

Learning-based slip detection for adaptive grasp control in robotic manipulation

Théo AYRAL

PhD Defense — 15 décembre 2025

Institut Cea-List, Nano-INNOV, Palaiseau

Composition du jury

- **Cédric CLEVY** Rapporteur
Professeur des universités, Université de Franche-Comté
- **Liming CHEN** – Rapporteur
Professeur des universités, Ecole Centrale de Lyon
- **Jean-Pierre GAZEAU** – Examineur
Ingénieur de recherche CNRS, Institut P'
- **Richard BEAREE** – Examineur
Professeur des universités, ENSAM Lille
- **Maria MAKAROV** – Examinatrice
Enseignant-chercheur, CentraleSupélec - Université Paris-Saclay

- **Mathieu GROSSARD** – Directeur de thèse
Directeur de recherche, CEA-List
- **Saifeddine Aloui** – Co-encadrant
Ingénieur de recherche, CEA-Leti

From pre-programmed pick-and-place to contact-rich manipulation

- Adaptation / Versatility ↓
- 1. Pre-programmed pick-and-place**
 - Hard-coded motions in **controlled environments**
 - 2. Force-controlled grasping**
 - Deformable and fragile objects
 - 3. Dexterous, contact-rich manipulation**
 - Adaptation to **unstructured environments**
 - Multi-contact planning for in-hand manipulation
 - Robust handling of unknown, irregular, and deformable objects



Boston Dynamics humanoid robot

Need for dexterity

Logistics

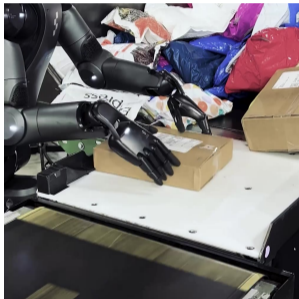
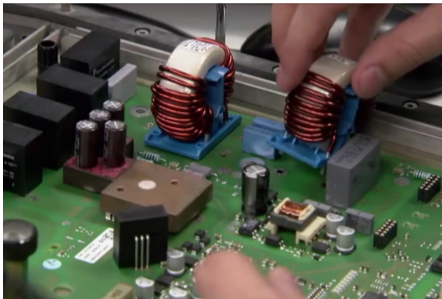


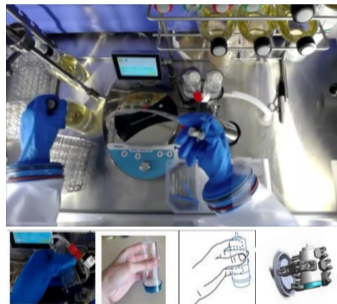
Figure A1

Manufacturing



Z-AXIS Inc.

Critical environments



EU project TraceBot

Roadmaps: EU robotics (SPARC/ADRA) call for **adaptive, tactile-aware** manipulation.

Enablers of dexterity 1/3

Versatile grippers

- Multi-digit grippers, articulated fingers
- Reconfigurability for human grasps
- Controlled contact forces

Increasing degrees of freedom (DoF) →



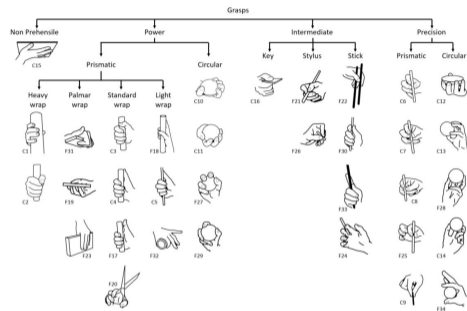
Robotiq



RBO hand TU Berlin



Shadow Robot



Escorcia-Hernández et al., 2023

Contribution

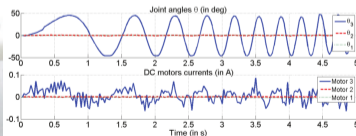
- ✓ Ensuring **stability** of multifingered grasps
- ✓ **Coordination** of contact forces

Enablers of dexterity 2/3

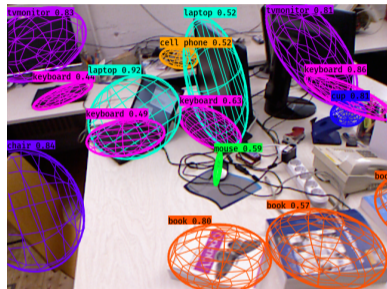
Perception for adaptation

- Vision for global scene understanding
- Tactile for local contact state
- Proprioception for internal state

→ Closing feedback loops



CEA Hand, Martin and Grossard, 2014
Garrec, P. 2008



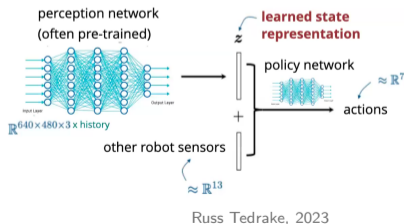
Contribution

- ✓ Tactile perception for object slip detection
- ✓ Feedback loop with **adaptive** force modulation

Enablers of dexterity 3/3

Learning robust policies

- High-DoF gripper control
- Multimodal sensor fusion
- Implicit models
- Data-driven **robustness** and **generalization**



Toyota Research Institute

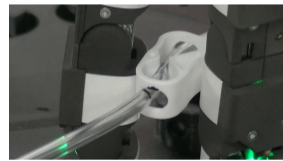
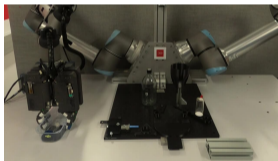
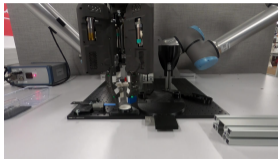
Contribution

- ✓ Learning **robust tactile perception**
- ✓ Data-driven **multimodal sensor fusion**

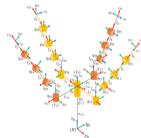
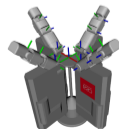
Experimental setup



