Vision and Pattern*
120 *Recognition (CVPR)*, pages 22508–22519, 2025. 1, 2

Table 3. Embodied Joint Codebook mapping... (Continued)

Embodiment	Joint Name	Embodiment ID (<i>e</i>)	Functional Category (<i>f</i>)	Rotation Axis (<i>r</i>)
Shadow Dexterous Hand	RF-MCP	1	2 (MCP)	2 (Abduction/Adduction)
	RF-MCP	1	2 (MCP)	3 (Rotation)
	RF-PIP	1	3 (PIP)	1 (Flexion/Extension)
	RF-DIP	1	4 (DIP)	1 (Flexion/Extension)
	LF-CMC	1	1 (CMC)	1 (Flexion/Extension)
	LF-CMC	1	1 (CMC)	2 (Abduction/Adduction)
	LF-CMC	1	1 (CMC)	3 (Rotation)
	LF-MCP	1	2 (MCP)	1 (Flexion/Extension)
	LF-MCP	1	2 (MCP)	2 (Abduction/Adduction)
	LF-MCP	1	2 (MCP)	3 (Rotation)
	LF-PIP	1	3 (PIP)	1 (Flexion/Extension)
	LF-DIP	1	4 (DIP)	1 (Flexion/Extension)
SCHUNK SVH Five-Finger Hand	T-CMC	3	1 (CMC)	1 (Flexion/Extension)
	T-CMC	3	1 (CMC)	2 (Abduction/Adduction)
	T-MCP	3	2 (MCP)	1 (Flexion/Extension)
	T-IP	3	3 (PIP)	1 (Flexion/Extension)
	IF-MCP	3	2 (MCP)	1 (Flexion/Extension)
	IF-MCP	3	2 (MCP)	2 (Abduction/Adduction)
	IF-PIP	3	3 (PIP)	1 (Flexion/Extension)
	MF-MCP	3	2 (MCP)	1 (Flexion/Extension)
	MF-MCP	3	2 (MCP)	2 (Abduction/Adduction)
	MF-PIP	3	3 (PIP)	1 (Flexion/Extension)
	RF-MCP	3	2 (MCP)	1 (Flexion/Extension)
	RF-MCP	3	2 (MCP)	2 (Abduction/Adduction)
	RF-PIP	3	3 (PIP)	1 (Flexion/Extension)
	LF-MCP	3	2 (MCP)	1 (Flexion/Extension)
	LF-MCP	3	2 (MCP)	2 (Abduction/Adduction)
LF-PIP	3	3 (PIP)	1 (Flexion/Extension)	
Tesla Optimus Gen 2 Hand	T-CMC	4	1 (CMC)	1 (Flexion/Extension)
	T-CMC	4	1 (CMC)	2 (Abduction/Adduction)
	T-MCP	4	2 (MCP)	1 (Flexion/Extension)
	IF-MCP	4	2 (MCP)	1 (Flexion/Extension)
	IF-PIP	4	3 (PIP)	1 (Flexion/Extension)
	MF-MCP	4	2 (MCP)	1 (Flexion/Extension)
	MF-PIP	4	3 (PIP)	1 (Flexion/Extension)
	RF-MCP	4	2 (MCP)	1 (Flexion/Extension)
	RF-PIP	4	3 (PIP)	1 (Flexion/Extension)
	LF-MCP	4	2 (MCP)	1 (Flexion/Extension)
	LF-PIP	4	3 (PIP)	1 (Flexion/Extension)
Robotiq	IF-MCP	5	2 (MCP)	1 (Flexion/Extension)
	IF-PIP	5	3 (PIP)	1 (Flexion/Extension)
	MF-MCP	5	2 (MCP)	1 (Flexion/Extension)
	MF-PIP	5	3 (PIP)	1 (Flexion/Extension)
	LF-MCP	5	2 (MCP)	1 (Flexion/Extension)
	LF-PIP	5	3 (PIP)	1 (Flexion/Extension)

Table 3. Embodied Joint Codebook mapping... (Continued)

