RoboMAN: Human-like Compliance Manipulation for Electronics Assembly via an Online Memory-Augmented Network*

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Abstract— **Traditional compliance control methods face limitations in precision assembly due to delicate contact transitions and rigid parameter tuning. This paper introduces an online memory-augmented compliance learning framework RoboMAN to achieve human-like compliance control in precision electronics assembly tasks. This framework is trained on a 6-DOF force-motion dataset collected via our developed bilateral teleoperation system. Experimental evaluations on four representative electronics assembly tasks demonstrate RoboMAN's superiority in memory efficiency (48% GPU utilization), training speed (65.25s per epoch), inference latency (0.25s per batch), task success rates (up to 98%), while demonstrating robust dynamic force adaptability during task execution. This work establishes a new paradigm for adaptive robotic compliance control by bridging biological compliance principles with efficient robotic execution, offering a scalable solution in precision contact-rich environments.**

I. INTRODUCTION

Robots are widely employed in industries such as manufacturing, agriculture, and healthcare to improve efficiency [1]. While they excel at tasks involving minimal contact (e.g., welding, drone spraying, ultraviolet disinfection), conventional compliance control methods exhibit limitations in electronic component assembly requiring stage-specific force regulation and tight tolerances. Specifically, passive compliance mechanisms relying on mechanical flexibility face accuracy constraints [2], while active approaches such as hybrid force/position control encounter stability issues during contact transitions [3]. Moreover, impedance control dependency on manual parameter tuning further restricts adaptability to dynamic conditions [4].

Human assembly strategies provide critical insights by leveraging adaptive force sensing and coordinated limb stiffness modulation. Inspired by these biological compliance mechanisms, we propose an end-to-end paradigm that enables robot force-responsive motion adaptation. One major implementation challenge arises from the lack of comprehensive force-motion interaction dataset on precision electronics assembly tasks [5]. Therefore, we develop a bilateral teleoperation platform (Fig.1) combining human operational expertise with robotic sensing. This system captures synchronized force and motion adjustments sequences through haptic feedback-enabled human interventions, establishing the dataset for the compliance learning framework.

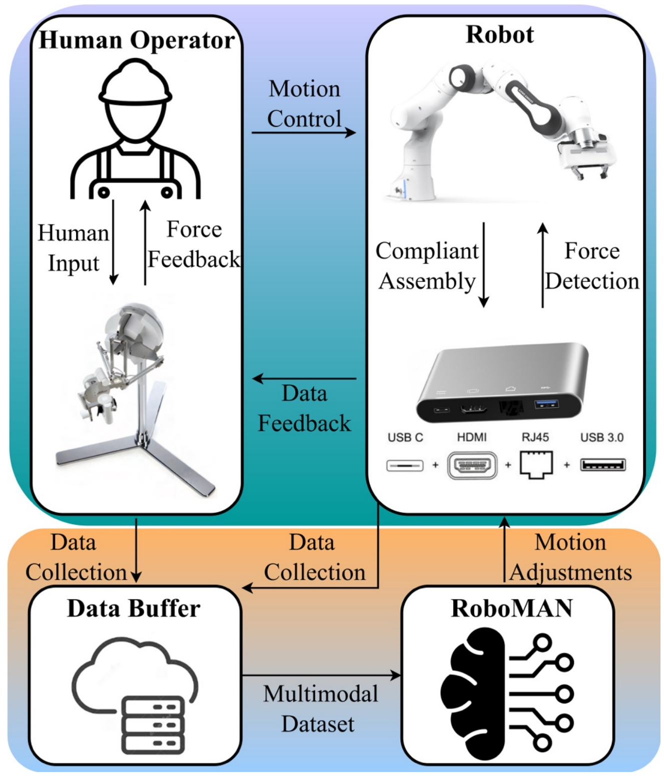

Fig. 1. Overview of the proposed framework for compliant electronics assembly control: The upper module represents a bilateral teleoperation system that synergizes human operator inputs with robotic motion control, enabling precise acquisition of force-motion interaction sequences. The lower module features the RoboMAN, which leverages multimodal dataset to perform global feature extraction, achieving human-like compliance assembly strategies.