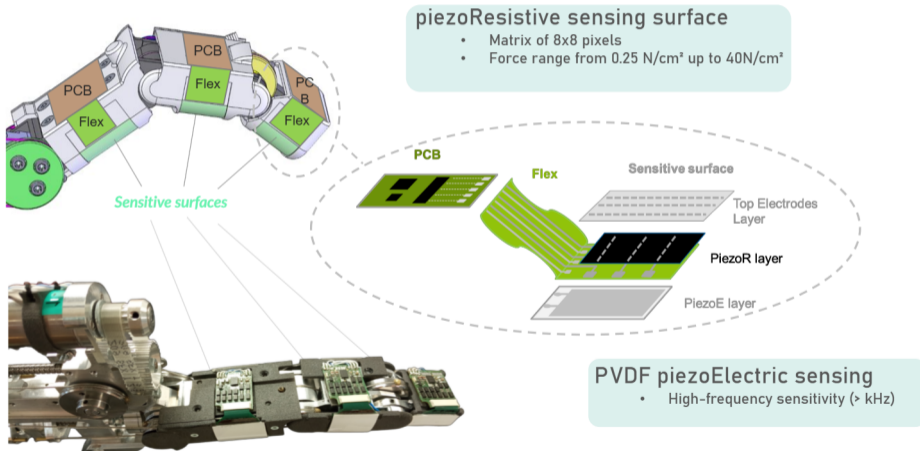
EU project TraceBot



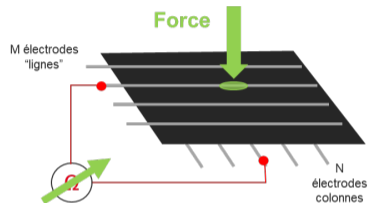
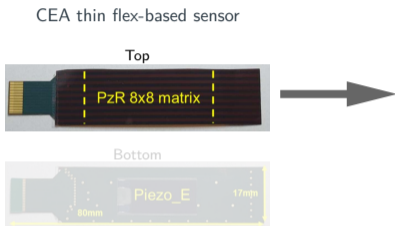
- **Four-fingered 14-DoF gripper**
- **Haptic sensing capabilities**
- **Hybrid tactile pads on each phalanx and palm**



Hybrid tactile sensor PzE / PzR



Piezoresistive sensor (PzR)

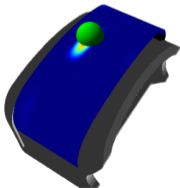


Piezoresistivity

Electrical **resistance** decreases locally under mechanical **pressure**.

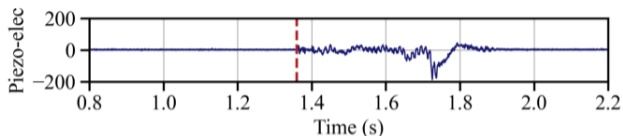
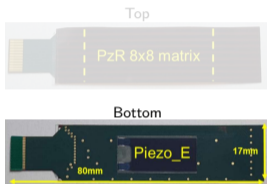
- 100 μm piezoresistive *VelostatTM* polymer
- Screen-printed silver ink electrodes
- Two orthogonal sheets for 8 \times 8 taxel matrix (lines \times columns)

→ **spatial distribution of pressure, contact points**



Piezoelectric sensor (PzE)

CEA thin flex-based sensor

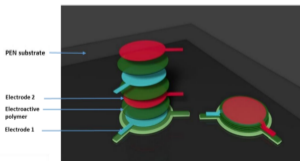


Piezoelectricity

Mechanical stress produces electric charge in the material.

- **PVDF-TrFE** transducers between *PEDOT:PSS* electrodes
- **10kHz sampling**, effective bandwidth 30 Hz–2.5 kHz.

→ detects high-frequency events and vibrations



Contributions

- **C1 — Early slip detection from tactile vibrations**
Detect **incipient slip** with spectro-temporal analysis in real-time.
- **C2 — Robustness in manipulation**
Avoid **false alarms** under perturbations by learning robustness with haptic data fusion.
- **C3 — Closed-loop grasp adjustment**
Stabilize multi-fingered grasp without explicit friction models.

Outline

1 - Introduction

2 - Learning-Based Slip Detection with Spectro-Temporal Features

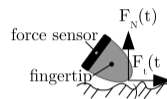
3 - Data-Driven Robustness for Tactile Slip Detection

4 - Reactive Slip Control in Multifingered Grasp

5 - Conclusion and perspectives

Tactile modalities for slip detection

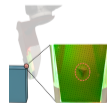
- **Forces/efforts** (FT, currents, torques):
 quantitative, global, bandwidth-limited
- **Contact pattern** (pressure/PzR):
 spatial array, contact positions (CoP, area)
- **Vibrations** (PzE):
 dynamic events, high bandwidth, ms-scale latency
- **Vision-based tactile** (GelSight & co.):
 high-dimensional, rich representation (learning)



Kappasov et al., 2015



Sundaram et al., 2019



Hogan et al., 2020

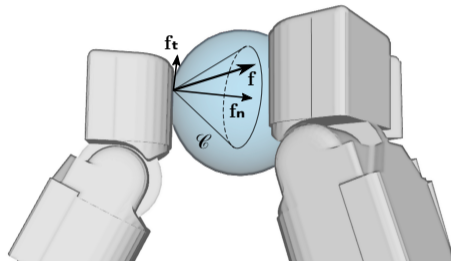
Slip detection state of the art: friction modeling

Classical model-based approach

Friction cone:

$$\|f_t\| \leq \mu \|f_n\|$$

- f_t : tangential contact force
- f_n : normal contact force
- μ : friction coefficient

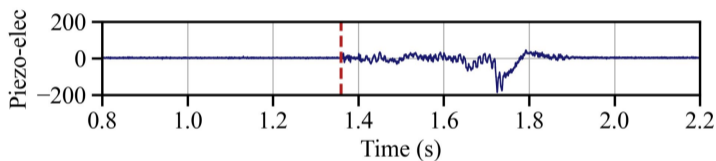


Practical challenges

- Bulky hardware (6D force/torque sensors)
- Uncertain μ estimates (material, surface, speed, humidity)

Recasting slip detection: from friction cones to practical cues

Vibration-based slip detection



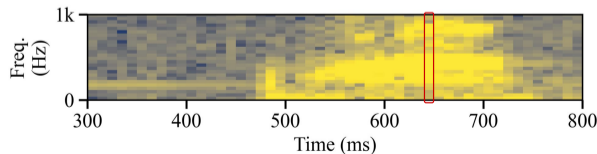
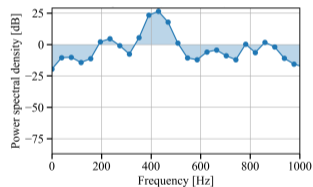
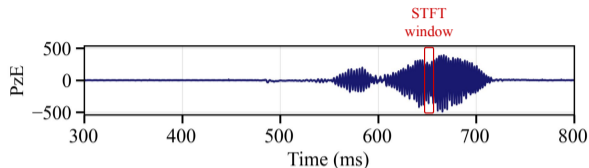
- **Direct physical cue:** friction-induced micro-vibrations at slip onset.
- **Fast and causal:** millisecond-scale windows, event-triggered.
- **Low instrumentation:** no *force/torque* sensing, no μ estimation.
- **Fits embodiment:** thin, flexible PzE pads on the finger surface.

