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INSTITUTE OF  
ELECTRONICS AND  
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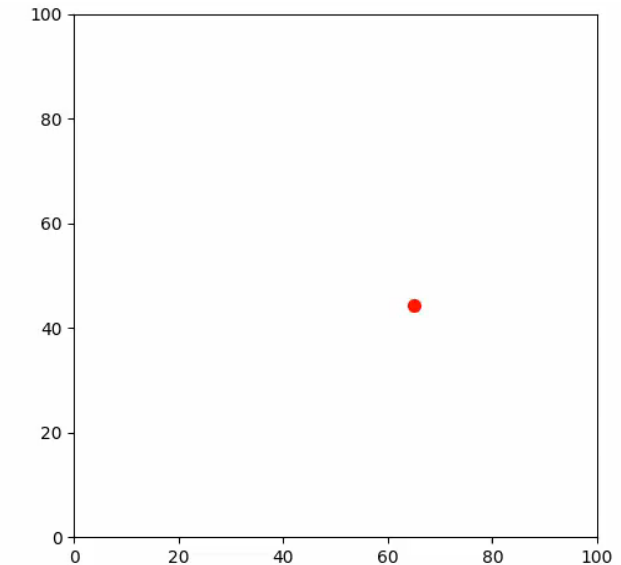
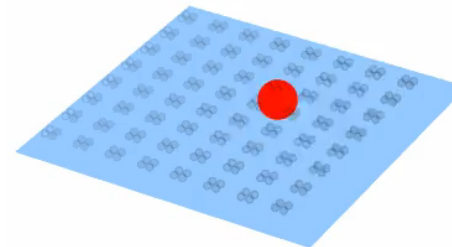
# My progress so far

Oskars Teikmanis

7th semester

# Recap of last time

- Current status:  
Researcher at the Institute of Electronics and Computer Science (EDI) and 4th year doctoral student at the University of Latvia
- Presented last time:
  - Work within 5G-ROUTES project: **self-driving vehicle publication**
  - Work within VPP-MOTE project: **differentiable physics for fluid manipulation**
  - Plans with quadrupedal robots



# 5G-ROUTES

- Summer tests for communication between vehicles via 5G.



- Video for project closure, featuring platooning and lane-change.





## Learning to Move Objects with Fluid Streams in a Differentiable Simulation

Kārlis Freivalds, Laura Leja, Oskars Teikmanis  
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**Abstract**—We introduce a method for manipulating objects in three-dimensional space using controlled fluid streams. To achieve this, we train a neural network controller in a differentiable simulation and evaluate it in a simulated environment consisting of an  $8 \times 8$  grid of vertical emitters. By carrying out various horizontal displacement tasks such as moving objects to specific positions while reacting to external perturbations, we demonstrate that a controller, trained with a limited number of iterations, can generalize to longer episodes and learn the complex dynamics of fluid-solid interactions. Importantly, our approach requires only the observation of the manipulated object's state, paving the way for the development of physical systems that enable contactless manipulation of objects using air streams.

**1. INTRODUCTION**

Real-time control of systems involving fluid and solid interactions presents inherent challenges due to the complex dynamics arising from their interactions and the high-dimensional state space. Designing a controller for such a system, for example, one that moves an object to a prescribed location with a fluid jet, is highly impractical through manual programming alone. However, by leveraging a suitable simulator in conjunction with modern deep learning techniques, it becomes feasible to train such a controller, which is the focus of this paper. We present an approach for controlling fluids using differentiable physics (DP) that only requires monitoring the state of the displaced solids, making it highly applicable to the design of physical fluid-based control systems. Advances in DP [1] have demonstrated significant potential for addressing simulated inverse problems and complex control applications [2]–[8]. In the context of computational fluid-solid interactions, there are several examples of applied DP [2], [4], [6], [9], [10]. However, to our knowledge, there is no existing research of DP in control tasks in which the fluid itself serves as the acting agent.

We propose a scenario in which controlled fluid streams are employed to displace objects in three-dimensional space with a grid of emitters. Using differentiable simulations, we train a neural network that produces a fluid velocity for each emitter such that objects are moved to a desired location, as shown in Fig. 1. The system observes only the state (position, velocity) of the objects to carry out its control policy. Consequently, unlike prior approaches that rely on the fluid state (velocity and pressure fields) for decision-making [11], [12], our approach has the potential for a real-world implementation.