Recent advances in large language model and vision-language model indicate the potential for analogous methods in compliance control. Among existing frameworks for sequence handling, Transformer [6] demonstrates robust modeling capabilities, but suffers from quadratic complexity, making it inefficient for robotic high-frequency sensor data processing. To overcome this limitation, we introduce the modular loss-guided incremental learning framework RoboMAN to efficiently address long-sequence processing in robotics. In contrast to Transformers, RoboMAN achieves lower complexity without compromising processing speed. Furthermore, compared to RNN [7] and LSTM [8] that often face gradient vanishing/explosion and catastrophic forgetting due to rigid memory mechanisms, RoboMAN adaptively balances fixed and modular loss components dynamically

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to achieve stability and plasticity. Specifically, it preserves historical knowledge through high-weight loss constraints while adaptively integrating new information via low-weight modules, ensuring consistent task performance and flexible adaptation to evolving data distributions. In summary, the principal contributions of this paper are as follows:

- **Bilateral teleoperation system and multimodal dataset:** We establish a bilateral teleoperation system providing force feedback to capture the comprehensive force-motion interaction dataset, which reflects human compliance strategies in diverse representative electronics assembly scenarios.
- **Online Memory-Augmented Compliance Learning:** The proposed RoboMAN framework pioneers an online memory-augmented network based on loss-guided modular adaptation, establishing the first implementation of online learning mechanisms for multidegree-of-freedom compliance control in precision electronics assembly.
- **State-of-the-art performance in adaptive compliance control:** Through extensive experiments on four representative electronics assembly tasks, RoboMAN establishes new benchmarks, outperforming existing methods in memory efficiency, inference speed, convergence stability, and task success rates. These results validate the efficacy and efficiency of the proposed framework in various electronics assembly tasks.

II. RELATED WORK

Compliance control with human-like flexibility is beneficial for applications requiring safety and precision in delicate environments. Therefore, the methods relied on arm stiffness estimation via electromyography [9] or least-squares fitting [10] to modulate robot compliance. Although effective for coarse tasks, these methods become susceptible to modeling inaccuracies and sensor noise in high-precision scenarios.

Modern learning-based approaches mitigate these limitations through adaptive compliance regulation. Reinforcement learning (RL) theoretically enables autonomous impedance tuning via Markov decision processes, yet struggles with reward specification, safety assurance, and sample inefficiency [11]. Imitation learning (IL) bypasses these challenges by extracting policies from expert demonstrations, excelling in tasks lacking quantitative success metrics [12]. While traditional IL architectures inadequately model temporal dependencies [13], contemporary solutions employ RNN [7] and Transformers [6] for enhanced sequence modeling. However, we summarize the critical limitations: (1) Underutilization of multimodal force-torque data in systems [14], [15], with some relying solely on simulated kinematics [15]; (2) Oversimplified force integration approaches such as environmental stiffness estimation [16] or vibration-based feedback [17]; (3) Computational compromises in temporal modeling through fixed windowing [18], [19] or sequence truncation [20]. Our framework addresses these gaps by collecting the comprehensive force-motion interaction dataset and biomimetic compliance control for complex electronics assembly tasks.

III. SYSTEM AND METHODS

A. Bilateral Teleoperation System

This work develops a bilateral teleoperation system that integrates the Sigma.7 haptic interface and the Franka Emika Panda robot to establish a bidirectional force-motion coupling framework. The hardware architecture combines the Sigma.7's high-fidelity force rendering (0.02mm spatial resolution, submillisecond latency) [21] with the Franka robot's multi-axis force/torque sensing (±0.1N accuracy) [22], enabling synchronized physical interaction perception. A distributed ROS-based software framework ensures real-time kinematic and dynamic computations, low-latency haptic transmission, and synchronized multimodal dataset, providing a robust foundation for subsequent data-driven framework learning.

