PACE
Proactive Assistance in Human-Robot Collaboration through Action-Completion Estimation

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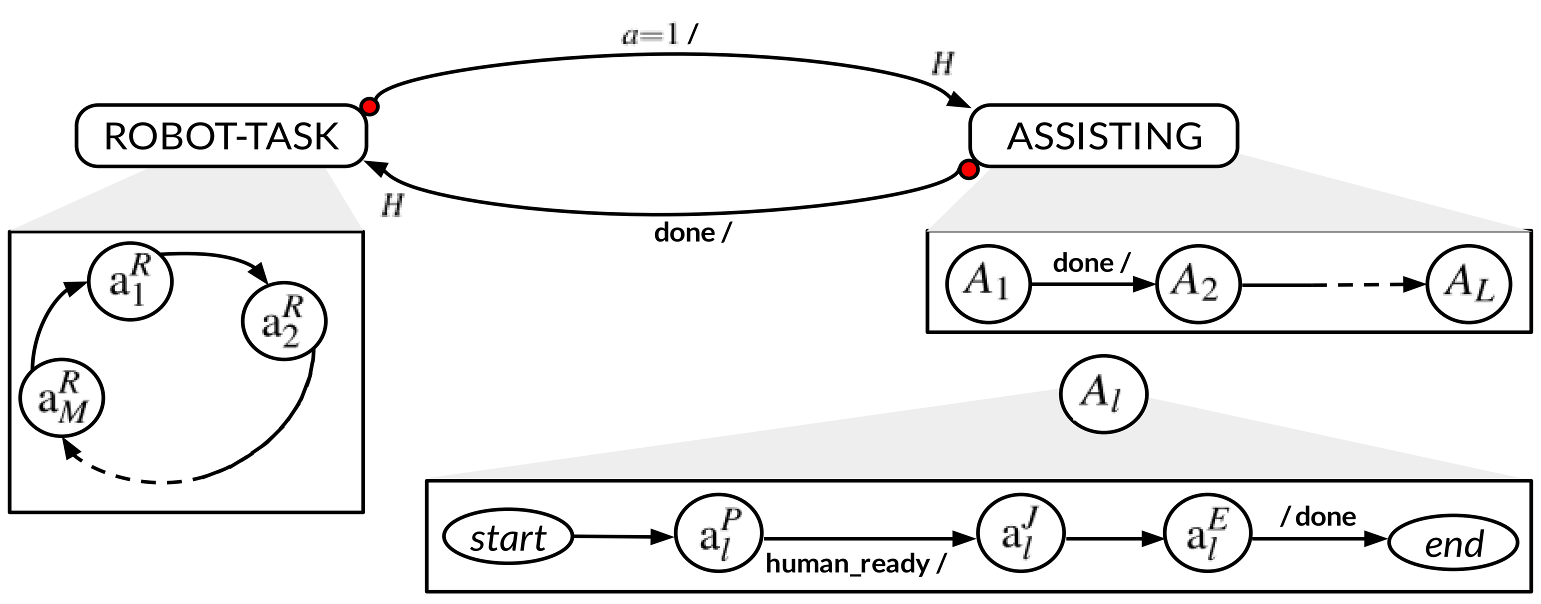
OVERVIEW

TL;DR: *We developed a* ***reinforcement learning*** *policy that proactively determines when to assist humans during assembly. We employ a new* ***Dynamic Time Warping*** *(DTW) algorithm to estimate the* ***completion percentage of the current human action****.*

Task

- **Human and robot concurrently perform separate tasks.**
- The robot performs a sequence of M *robot-task* actions (a_i^R).
- The human performs a sequence of N *human* actions (a_j^H).
- **The robot shall help the human to perform *joint* actions** (a_l^J).
- Prior to performing a *joint* action, the robot must pause its task and perform a *preparatory* action (e.g., collecting a tool).