**Our key contributions** are the following: (1) present a sample-efficient DP-based learning method to train a neural network controller for moving objects around a horizontal surface with fixed vertical emitters, using only the state of the object as a control input, and (2) demonstrate versatile horizontal object displacement using fixed vertical emitters in a simulated environment.

The remainder of this paper is structured as follows: Section II describes the simulation environment and governing fluid dynamics equations. Section III offers insights into our controller design, and Section IV describes the training process. An evaluation of all experiments we performed with the controller is available in Section V. Lastly, Section VI puts the developed system into perspective, discussing its limitations and applicability in real-life counterparts.

**A. Related Work**

Through the application of gradient-based optimization, DP has been effectively applied to solve simulated inverse problems [2]–[4]. Hu et al. [2] leverage the differentiable programming language Taichi to conduct complex simulations

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## Towards Three-Dimensional Fluid-Directed Rigid Body Control on a Physical System

Oskars Teikmanis, Student Member, IEEE, Rodions Salanovs, Kārlis Freivalds

**Abstract**—This article presents ongoing work on the “Flow Grid”, a novel floor-standing device for fluid-directed, contactless manipulation of objects using air. It features a horizontal surface with 60 upward-facing nozzles connected to an air compressor and is controlled by a neural network. The design also integrates real-time depth camera measurements for the accurate tracking of objects across the device's surface. We describe key components and design decisions, providing insights into the device's intended use in evaluating machine learning algorithms for three-dimensional fluid-solid interactions, with potential applications in the non-prehensile manipulation of delicate objects.

**1. INTRODUCTION**

Contactless object manipulation has historically been limited to very small objects, as in the case of acoustic levitation [1], or to objects with special properties such as magnetism [2]. Furthermore, while there has been some research pushing the boundaries of air-based displacement of objects [3], [4], much of the technology remains similar to simple “air bearings,” like the ones used in air-hockey tables [5]. The complex dynamics of air are difficult to model, making it challenging to use air nozzles as precise controllers.

Due to the high state-space dimensionality of computational fluids, the majority of work in the field of fluid-directed object manipulation exists in purely simulated environments [6]–[8]. Ma et al. (2018) [6] use reinforcement learning (RL) to train movable fluid spots to interact with rigid objects in a two-dimensional environment. In our previous work [8], we leveraged a differentiable simulator [9] to represent a three-dimensional system with an array of upward-pointing outlets. It is capable of learning control policies for displacing objects without the need to observe the motion state of the fluid. We applied gradient-based training to perform different manipulations with spherical objects, such as holding them in place and moving them to specified locations, while reacting to external perturbations.

Recently, Google DeepMind published their work on fluid-directed rigid body control on a bench-top device called “Box o’ Flows” [4]. It features an array of spots that can perform complex contactless manipulations with rigid objects in a pseudo-2D environment, and showcases the potential of applied RL in implementing fluid-based control.

**II. FLOW GRID - DESIGN**

Fig. 1 shows a schematic model of the Flow Grid. The 80 × 120 cm work surface features 60 outlets with individually controllable nozzles, connected to an air compressor. A set of designs for the outlets is shown in Fig. 3 (left). The top part of the device features an RGBD camera that covers the working surface of the device and observes the motion of the

## Learning Fluid-Directed Rigid Body Control

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**Abstract**

We introduce a method for contactless manipulation of objects in three-dimensional space using controlled fluid streams. To achieve this, we train a neural network controller in a differentiable simulation and evaluate it in a simulated environment consisting of a grid of vertical emitters. By carrying out various horizontal displacement tasks such as moving objects to specific positions while reacting to external perturbations, we demonstrate that a controller, trained with a limited number of iterations, can generalize to longer episodes and learn the behavior of fluid-solid interactions. We are in the process of building a floor-standing device that embodies the proposed method, and we describe its key components and design decisions towards displacing and manipulating delicate objects on the device's surface.

**1 Introduction**

Contactless object manipulation has historically been limited to very small objects, as in the case of acoustic levitation (Chen et al., 2019), or to objects with special properties such as magnetism (Xie et al., 2021). Furthermore, while there has been some research pushing the boundaries of air-based displacement of objects (Swaki et al., 2011; Bhardwaj et al., 2024), much of the technology remains similar to simple “air bearings,” like the ones used in air-hockey tables (Laurent and Moon, 2015).