To model human-like compliance control, we adapt position-based impedance control as the fundamental mathematical model, where interaction wrenches are translated into corrective motion adjustments. Formally, our mathematical model follows a second-order differential equation:

$$m\Delta\ddot{\boldsymbol{X}} + b\Delta\dot{\boldsymbol{X}} + k\Delta\boldsymbol{X} = \boldsymbol{F} \tag{1}$$

where $\Delta\ddot{\boldsymbol{X}}$, $\Delta\dot{\boldsymbol{X}}$ and $\Delta\boldsymbol{X}$ respectively denote the acceleration, velocity, and displacement adjustments of the Sigma.7 end-effector, while m, b and k represent the system's effective inertia, damping, and stiffness coefficients, and $\boldsymbol{F}$ is the external force/torque sensed at the robot end-effector.

In precision electronics assembly, operational velocities are generally low, minimizing the influence of velocity and acceleration errors. Moreover, our approach addresses multidimensional dynamics by mapping force/torque inputs to motion outputs across all six degrees of freedom (DoF), surpassing the limitations of single-DoF solutions.

Consequently, the force-motion interaction dataset is constructed via closed-loop control. At each time instant t_i, the human operator—using the Sigma.7 haptic interface—perceives the robot's end-effector wrenches $\boldsymbol{F}(t_i)$ and adjusts the Sigma.7 end-effector pose $\Delta\boldsymbol{X}(t_i)$ to counteract undesired contact wrenches. This synchronized time series dataset $(t_i, \boldsymbol{F}(t_i), \Delta\boldsymbol{X}(t_i))$ establishes essential correlations between contact forces and compensatory motions for human-like compliance learning. Detailed dataset characteristics are analyzed in Section IV-A.

B. Architecture of the Online Memory-Augmented Network

We propose the online memory-augmented network (RoboMAN) to balance stability and plasticity through a modular loss function and dynamic weight redistribution. The algorithm's main concept is to embed inputs and outputs into a low-weight module during initial training. This module contributes to the overall loss function and is adaptively adjusted as new data arrive. During incremental learning, the algorithm dynamically redistributes the module's weights to incorporate new dataset, while still preserving the knowledge acquired from previous dataset. Through iterative optimization, the network increasingly improves its performance across the assembly situations. RoboMAN employs a multi-layer perceptron trained on multimodal dataset, where end-effector force/torque measurements serve as state variables, and motion corrections are action variables. The hidden layers extract nonlinear relationships. The network parameters are incrementally updated via stochastic gradient descent:

$$\theta_{t+1} = \theta_t - \eta \nabla_{\theta_t} L(t) \tag{2}$$

where θ_t is the network parameters (including weights and biases) at time step t, η is the learning rate, and $\nabla_{\theta_t} L(t)$ is the total loss gradient.

The core of this framework lies in designing a suitable loss function that addresses catastrophic forgetting. Specifically, the total loss combines a fixed term and a modular term.

The fixed loss term ensures alignment between the predicted and operator-executed adjustments:

$$\mathrm{L}_{\text{fixed}} = \frac{1}{N} \sum_{i=1}^{N} \left(\Delta \boldsymbol{X}_{\text{pred}}(t_i) - \Delta \boldsymbol{X}_{\text{act}}(t_i) \right)^2 \tag{3}$$

Modular loss term adapts to new data while preserving historical knowledge:

$$\mathrm{L}_{\text{mod}} = \frac{1}{N} \sum_{i=1}^{N} \left(\Delta \boldsymbol{X}_{\text{mod}}(t_i) - \Delta \boldsymbol{X}_{\text{act}}(t_i) \right)^2 \tag{4}$$

where $\Delta \boldsymbol{X}_{\text{mod}}(t_i) = G^{(k)}(\boldsymbol{F}(t_i))$ is the posture adjustment computed using the mapping function $G^{(k)}$ learned through current training and $G^{(k)}$ is a time-varying mapping function. Specifically, the initial network parameters $G^{(0)}$ are derived from the baseline training data, with subsequent parameter updates $G^{(k)}$ generated upon the assimilation of new data batches. The weighting factor $\lambda^{(k)}$ balances the losses:

$$\lambda^{(k)} = \lambda^{(k)} \cdot \exp\left(-\eta \cdot \frac{\mathrm{L}_{\text{total}}^{(k-1)} - \mathrm{L}_{\text{total}}^{(k)}}{\mathrm{L}_{\text{total}}^{(k-1)}} \right) \tag{5}$$

with total loss $\mathrm{L}_{\text{total}}^{(k)} = \lambda^{(k)} \mathrm{L}_{\text{fixed}} + (1 - \lambda^{(k)}) \mathrm{L}_{\text{mod}}$. This loss function employs a dual-component architecture: a stable high-weight fixed loss term preserving fundamental task, and an adaptive low-weight modular loss term accommodating emerging patterns. The fixed component ensures directional consistency in optimization trajectories, while the dynamic submodule facilitates catastrophic forgetting mitigation through progressive knowledge assimilation. This configuration enables simultaneous conservation of acquired characteristic of dataset while permitting controlled integration of novel information, thereby addressing the stability-plasticity dilemma inherent in learning systems. In summary, the online learning framework is detailed in Algorithm 1.

By capturing the fundamental mapping between inputs and kinematic adjustments, RoboMAN enables human-like compliant control, as verified by subsequent experiments and supplemental video demonstrations. Detailed implementation guidelines, hyperparameter and stability proof for RoboMAN are documented in our GitHub repository, with further elaboration omitted here due to space constraints.

Algorithm 1 RoboMAN: Online Learning Framework

Initialize network parameters θ, weight λ_{prev}, learning rate η, buffer B, total loss $L_{\text{total\_prev}}$
while not converged **do**
  New dataset $(t_i, F(t_i), \Delta X(t_i))$, store in B
  $\Delta X_{\text{pred}} \leftarrow \text{NeuralNetworkPredict}(\theta, F(t_i))$
  Fixed loss $L_{\text{fixed}} \leftarrow \text{MSE}(\Delta X_{\text{pred}}, \Delta X(t_i))$
  if mapping function $G \neq$ None **then**
    Modular loss $L_{\text{mod}} \leftarrow \text{MSE}(G(F(t_i)), \Delta X(t_i))$
  else
    Modular loss $L_{\text{mod}} \leftarrow 0$
  Total loss $L_{\text{total}} \leftarrow \lambda_{\text{prev}} \cdot L_{\text{fixed}} + (1 - \lambda_{\text{prev}}) \cdot L_{\text{mod}}$
  Update parameters $\theta \leftarrow \theta - \eta \cdot \nabla_\theta L_{\text{total}}$
  if B has sufficient data **then**
    $G \leftarrow \text{TrainNewMapping}(B)$
    Improvement $\leftarrow \frac{L_{\text{total\_prev}} - L_{\text{total}}}{L_{\text{total\_prev}}}$
    $\lambda_{\text{prev}} \leftarrow \lambda_{\text{prev}} \cdot \exp(-\eta \cdot \text{Improvement})$
    Clear B, update $L_{\text{total\_prev}} \leftarrow L_{\text{total}}$
return ΔX_{pred}

IV. EXPERIMENTS

A. Implementation Details

Four representative electronic component assemblies were experimentally studied (Fig. 2). For each component type, 50 assembly trajectories were collected using a bilateral teleoperation system with randomized initial positions of both components and end-effector. Variations in component geometry and structural complexity significantly affected assembly success rates. Therefore, each trial duration spanned 7-13 seconds at a 750 Hz sampling rate, yielding 262.5k-487.5k temporal steps per category. The teleoperation system ran on a Legion 5 workstation (Intel i7-11800H, NVIDIA RTX 3060), while framework training was conducted on a computing cluster equipped with dual NVIDIA L40S GPUs.