Embodiment	Joint Name	Embodiment ID (e)	Functional Category (f)	Rotation Axis (r)
Inspire Robots	T-CMC	6	1 (CMC)	1 (Flexion/Extension)
	T-CMC	6	1 (CMC)	2 (Abduction/Adduction)
	T-MCP	6	2 (MCP)	1 (Flexion/Extension)
	IF-MCP	6	2 (MCP)	1 (Flexion/Extension)
	IF-PIP	6	3 (PIP)	1 (Flexion/Extension)
	MF-MCP	6	2 (MCP)	1 (Flexion/Extension)
	MF-PIP	6	3 (PIP)	1 (Flexion/Extension)
	RF-MCP	6	2 (MCP)	1 (Flexion/Extension)
	RF-PIP	6	3 (PIP)	1 (Flexion/Extension)
	LF-MCP	6	2 (MCP)	1 (Flexion/Extension)
	LF-PIP	6	3 (PIP)	1 (Flexion/Extension)
xHand	T-CMC	7	1 (CMC)	1 (Flexion/Extension)
	T-CMC	7	1 (CMC)	2 (Abduction/Adduction)
	T-CMC	7	1 (CMC)	3 (Rotation)
	T-MCP	7	2 (MCP)	1 (Flexion/Extension)
	T-IP	7	3 (PIP)	1 (Flexion/Extension)
	IF-CMC	7	1 (CMC)	1 (Flexion/Extension)
	IF-CMC	7	1 (CMC)	2 (Abduction/Adduction)
	IF-CMC	7	1 (CMC)	3 (Rotation)
	IF-MCP	7	2 (MCP)	1 (Flexion/Extension)
	IF-MCP	7	2 (MCP)	2 (Abduction/Adduction)
	IF-PIP	7	3 (PIP)	1 (Flexion/Extension)
	IF-DIP	7	4 (DIP)	1 (Flexion/Extension)
	MF-MCP	7	2 (MCP)	1 (Flexion/Extension)
	MF-MCP	7	2 (MCP)	2 (Abduction/Adduction)
	MF-PIP	7	3 (PIP)	1 (Flexion/Extension)
	RF-MCP	7	2 (MCP)	1 (Flexion/Extension)
	RF-MCP	7	2 (MCP)	2 (Abduction/Adduction)
	RF-PIP	7	3 (PIP)	1 (Flexion/Extension)
	LF-MCP	7	2 (MCP)	1 (Flexion/Extension)
	LF-MCP	7	2 (MCP)	2 (Abduction/Adduction)
LF-PIP	7	3 (PIP)	1 (Flexion/Extension)	
OYMotion	T-CMC	8	1 (CMC)	1 (Flexion/Extension)
	T-CMC	8	1 (CMC)	2 (Abduction/Adduction)
	T-CMC	8	1 (CMC)	3 (Rotation)
	T-MCP	8	2 (MCP)	1 (Flexion/Extension)
	T-IP	8	3 (PIP)	1 (Flexion/Extension)
	IF-MCP	8	2 (MCP)	1 (Flexion/Extension)
	IF-MCP	8	2 (MCP)	2 (Abduction/Adduction)
	IF-PIP	8	3 (PIP)	1 (Flexion/Extension)
	MF-MCP	8	2 (MCP)	1 (Flexion/Extension)
	MF-MCP	8	2 (MCP)	2 (Abduction/Adduction)
	MF-PIP	8	3 (PIP)	1 (Flexion/Extension)
	RF-MCP	8	2 (MCP)	1 (Flexion/Extension)
	RF-MCP	8	2 (MCP)	2 (Abduction/Adduction)
	RF-PIP	8	3 (PIP)	1 (Flexion/Extension)
	LF-MCP	8	2 (MCP)	1 (Flexion/Extension)
	LF-MCP	8	2 (MCP)	2 (Abduction/Adduction)
	LF-PIP	8	3 (PIP)	1 (Flexion/Extension)

Table 3. Embodied Joint Codebook mapping... (Continued)