Objective

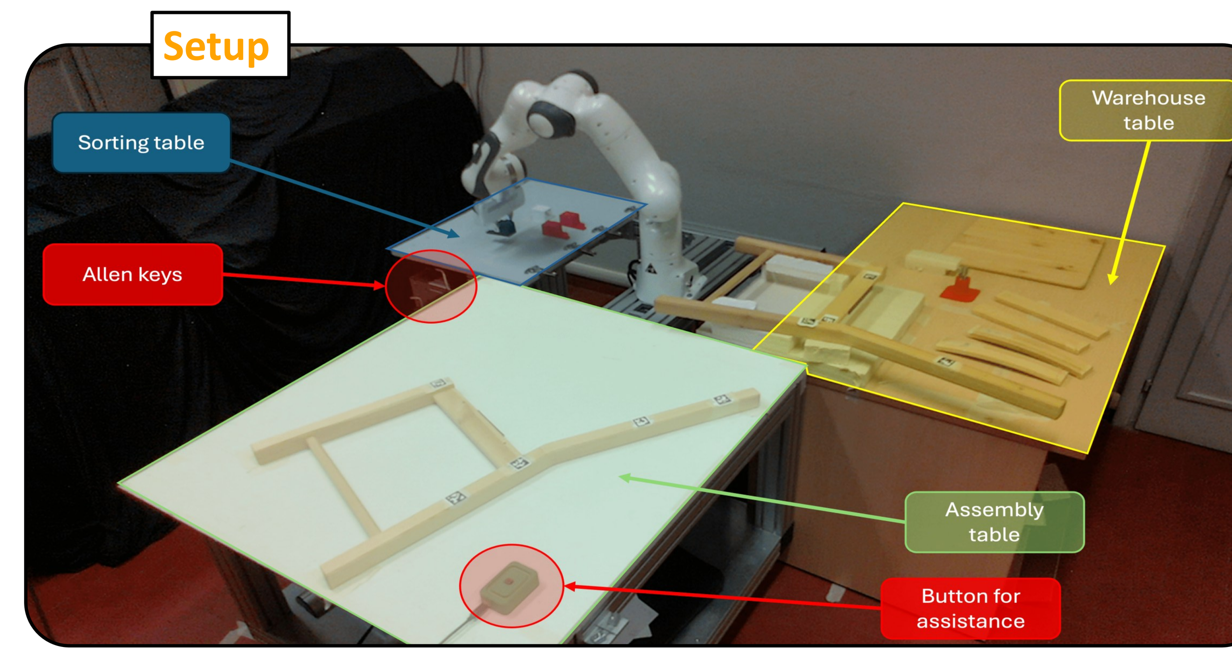
Assist the human at the right time to **minimize total idle time**:

$$\Delta^R_{\text{total idle}} + \lambda \Delta^H_{\text{total idle}}$$

Data

20 **demonstrations** including action durations and human hand trajectories.