Online spectral representation of the tactile signal

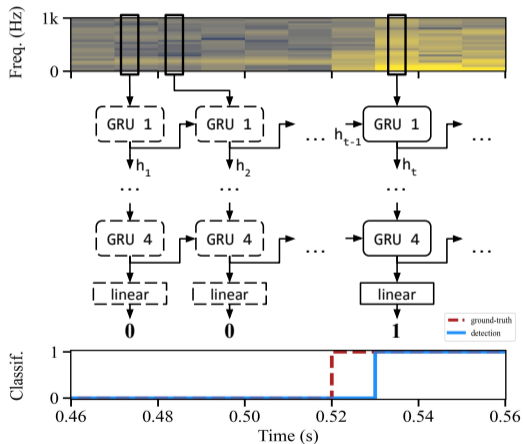
- **Fast Fourier Transform (FFT)**
→ power spectral density (PSD)
- **Sliding window**
- Building the **spectrogram**

Discrete Fourier transform (length N):

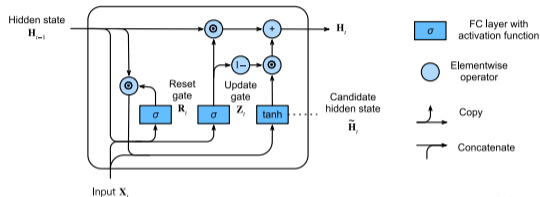
$$X[k] = \sum_{n=0}^{N-1} x[n] e^{-j2\pi kn/N}$$



Neural network GRU



Gated Recurrent Unit (GRU)



d2l.ai

- Identify **spectral patterns** of friction
- Analyse **temporal evolution** with recurrence
- 100Hz classification** with binary classes
- Training** with binary cross entropy loss (BCE)

$$\mathcal{L}_{\text{BCE}} = -\frac{1}{N} \sum_t \log p_t^*$$

Slip-detection pipeline

PiezoElectric Sensor, 10kHz

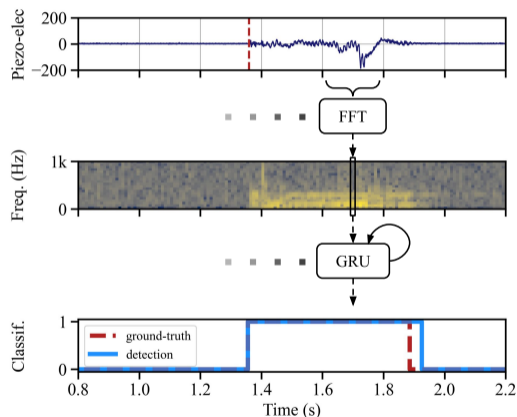
- reacts to **pressure changes at contact**
- captures **slip-related vibrations**

Fast Fourier Transform (FFT)

- efficient **spectral representation**
- **vibratory signature** of events

Gated Recurrent Units (GRU)

- **data-oriented** for unmodeled spectral profiles
- analyze the **temporal evolution** of the events
- processing in **real time**

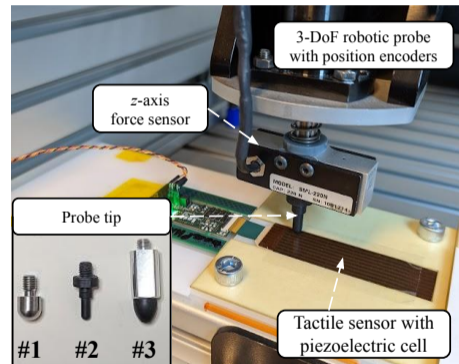


Slip classifier pipeline (10 kHz → FFT → GRU)

Data collection setup

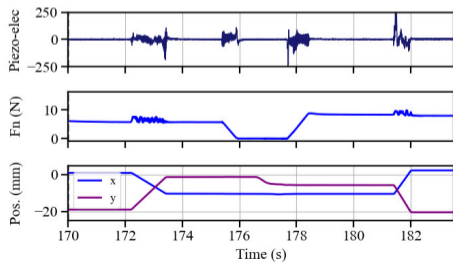
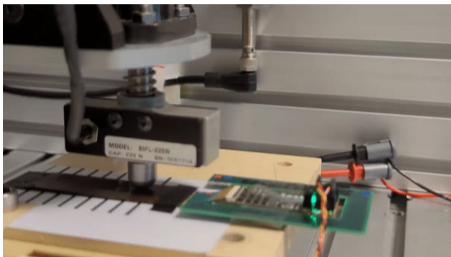
Data collection on a robotic bench

- Piezoelectric sensor on a flat surface
- Robotic probe applying normal force
- Sliding motion generated

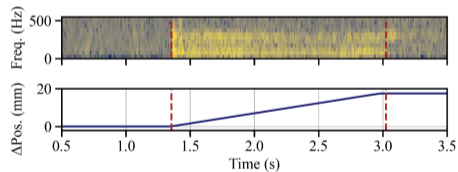


CAROUSEL bench (CEA)

Accurate labels



Slippage timing from ground-truth position



Automatic data-collection

Randomly parametrized slip trajectories

- 2–10 N force
- 10–32 mm travel
- 200–2000 mm/min speed

Dataset

- 3,200 recordings
- ~ 1.5 s slip duration



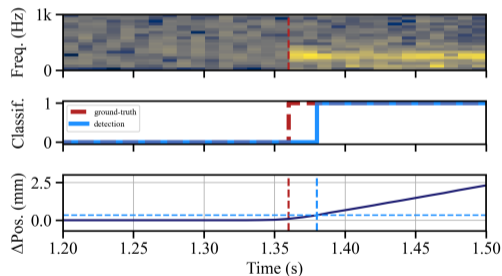
Ablation study

Input	Model (size)	Params	F1	Acc.
FFT	GRU (d=32)	23k	0.9781	98.70%
FFT	GRU (d=128)	352k	0.9787	98.73%
raw	GRU (d=32)	22k	0.9157	94.71%
FFT	MLP (d=128, <i>no temporal</i>)	51k	0.7941	89.39%
FFT	TCN (d=128, ker=32, <i>causal</i>)	1.6M	0.9694	98.26%

Results

- **C1 — Early slip detection from tactile vibrations**

Detect **incipient slip** (8.5 ms average delay) with **spectro-temporal** analysis in **real-time**.