Embodiment	Joint Name	Embodiment ID (<i>e</i>)	Functional Category (<i>f</i>)	Rotation Axis (<i>r</i>)
DLR Hand Arm System	T-CMC	9	1 (CMC)	1 (Flexion/Extension)
	T-CMC	9	1 (CMC)	2 (Abduction/Adduction)
	T-MCP	9	2 (MCP)	1 (Flexion/Extension)
	T-IP	9	3 (PIP)	1 (Flexion/Extension)
	IF-CMC	9	1 (CMC)	1 (Flexion/Extension)
	IF-MCP	9	2 (MCP)	1 (Flexion/Extension)
	IF-MCP	9	2 (MCP)	2 (Abduction/Adduction)
	IF-PIP	9	3 (PIP)	1 (Flexion/Extension)
	MF-CMC	9	1 (CMC)	1 (Flexion/Extension)
	MF-MCP	9	2 (MCP)	1 (Flexion/Extension)
	MF-MCP	9	2 (MCP)	2 (Abduction/Adduction)
	MF-PIP	9	3 (PIP)	1 (Flexion/Extension)
	RF-CMC	9	1 (CMC)	1 (Flexion/Extension)
	RF-MCP	9	2 (MCP)	1 (Flexion/Extension)
	RF-MCP	9	2 (MCP)	2 (Abduction/Adduction)
	RF-PIP	9	3 (PIP)	1 (Flexion/Extension)
	LF-CMC	9	1 (CMC)	1 (Flexion/Extension)
	LF-MCP	9	2 (MCP)	1 (Flexion/Extension)
LF-MCP	9	2 (MCP)	2 (Abduction/Adduction)	
LF-PIP	9	3 (PIP)	1 (Flexion/Extension)	
Foxtech Robotics	T-CMC	10	1 (CMC)	1 (Flexion/Extension)
	T-CMC	10	1 (CMC)	2 (Abduction/Adduction)
	T-MCP	10	2 (MCP)	1 (Flexion/Extension)
	IF-MCP	10	2 (MCP)	1 (Flexion/Extension)
	IF-PIP	10	3 (PIP)	1 (Flexion/Extension)
	MF-MCP	10	2 (MCP)	1 (Flexion/Extension)
	MF-PIP	10	3 (PIP)	1 (Flexion/Extension)
	RF-MCP	10	2 (MCP)	1 (Flexion/Extension)
	RF-PIP	10	3 (PIP)	1 (Flexion/Extension)
	LF-MCP	10	2 (MCP)	1 (Flexion/Extension)
LF-PIP	10	3 (PIP)	1 (Flexion/Extension)	
Allegro Hand	T-CMC	2	1 (CMC)	1 (Flexion/Extension)
	T-CMC	2	1 (CMC)	2 (Abduction/Adduction)
	T-MCP	2	2 (MCP)	1 (Flexion/Extension)
	T-IP	2	3 (PIP)	1 (Flexion/Extension)
	IF-CMC	2	1 (CMC)	1 (Flexion/Extension)
	IF-MCP	2	2 (MCP)	1 (Flexion/Extension)
	IF-MCP	2	2 (MCP)	2 (Abduction/Adduction)
	IF-PIP	2	3 (PIP)	1 (Flexion/Extension)
	IF-DIP	2	4 (DIP)	1 (Flexion/Extension)
	MF-CMC	2	1 (CMC)	1 (Flexion/Extension)
	MF-MCP	2	2 (MCP)	1 (Flexion/Extension)
	MF-MCP	2	2 (MCP)	2 (Abduction/Adduction)
	MF-PIP	2	3 (PIP)	1 (Flexion/Extension)
	MF-DIP	2	4 (DIP)	1 (Flexion/Extension)
	RF-CMC	2	1 (CMC)	1 (Flexion/Extension)
	RF-MCP	2	2 (MCP)	1 (Flexion/Extension)
	RF-MCP	2	2 (MCP)	2 (Abduction/Adduction)
	RF-PIP	2	3 (PIP)	1 (Flexion/Extension)
RF-DIP	2	4 (DIP)	1 (Flexion/Extension)	