Setup

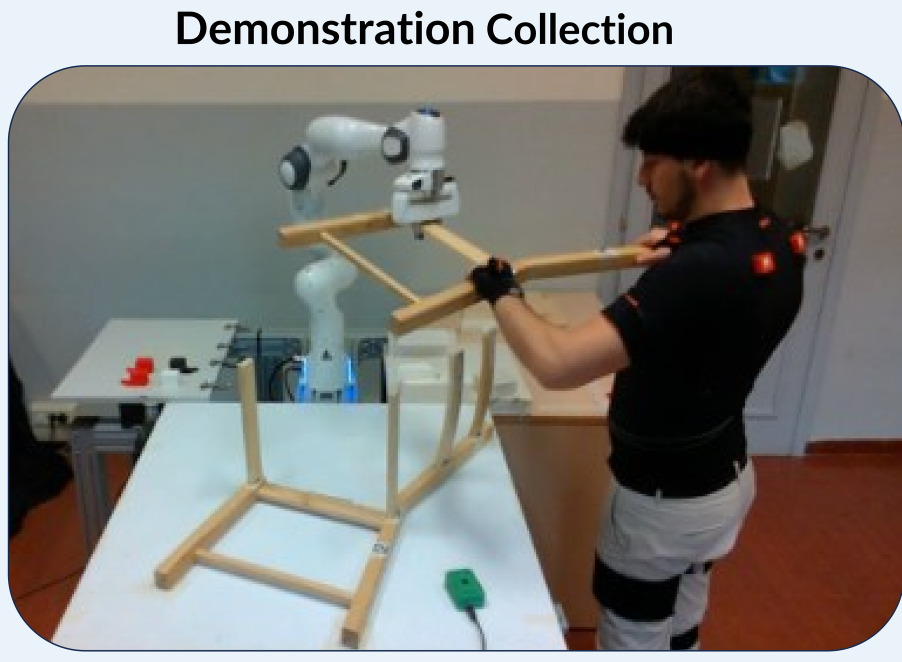


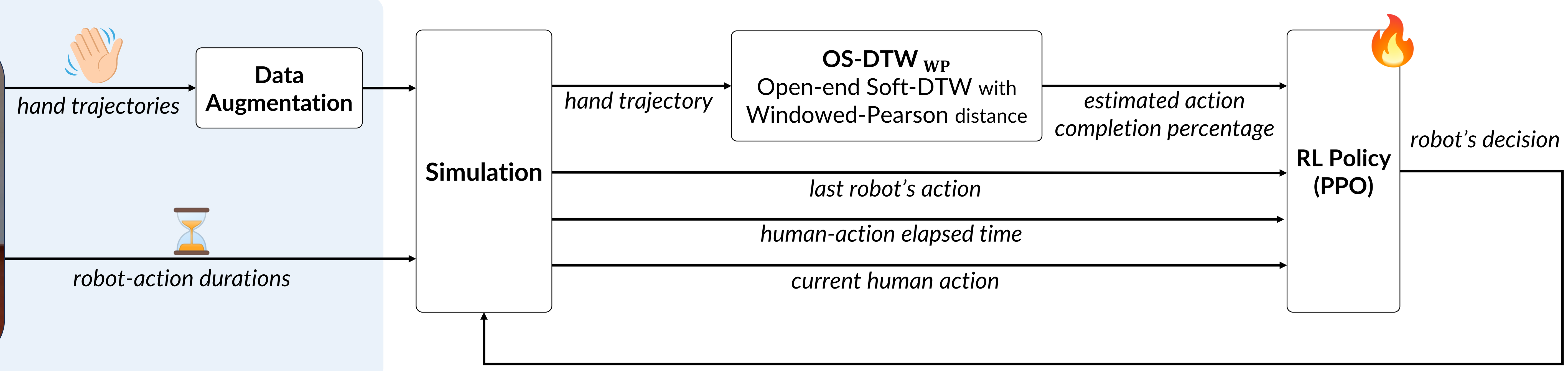
Contributions

- **OS-DTW $_{WP}$**: NEW Open-end Soft **Dynamic Time Warping** with **Windowed-Pearson** distance for real-time action completion estimation.
- **PACE Framework**: RL agent proactively assists humans, ensuring seamless collaboration.
- **Real-world Validation**: **Collaborative chair assembly**, showing improved collaboration efficiency, quantitative + subjective evaluations.
- **SotA real-time human action completion estimation**: OS-DTW $_{WP}$ outperforms existing DTW-based methods on real data.