Paper published at AIM 2023

Spectro-Temporal Recurrent Neural Network for Robotic Slip Detection with Piezoelectric Tactile Sensor
2023 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM)

Outline

1 - Introduction

2 - Learning-Based Slip Detection with Spectro-Temporal Features

3 - Data-Driven Robustness for Tactile Slip Detection

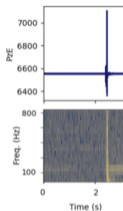
4 - Reactive Slip Control in Multifingered Grasp

5 - Conclusion and perspectives

Manipulation perturbations: false alarms in slip detection

Transient perturbations:

- Short, impulsive events
- Brief broadband spikes



External disturbances (Collisions with the environment)



Shadow Robot

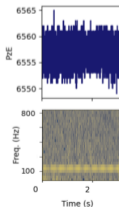
Intentional events (squeezing, regrasp)



IEEE RAS

Ambient perturbations:

- Vibratory background
- Persistent narrow-band noise



Environmental vibrations (tool vibration)



Max Plank Institute

Actuation noise (motor vibration)



Freepik

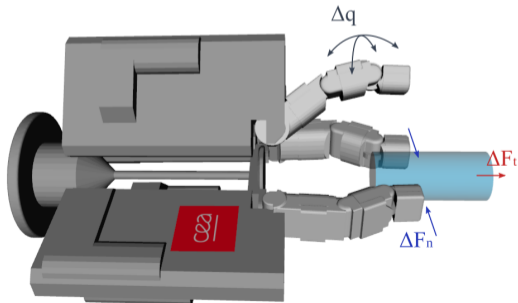
Generating perturbations for training

Perturbation taxonomy

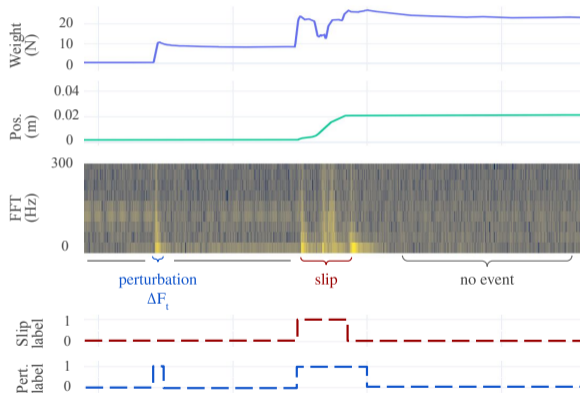
ΔF_n — **Grasp effort variations**: normal force (tighten/release)

ΔF_t — **External load variations**: tangential load (shear/traction)

Δq — **Actuation noise**: structural vibrations



Data-imbalance issue



Binary classification: *slip vs. non-slip*

Short and rare events

→ weak learning signal

Learning from perturbations with weighted losses

Binary Cross Entropy loss (BCE)

$$\mathcal{L}_{\text{BCE}} = -\frac{1}{N} \sum_t \log p_t^*$$

p_t^* : predicted probability of the true class y_t ;

N : number of frames.

Perturbation-aware weighting (ω)

Balance data types :

- *slip / no-slip.*
- *clean no-slip / perturbation.*

$$\mathcal{L}_w = -\frac{1}{\sum_t \omega_t} \sum_t \omega_t \log p_t^*$$

ω_t computed from perturbation time labels

Focal loss (γ)

Alternative without perturbation labels

focus on *difficult* predictions

$$\mathcal{L}_{\text{focal}} = -\frac{1}{N} \sum_t (\mathbf{1} - \mathbf{p}_t^*)^\gamma \log p_t^*.$$

Tuned parameter γ defines focal temperature.

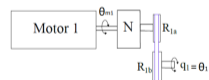
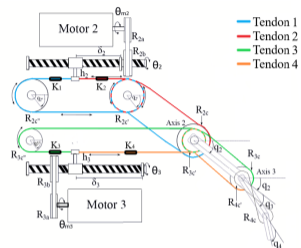
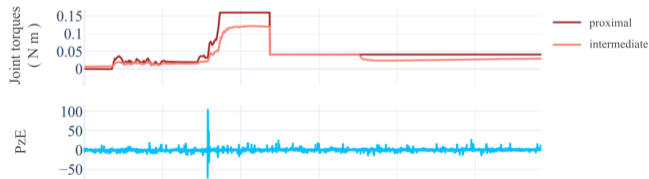
Haptic data fusion

Joint torque estimation (τ)
with backdrivable finger actuation

Multimodal input

- tactile
- proprioception

→ disambiguate intentional events from true slip



Escorcia-Hernández et al., 2023

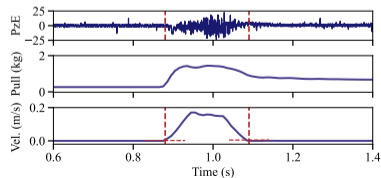
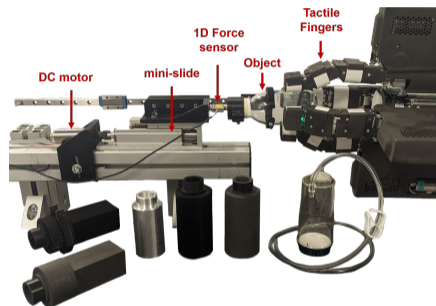
Data-collection bench: slip generation & ground truth

Grasped object secured to actuated slide

Randomized slip trajectories

- accel/velocity/duration
- grasp configurations
- object shapes and textures

→ Slip and perturbation ground-truth



Dataset details

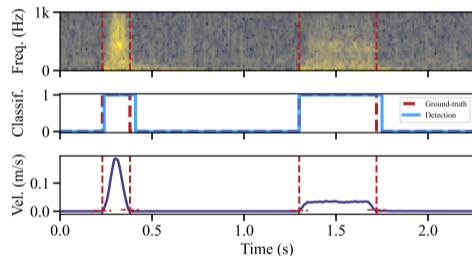
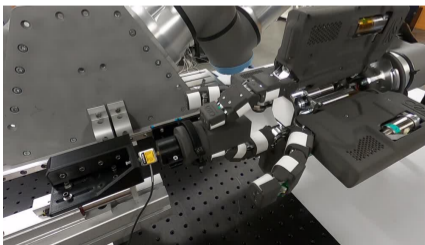
Segments:

2056 total (5 s)

~50% slip / 50% no-slip

extra 300 *perturbation-only*.