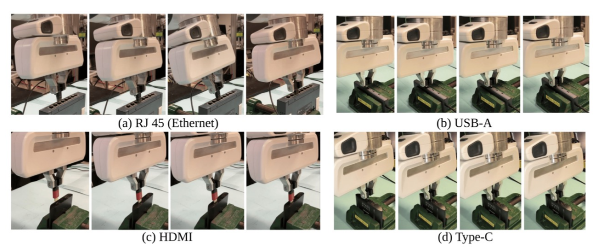

Fig. 2. Four typical electronic component assembly tasks: RJ45 (polygonal), USB-A (rectangular), HDMI (trapezoidal), and Type-C (oval) connectors with 0.1-0.2 mm assembly tolerances. The high precision of the assembly tolerances and different sizes require compliance control of pose and wrenches, with experimental validation video in the supplement.

B. Comparative Evaluation of Methods Performance

In evaluating electronics assembly performance, we compared the proposed RoboMAN framework with four SOTA methods: Action Chunking with Transformers (ACT) [14], Compliance Control via Action Chunking with Transformers (Comp-ACT) [17], a Long-Short-Term Memory (LSTM) approach [8] and Imitation Learning Based on Bilateral Control and Transformers (ILBiT) [16]. All experiments followed standardized hardware configurations and training protocols. The evaluations span five metrics: computational

TABLE I
OVERALL RESULTS WITH DIFFERENT METHODS

Method	Memory Usage (%)	Training Time (s)	Inference Time (s)	Minimum Loss	Convergence Epochs	Success Rate RJ45	Success Rate USB-A	Success Rate HDMI	Success Rate Type-C
ACT	62	154.36	0.65	0.2598	105	0.72	0.80	0.88	0.95
Comp-ACT	67	180.67	0.89	0.1258	113	0.79	0.81	0.92	0.98
LSTM	50	85.98	0.35	0.2293	95	0.70	0.81	0.82	0.82
ILBiT	70	190.24	1.26	0.3061	150	0.75	0.76	0.83	0.89
RoboMAN (Ours)	**48**	**65.25**	**0.25**	**0.0774**	**80**	**0.86**	**0.85**	**0.93**	**0.98**

efficiency (GPU memory utilization), temporal performance (training/inference latency), optimization quality (validation loss), convergence speed (epochs to peak performance) and the success rates of electronics assembly.

As shown in Table I, RoboMAN achieves SOTA performance, demonstrating 48% GPU memory efficiency—surpassing LSTM (50%) and ACT (62%). It exhibits dual temporal superiority: 65.25s/epoch (24.1% faster than LSTM) and 0.25s/batch inference (28.6% faster than LSTM). Transformer-based methods incur 2.37–2.92× longer training durations compared to RoboMAN. With a record-low validation loss (0.0774, 38.5% lower than Comp-ACT) and accelerated convergence (80 epochs, 15.6–46.7% faster than baselines), RoboMAN achieves task success rates of 86% (RJ45), 85% (USB-A), 93% (HDMI) and 98% (Type-C). Prior methods exhibited suboptimal force feedback integration, leading to compliance adaptation failures and performance decline during electronics assembly phases.

C. Adaptive Force Control in Electronics Assembly

A comparison of axial force regulation was conducted between the top-performing models in assembly success rate, RoboMAN and Comp-ACT. Two representative cases were examined: Type-C connector insertion and RJ45-to-HDMI transitions. In Type-C insertion (Fig.3, top), Comp-ACT exhibited significant fluctuations exceeding 12N with broader operational variability. RoboMAN maintained stable axial forces (0-3N range, mean 2N) with minimal variance, demonstrating superior force consistency.

To better illustrate performance differences, force trajectories were temporally aligned across 370 time steps during RJ45-HDMI transitions (Fig.3, bottom), RoboMAN achieved force stabilization (0-3N) through adaptive gain modulation, sustaining 4N forces with narrow variance. Comp-ACT displayed recurrent surges up to 9.5N due to static CVAE architecture limitations. Post-step 210, RoboMAN preserved force consistency while Comp-ACT showed amplified oscillations. The results demonstrate RoboMAN's dynamic latent space optimization, which enables robust force adaptation, contrasting with Comp-ACT's rigid control framework that induces force instability. These findings underscore RoboMAN's superior environmental robustness and compliance control, critical for electronics assembly scenarios.