Real-time control of systems involving fluids and solids present inherent challenges due to the complex dynamics arising from their interactions and high-dimensional state space. In addition, the nonlinear nature of these interactions make the application of classic control approaches, such as PID, highly impractical for moving objects using fluid jets. In this paper, we overcome this difficulty by leveraging a differentiable physics simulator in conjunction with deep learning techniques. The majority of the work in the field of fluid-directed object manipulation exists in purely simulated environments (Ramos et al., 2022; Freivalds et al., 2024). A prominent work by Ma et al. (2018) uses reinforcement learning (RL) to train movable fluid spots to interact with rigid objects in a two-dimensional environment. Recently, Google DeepMind published their work on fluid-directed rigid body control on a bench-top device called “Box o’ Flows” (Bhardwaj et al., 2024). It showcases the potential of RL in implementing fluid-based control by using an array of spots that can perform complex contactless manipulations with rigid objects in a 3D environment.

Our approach for training control policies is based on differentiable physics (DP) simulations. Advances in DP (Therapy et al., 2021) have demonstrated significant potential for addressing simulated inverse problems and complex control applications (Hu et al., 2019; Hill et al., 2020; Du et al., 2021; Fang et al., 2022; Ramos et al., 2022; Ramos et al., 2023; Ichimaru et al., 2023; Jatharwankar et al., 2023). In the context of computational fluid-solid interactions, there are several examples of applied DP (Ramos et al., 2022; Ma et al., 2018; Hu et al., 2019; Du et al., 2021; Li et al., 2023). However, to our knowledge, there is no existing research where DP is applied for controlling real devices in which the fluid serves as the acting agent.

Machine Learning and the Physical Sciences Workshop, NeurIPS 2024.

## Shaping Flames with Differentiable Physics Simulations

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 Address  
 email

**Abstract**

We introduce a method for shaping simulated flames into customizable forms, with the goal of overcoming the limitations of current pyrotechnic systems, which are typically restricted to producing basic fire columns with minimal control over the resulting shape. Our approach leverages differentiable physics and combustion simulations. We demonstrate the use of differentiable physics-based training to produce simulated letter-shaped flames, and take initial steps towards implementing this method on real flame projectors by aligning the simulation with a physical device. The ability to control flame shape would significantly expand the possibilities for stage pyrotechnics and creative applications in performance art.

**1 Introduction**

paper does not really bring the field on ML, or physics-based model

Fire effects have long been a central element in the performing arts, delivering a strong visual impact at concerts, artistic performances and other live events. Despite their dramatic appeal, traditional stage flames are constrained in their versatility, typically limited to producing basic shapes controlled by manual or rudimentary systems. These restrictions hinder the creative potential of artists and directors aiming to push the boundaries of visual storytelling. As a result, there is growing demand for advanced fire effects that offer visually impressive, customizable, and interactive designs—such as the concept illustrated in Fig. 1.

We explore the possibilities of generating flame shapes by optimizing flame projection timings, using machine learning (ML) and flame simulations to control the intricate dynamics of the combustion process. Our method is based on differentiable physics (DP) simulations, which have proven to be a powerful tool for controlling dynamic systems. DP enables gradient-based optimization, allowing the training of neural networks to control complex and highly dynamic tasks. It has become particularly influential in fluid flow control, facilitating precise manipulation and optimization of liquid and airflow characteristics. Hu et al. (2019) introduced a differentiable programming language enabling precise, real-time control and optimization of physical simulations, including fluid dynamics. (Fratini and Lechman, 2004) introduced a method to control smoke dynamics using guiding forces, allowing animators to create realistic smoke effects efficiently. Shi and Yu (2005) focuses on controlling fluid behaviour to adapt rapidly changing targets shapes while preserving natural motion. A more recent work by (Freivalds et al., 2023) extended the application of DP by developing a method for controlling objects in 3D space through fluid flows. This

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NeurIPS 2024, Vancouver



# MOTE (VPP-EM-FOTONIKA)



### Towards Three-Dimensional Fluid-Directed Rigid Body Control on a Physical System

Oskars Teikmanis, Student Member, IEEE, Roldans Sultansovs, Kārlis Freivalds

**Abstract**—This article presents ongoing work on the “Flow Grid”, a novel floor-standing device for fluid-directed, contactless manipulation of objects using air. It features a horizontal surface with 60 upward-facing nozzles connected to an air compressor and is controlled by a neural network. The design also integrates real-time depth camera measurements for the accurate tracking of objects across the device’s surface. We describe key components and design decisions, providing insights into the device’s intended use in evaluating machine learning algorithms for three-dimensional fluid-solid interactions, with potential applications in the non-prehensile manipulation of delicate objects.