Slip duration: 330 ± 193 ms on average.



Successive slip events successfully detected.

Baselines under manipulation perturbations

Model	Data	Acc@100Hz	Delay (ms)	Clean F1	Robust. (%)
PzE-Threshold	Clean	74.0	6.3 ± 61.9	0.97	38.6
	+Perturb.	71.3	8.0 ± 82.4	0.94	62.1
FFT-LogReg	Clean	95.6	25.4 ± 40.1	1.00	20.8
	+Perturb.	94.3	21.9 ± 27.5	1.00	25.0
FFT-GRU (baseline)	Clean	98.1	16.8 ± 8.7	1.00	5.3
	+Perturb.	95.8	18.3 ± 12.4	1.00	42.1

- All classifiers perform well on *clean* data but fail on perturbations.
- Training with perturbation data improves robustness but remains **insufficient** without targeted supervision.

Robustness via targeted supervision (FFT-GRU)

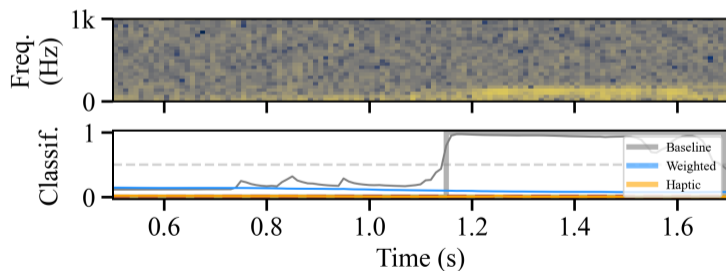
Model	Delay (ms)	Clean F1	Δq	ΔF_n	ΔF_t
FFT-GRU <i>baseline</i>	17.8 ± 9.5	1.000	52.8	43.9	19.6
FFT-GRU <i>focal</i> ($\gamma=2$)	25.3 ± 21.2	0.998	65.0	50.7	36.8
FFT-GRU <i>weighted</i> (ω)	22.5 ± 16.2	1.000	96.8	56.7	97.0
FFT-GRU <i>haptic</i> ($\omega, +\tau$)	24.1 ± 18.0	1.000	96.8	79.4	95.1

- **Weighting** improves robustness on Δq / ΔF_t (specificity $\sim 97\%$).
- **Focal loss** provides a lower-performing alternative with no perturbation labels.
- **Haptic data** helps for ΔF_n (up to **79.4%**)

Robustness to motor vibrations

Actuation noise Δq

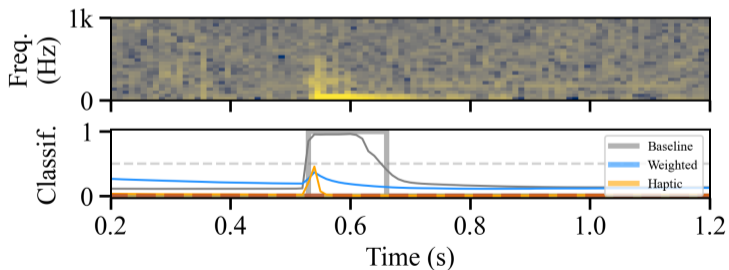
- *Baseline* model continuously fails, **predicting slip class**.
- *Weighted* and *Haptic* models are robust.



Robustness to object load variation

External perturbation ΔF_t

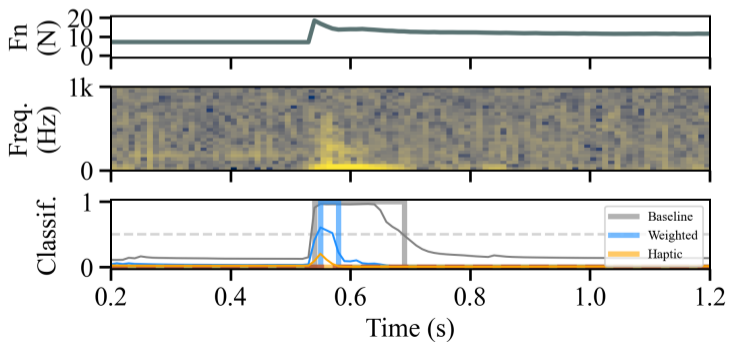
- *Baseline* model triggers **false positive**.
- *Weighted* and *Haptic* models are robust.



Robustness to intentional grasp effort variation

Intentional perturbation ΔF_n

- *Baseline* and *Weighted* models fail.
- *Haptic fusion* avoids false alarm.



Robust slip detection: summary

- **C2 — Data-driven robustness to perturbations**

Fewer false alarms under transient events and actuation noise (robustness: 38.77% \rightarrow 90.43%).

Perfect recall on slip events and *low detection delay* (24.1 ms average).

Paper submitted to CoDIT 2026

Robust Tactile Slip Detection under Manipulation Perturbations

Outline

1 - Introduction

2 - Learning-Based Slip Detection with Spectro-Temporal Features

3 - Data-Driven Robustness for Tactile Slip Detection

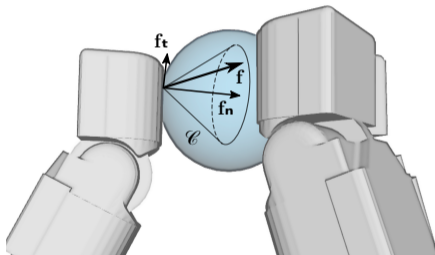
4 - Reactive Slip Control in Multifingered Grasp

5 - Conclusion and perspectives

Grasp force optimization - State of the art 1/2

Model-based approach

with friction cone constraints



Solve for the **full contact wrench**:

Minimize $\|f\|$

subject to :

- **Object equilibrium** under external perturbation w_{ext} , with grasp matrix G :

$$w_{\text{ext}} + Gf = 0$$

- **Friction constraints** per contact i :

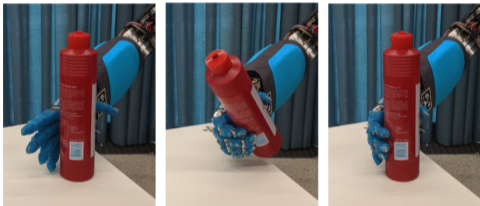
$$\|f_{t,i}\| \leq \mu_i f_{n,i}$$

- **Feasibility** with joint torques τ and hand jacobian J :

$$\tau = J^T f, \quad \tau_{\min} \leq \tau \leq \tau_{\max}, \quad f_n > 0.$$

Grasp force optimization - State of the art 2/2

Grasp force increase



Pfanne et al., 2020

Unbalanced forces across fingers inducing a net object torque \Rightarrow rotation/slip.