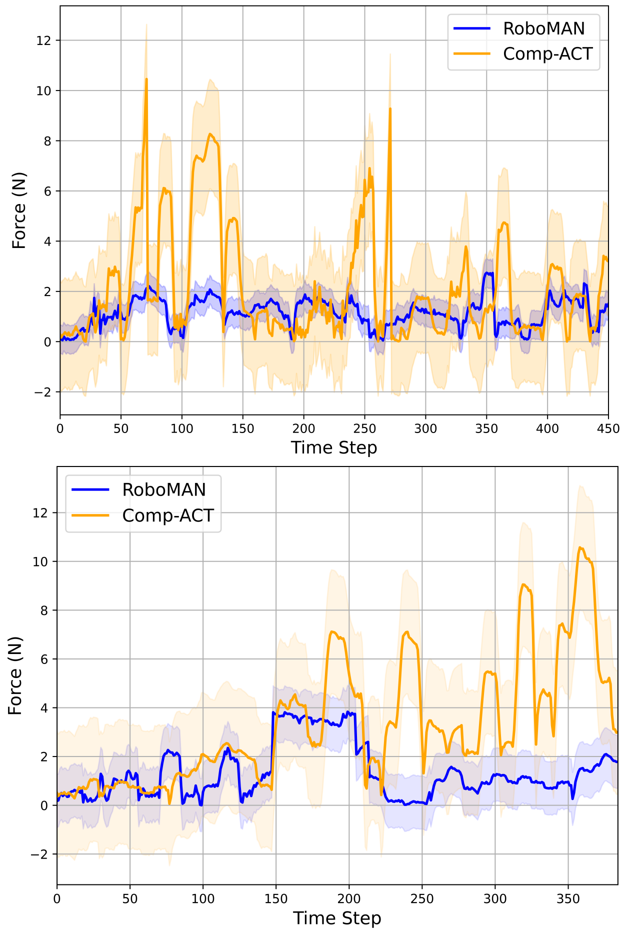

Fig. 3. Comparative analysis of assembly contact forces. Top: The contact force measured during Type-C assembly with RoboMAN and Comp-ACT Bottom: Comparison of contact force between RoboMAN and Comp-ACT during the transition between variable assembly tasks. The transition occurs at approximately the 150th time step and ends around the 210th step.

V. CONCLUSIONS

This study introduces RoboMAN, an innovative framework for human-like compliance control through an online memory-augmented network architecture. The proposed system demonstrates superior performance compared to existing methodologies in different electronics assembly environments, achieved via online learning from a multimodal dataset acquired through our developed bilateral teleoperation system. RoboMAN effectively addresses a critical gap in force-aware manipulation research by establishing new benchmarks in adaptive control precision.

Future investigations will explore the integration of additional sensory input, such as visual perception, and the extension of this framework to broader applications.

REFERENCES

[1] Y. Tsushima, S. Yamamoto, A. A. Ravankar, J. V. S. Luces, and Y. Hirata, "Task planning for a factory robot using large language model," *IEEE Robotics and Automation Letters*, 2025.

[2] Q. K. Luu, A. Albini, P. Maiolino, *et al.*, "Taclink-integrated robot arm toward safe human-robot interaction," in *2024 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2024, pp. 12 356–12 362.

[3] N. Harmatz, A. Zahra, A. Abdelmalak, S. Purohit, T. Shin, and A. D. Mazzeo, "Hybrid force-position control of an elastic tendon-driven scrubbing robot (tedsr)," in *2024 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2024, pp. 4693–4699.

[4] K. Karacan, R. J. Kirschner, H. Sadeghian, F. Wu, and S. Haddadin, "Tactile robot programming: Transferring task constraints into constraint-based unified force-impedance control," in *2024 IEEE International Conference on Robotics and Automation (ICRA)*, 2024, pp. 204–210.

[5] W. Liu, J. Wang, Y. Wang, W. Wang, and C. Lu, "Forcemimic: Force-centric imitation learning with force-motion capture system for contact-rich manipulation," *arXiv preprint arXiv:2410.07554*, 2024.