RL POLICY TRAINING

Demonstration Collection

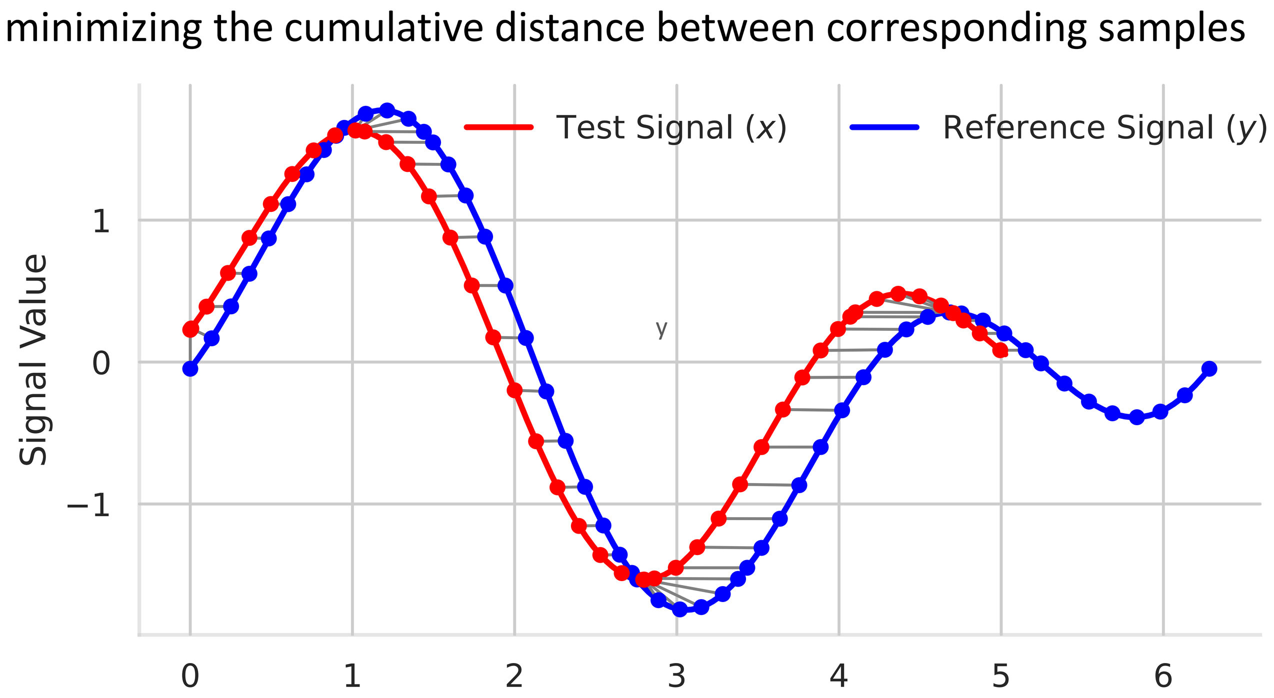




HUMAN ACTION COMPLETION ESTIMATION

Open-End Dynamic Time Warping

Open-end DTW aligns a signal to a percentage of a reference by minimizing the cumulative distance between corresponding samples



OS-DTW $_{WP}$

	Soft-minimum	Distance
OE-DTW	✗	Euclidean (EU)
OS-DTW $_{EU}$ (ours)	✓	Windowed-Pearson (WP)
OS-DTW $_{WP}$ (ours)	✓	Windowed-Pearson (WP)

Alignment cost (informal):

$$\propto \min_{\pi}{}^{\gamma} \sum_i \delta\left(x_i, y_{\pi(i)}\right)$$

Soft-minimum operator:
- introduces a smoothing factor that weighs all possible paths
- ensures that slight distortions do not dominate the final alignment

Euclidean distance:
- ✓ effective for signals with consistent absolute magnitudes across trials
- × sensitive to vertical offsets and amplitude variations

Windowed-Pearson distance:
- ✓ invariant to absolute shifts
- ✓ effectively captures local patterns