Grasp matrix G : *contacts* \rightarrow *object wrench*

$$w = G f$$

Internal forces in the kernel of G

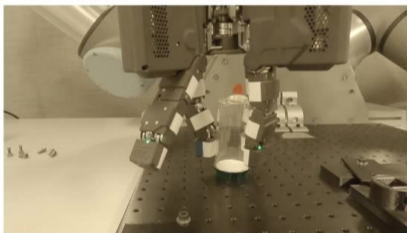
$$f = f_{\text{manip}} + f_0,$$

with $G f_0 = 0$, $f_0 \in \mathcal{N}(G)$

Stabilize object by *increasing* internal forces f_0

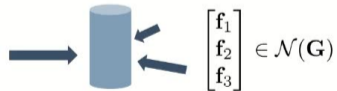
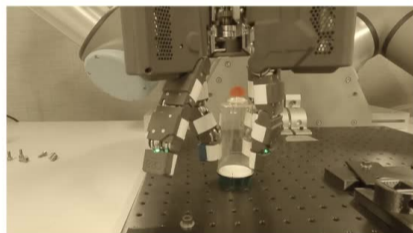
Internal force increase: Experimental validation

Uniform forces → Failure



$$\|f_1\| = \|f_2\| = \|f_3\|$$

Internal forces → Stable Grasp

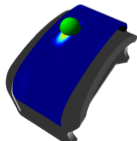
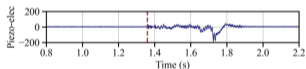


Our approach: Reactive slip control (RSC)

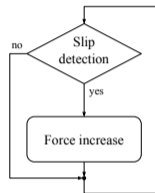
Practical constraints

- no force/torque sensing
- no estimation of friction coefficient μ

Hybrid tactile sensing



Tactile feedback loop



Slip detection

- Learning-based perception of **friction vibrations**

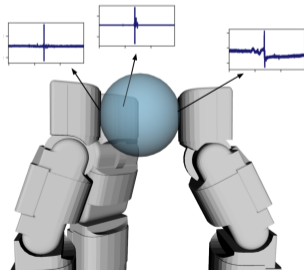
Force increase

- Coordination of **internal forces**
- Grasp matrix built from **contact points**

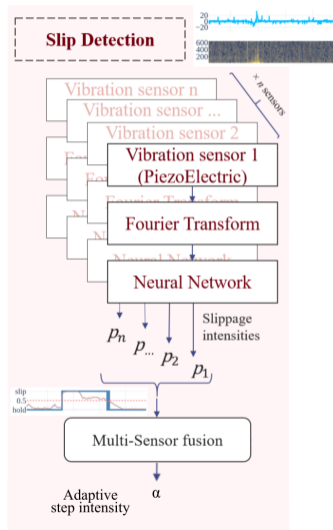
Reactive slip control in multifingered grasp - Slip detection

- Parallel inference for slip detection
→ per-contact slip scores p_1, \dots, p_n
- Fusion of scores (e.g., first-hit, max, average)
→ trade-off *delay vs robustness* via redundancy
- Global response with a single adaptive force step decision

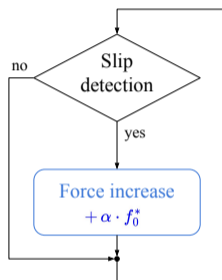
α



Multiple sensors in contact

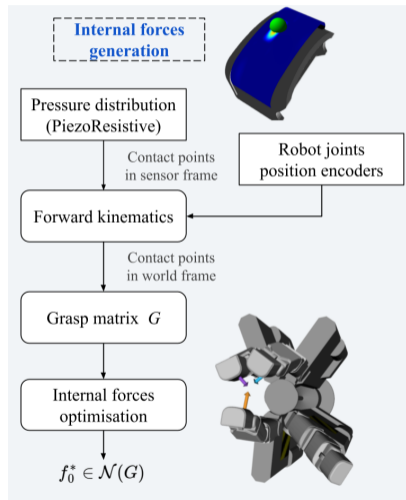


Internal force optimization pipeline



Internal force increase at each step: $\Delta f_0 = \alpha \cdot f_0^*$

- Step force **intensity**, scaling factor α
- Normalized **force profile** $f_0^* \in \mathcal{N}(G)$



Reactive Slip Control — Internal Force Optimization

Selecting an internal-force profile f_0^* in $\mathcal{N}(G)$

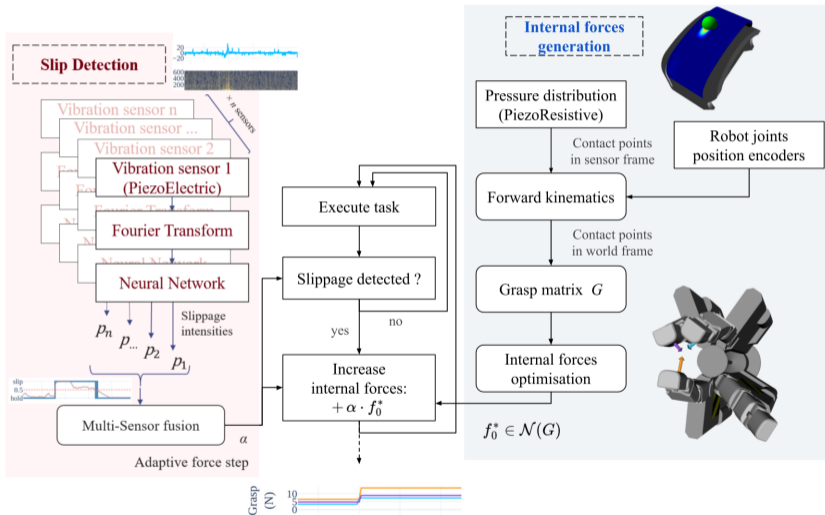
$$\max_{f_0^*} \left(\underbrace{\sum_{i=1}^{N_c} f_{n,i}^*}_{\text{promote normals}} - \underbrace{\sum_{i=1}^{N_c} \|f_{t,i}^*\|^2}_{\text{penalize tangential}} - \underbrace{\frac{1}{N_c} \sum_{i=1}^{N_c} (f_{n,i}^* - \bar{f}_n^*)^2}_{\text{distribute across contacts}} \right)$$

s.t. $Gf_0^* = 0, \quad \tau_{\min} \leq J^\top f_0^* \leq \tau_{\max}, \quad f_{n,i}^* \geq 0 \quad \forall i.$

Key ideas

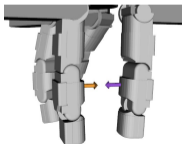
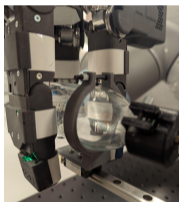
- Work *inside* the grasp null space: $f_0^* \in \mathcal{N}(G)$.
- Increase normal components, avoid tangential ones, favor effort sharing across contacts.
- Respect actuation limits via $J^\top f_0^*$ box constraints, nonnegative normals.