[6] X. Chen, H. Peng, D. Wang, H. Lu, and H. Hu, "Seqtrack: Sequence to sequence learning for visual object tracking," in *2023 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2023, pp. 14 572–14 581.

[7] P. Song, P. Li, E. Aertbeliën, and R. Detry, "Robot trajectron: Trajectory prediction-based shared control for robot manipulation," in *2024 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2024, pp. 5585–5591.

[8] A. Sasagawa, K. Fujimoto, S. Sakaino, and T. Tsuji, "Imitation learning based on bilateral control for human–robot cooperation," *IEEE Robotics and Automation Letters*, vol. 5, no. 4, pp. 6169–6176, 2020.

[9] R. V. Godoy, B. Guan, A. Dwivedi, and M. Liarokapis, "An affordances and electromyography based telemanipulation framework for control of robotic arm-hand systems," in *2023 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2023, pp. 6998–7004.

[10] K. Choi, J. Song, W. Yun, D. Lee, and S. Oh, "Identification of flexible joint robot inertia matrix using frequency response analysis," in *2024 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2024, pp. 8704–8710.

[11] H. Zhang, G. Solak, G. J. G. Lahr, and A. Ajoudani, "Srl-vic: A variable stiffness-based safe reinforcement learning for contact-rich robotic tasks," *IEEE Robotics and Automation Letters*, vol. 9, no. 6, pp. 5631–5638, 2024.

[12] G. N. S. Gubbala, M. Nagashima, H. Mori, Y. A. Seong, H. Sato, R. Niiyama, Y. Suga, and T. Ogata, "Augmenting compliance with motion generation through imitation learning using drop-stitch reinforced inflatable robot arm with rigid joints," *IEEE Robotics and Automation Letters*, vol. 9, no. 10, pp. 8595–8602, 2024.

[13] C. Weaver, C. Tang, C. Hao, K. Kawamoto, M. Tomizuka, and W. Zhan, "Betail: Behavior transformer adversarial imitation learning from human racing gameplay," *IEEE Robotics and Automation Letters*, vol. 9, no. 8, pp. 7302–7309, 2024.

[14] T. Z. Zhao, V. Kumar, S. Levine, and C. Finn, "Learning Fine-Grained Bimanual Manipulation with Low-Cost Hardware," in *Proceedings of Robotics: Science and Systems*, 2023.

[15] J. Huang, Q. Shi, D. Xie, Y. Ma, X. Liu, C. Li, and X. Duan, "Visuomotor policy learning for task automation of surgical robot," *IEEE Transactions on Medical Robotics and Bionics*, 2024.

[16] M. Kobayashi, T. Buamanee, Y. Uranishi, and H. Takemura, "Ilbit: Imitation learning for robot using position and torque information based on bilateral control with transformer," *arXiv preprint arXiv:2401.16653*, 2024.

[17] T. Kamijo, C. C. Beltran-Hernandez, and M. Hamaya, "Learning variable compliance control from a few demonstrations for bimanual robot with haptic feedback teleoperation system," in *2024 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2024, pp. 12 663–12 670.

[18] T. Buamanee, M. Kobayashi, Y. Uranishi, and H. Takemura, "Bi-act: Bilateral control-based imitation learning via action chunking with transformer," *arXiv preprint arXiv:2401.17698*, 2024.

[19] X. Xu, Y. Liang, B. Huang, Z. Lan, and K. Shu, "Integrating mamba and transformer for long-short range time series forecasting," *arXiv preprint arXiv:2404.14757*, 2024.

[20] T. Tsuji, "Mamba as a motion encoder for robotic imitation learning," *arXiv preprint arXiv:2409.02636*, 2024.

[21] Y. Michel, Y. Abdelhalem, and G. Cheng, "Passivity-based teleoperation with variable rotational impedance control," *IEEE Robotics and Automation Letters*, 2024.

[22] V. Fortineau, V. Padois, and D. Daney, "Prediction of pose errors implied by external forces applied on robots: towards a metric for the control of collaborative robots," in *2024 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2024, pp. 1247–1253.