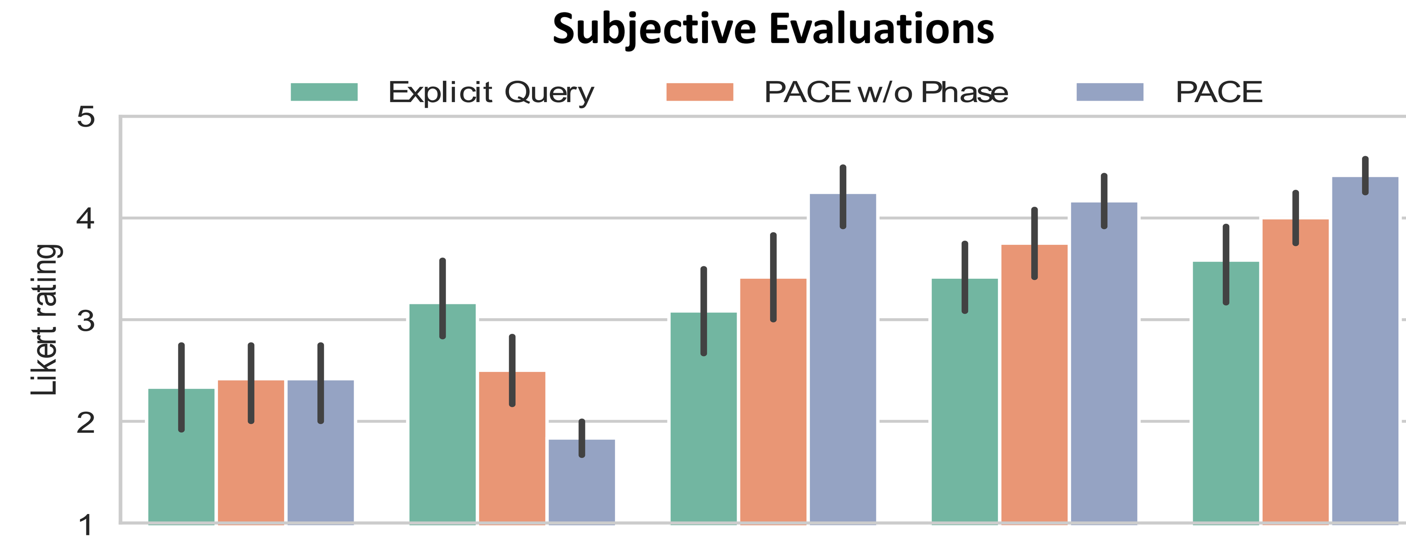
$$\delta^w_{\mathrm{WP}}(\mathbf{x}_i, \mathbf{y}_j) := \sum_{k=0}^{d-1}\left(1 - \frac{\mathrm{Cov}\left(\mathbf{x}_{i-w+1:i,k},\ \mathbf{y}_{j-w+1:j,k}\right)}{\sqrt{\mathrm{Var}\left(\mathbf{x}_{i-w+1:i,k}\right)\,\mathrm{Var}\left(\mathbf{y}_{j-w+1:j,k}\right)}}\right)$$

EXPERIMENTS & RESULTS

Quantitative Results

Method	Robot Idle Time [s]				Human Idle Time [s]				Total Cost ($\lambda = 3$)
	Rail Placing	Screw Placing	Screwing	Total	Rail Placing	Screw Placing	Screwing	Total	
Explicit query	0.0	0.0	0.0	0.0	14.00	11.28	12.15	37.43	112.3
PACE w/o phase (ours)	**1.56**	3.48	11.64	16.68	1.79	1.02	**1.06**	**3.87**	28.29
PACE (ours)	1.93	**2.65**	**1.28**	**5.86**	**1.20**	**0.56**	2.56	4.32	**18.81**

Subjective Evaluations



Rail Placing

Screw Placing

Handover (Joint Action)

Screwing

Phase Estimation MSE	Rail Placing	Screw Placing	Screwing
OE-DTW	0.100	0.091	0.168
OS-DTW $_{EU}$ (ours)	0.012	0.013	0.052
OS-DTW $_{WP}$ (ours)	**0.002**	**0.012**	**0.006**