Summary of our approach



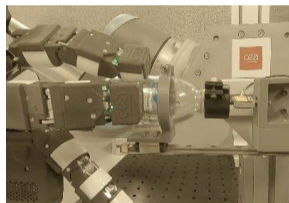
Experimental validation

Symmetric 2-finger grasp (parallel claw)



Trivial force coordination

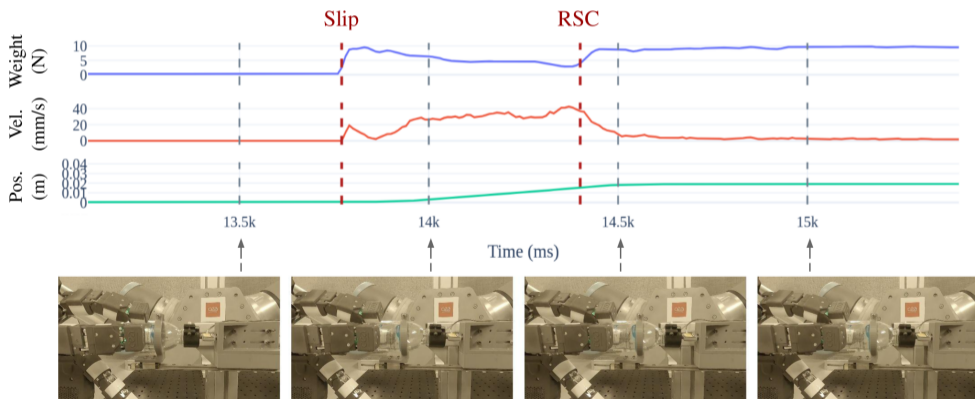
Asymmetric 3-finger grasp on a cylinder (planar)



Internal forces in $\mathcal{N}(G)$

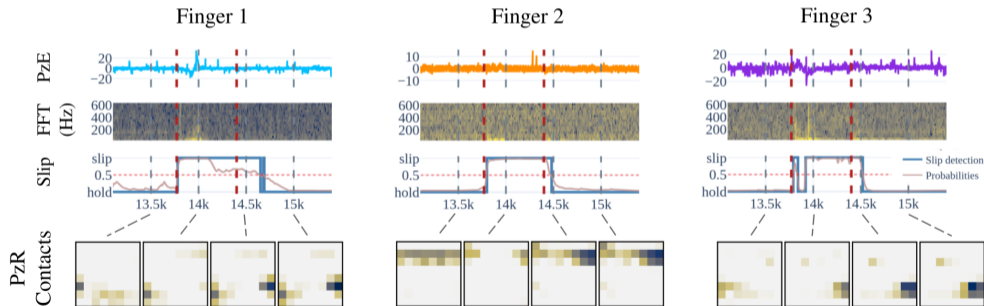
Experimental validation

Asymmetric 3-finger grasp on a cylinder (planar)



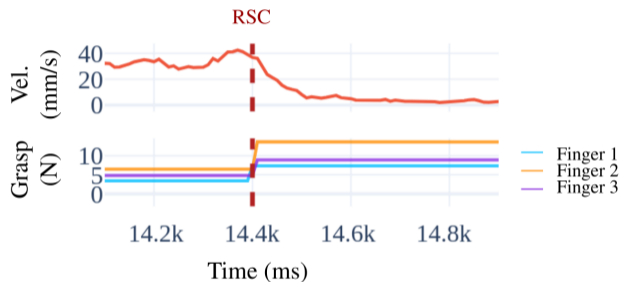
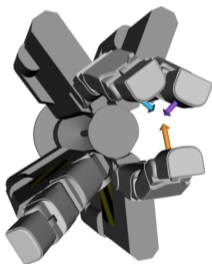
Experimental validation

Asymmetric 3-finger grasp on a cylinder (planar)



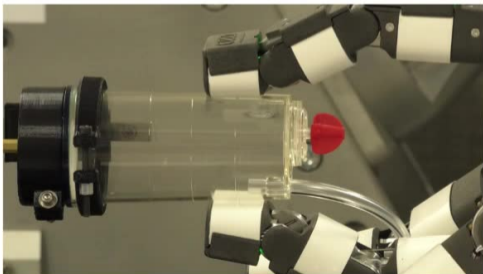
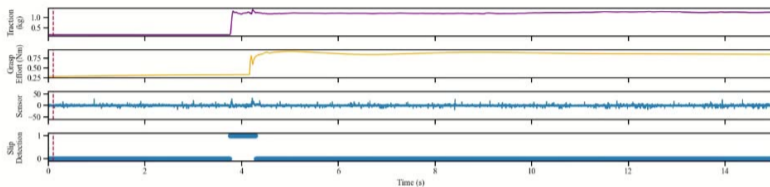
Experimental validation

Asymmetric 3-finger grasp on a cylinder (planar)



- non-trivial internal force coordination in $\mathcal{N}(G)$
- RSC triggers after ~ 130 ms
- 19 mm object travel before stop

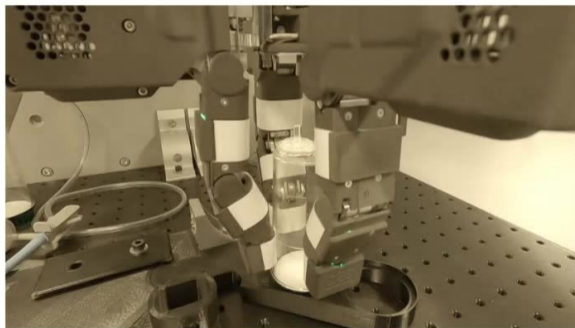
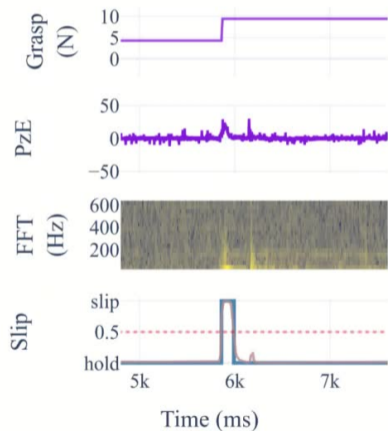
Experimental validation



Slip detection triggers
grasp force increase
to stop object slip

Experimental validation

Adaptive grasp forces



Reactive slip control: Conclusion

- **C3 — Closed-loop adaptation of grasp forces**

Stabilize **multi-finger grasps** by injecting **internal forces** without explicit friction models.

Reference	Reaction time	Method (signal → action)
Human baseline	~70 ms	Tactile perception → reflex force
Zeng et al., 2022	45–190 ms	Prosthetic hand; DWT slip cue
Wettels et al., 2009	~750 ms	Biomimetic tactile → Bayesian/Kalman
ours (theoretical)	35–40 ms	PzE 10 kHz → FFT + small GRU (causal)

Paper accepted at ICRA 2026

Reactive Slip Control in Multifingered Grasping: Hybrid Tactile Sensing and Internal-Force Optimization

Patent application:

Robotic gripper and control method

US Patent Application 19/011,931, 2025

Outline

1 - Introduction

2 - Learning-Based Slip Detection with Spectro-Temporal Features

3 - Data-Driven Robustness for Tactile Slip Detection

4 - Reactive Slip Control in Multifingered Grasp

5 - Conclusion and perspectives

Conclusion

- **C1 — Early slip detection from tactile vibrations**

Detect **incipient slip** with a *piezoelectric sensor* capturing friction vibrations
Learning-based spectro-temporal analysis in **real-time** (100Hz)

- **C2 — Data-driven robustness to perturbations**

Fewer false alarms under transient events and actuation noise (robustness: 38.77% → 90.43%)
Perfect recall on slip events and *low detection delay* (24.1 ms average)

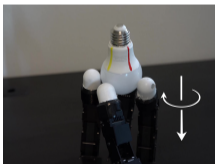
- **C3 — Closed-loop adaptation of grasp forces**

Stabilize **multi-finger grasps** by injecting **internal forces** *without explicit friction models*
Tactile feedback loop leveraging slip detection for **short reaction time**

Perspectives 1/3

Reactive low-force control and dexterity

- *Slip control* and *manipulation* in parallel.
- Controlling manipulation forces and internal forces **independently**.
- *Minimal contact forces* enable faster and more agile **finger movements**, instead of rigid grasps.



Qi et al. (2025)

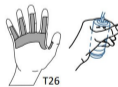
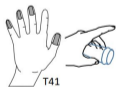
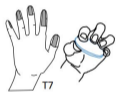
Hierarchical reorientation policy



Perspectives 2/3

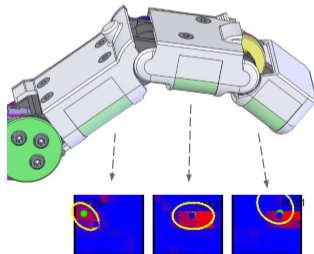
Rich contact modeling and deformable objects

- Generalize **beyond point-contact models** to exploit distributed whole-hand tactile information.
- Design models and controllers for **continuous contact regions**.



Precision grasps

Power grasps

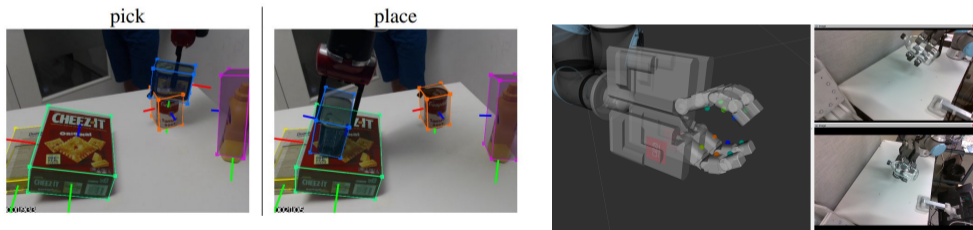


EU Project TraceBot

Perspectives 3/3

Multimodal perception

- Fuse **tactile sensing** with **vision** for robust, anticipatory grasp control.
- Interpret slip events in the context of *object pose*, *scene dynamics*, and *task goals*.



Tremblay et al. (2018)

Questions

Thank you for your attention

Publications

Paper published at AIM 2023

Spectro-Temporal Recurrent Neural Network for Robotic Slip Detection with Piezoelectric Tactile Sensor

Théo Ayral, Saifeddine Aloui and Mathieu Grossard,

2023 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM),

Jun 2023, Seattle (USA), United States

Paper submitted to CoDIT 2026

Robust Tactile Slip Detection under Manipulation Perturbations

Théo Ayral, Saifeddine Aloui, Mathieu Grossard

Paper accepted at ICRA 2026

Reactive Slip Control in Multifingered Grasping: Hybrid Tactile Sensing and Internal-Force Optimization

Théo Ayral, Saifeddine Aloui, Mathieu Grossard

Patent application:

Robotic gripper and control method

M Grossard, S Aloui, T AYRAL

US Patent Application 19/011,931, 2025

Learning-based slip detection for adaptive grasp control in robotic manipulation

Théo AYRAL

PhD Defense — 15 décembre 2025

Institut Cea-List, Nano-INNOV, Palaiseau

Composition du jury

- **Cédric CLEVY** Rapporteur
Professeur des universités, Université de Franche-Comté
- **Liming CHEN** – Rapporteur
Professeur des universités, Ecole Centrale de Lyon
- **Jean-Pierre GAZEAU** – Examineur
Ingénieur de recherche CNRS, Institut P'
- **Richard BEAREE** – Examineur
Professeur des universités, ENSAM Lille
- **Maria MAKAROV** – Examinatrice
Enseignant-chercheur, CentraleSupélec - Université Paris-Saclay

- **Mathieu GROSSARD** – Directeur de thèse
Directeur de recherche, CEA-List
- **Saifeddine Aloui** – Co-encadrant
Ingénieur de recherche, CEA-Leti