#### I. INTRODUCTION

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Recently, Google DeepMind published their work on fluid-directed rigid body control on a bench-top device called “Box o’ Flows” [4]. It features an array of spots that can perform complex contactless manipulations with rigid objects in a pseudo-2D environment, and showcases the potential of applied RL in implementing fluid-based control.

This research is funded by the Latvian Council of Science, project “Smart Materials, Photonics, Technologies and Engineering Ecosystem”, project No. VPP-EM-FOTONIKA-2022/1-0001. The authors are with the Institute of Electronics and Computer Science (IEDI) in Riga, Latvia. Contact: oskars.teikmanis@edi.lv.

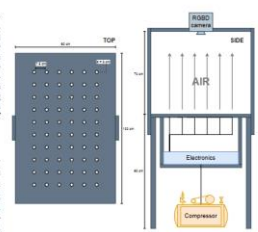
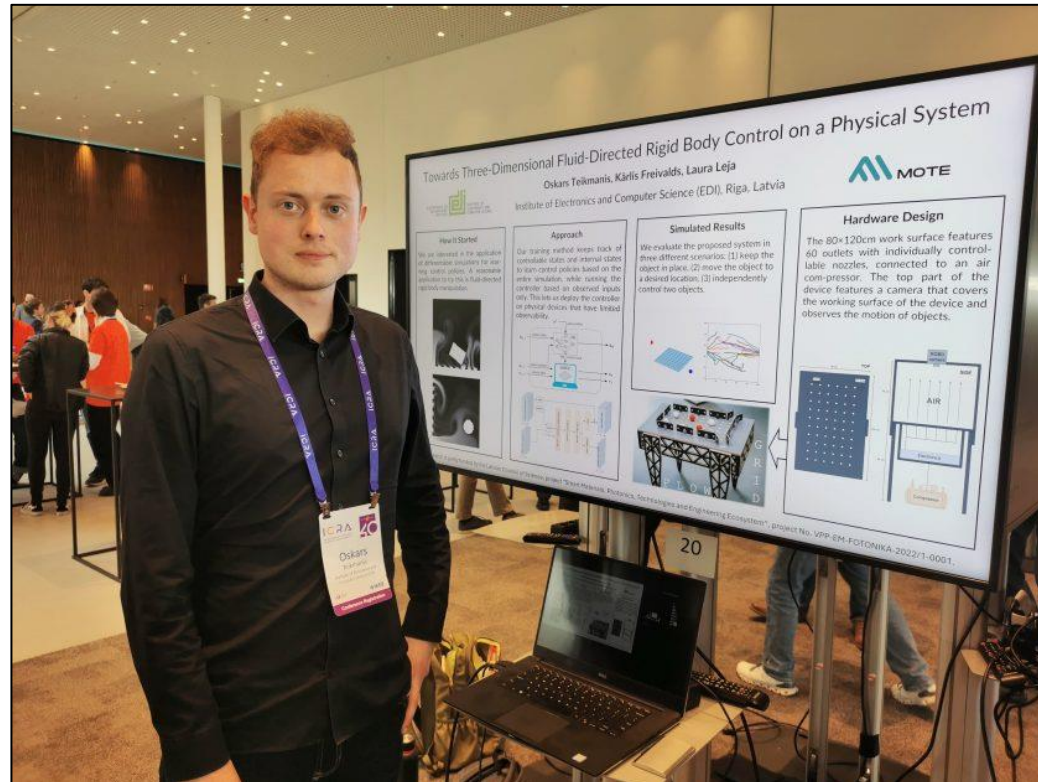


Fig. 1. Flow Grid: a device for air-based manipulation of rigid objects. It consists of an array of 6 × 10 individually controllable nozzles that output compressed air. An RGBD camera is placed above the table to observe the movement of the objects.



### Towards Three-Dimensional Fluid-Directed Rigid Body Control on a Physical System

Oskars Teikmanis, Kārlis Freivalds, Laura Leja  
Institute of Electronics and Computer Science (IEDI), Riga, Latvia

#### How it Started

We are interested in the application of deep learning solutions for the task of rigid body control on a physical system. A research challenge in this field is directed towards manipulation.

#### Approach

Our training method leverages a stack of controllable tubes and external states to learn control policies based on the entire simulation, while training the controller based on observed signals only. This task is deployed for control on a physical system that has limited observability.

#### Simulated Results

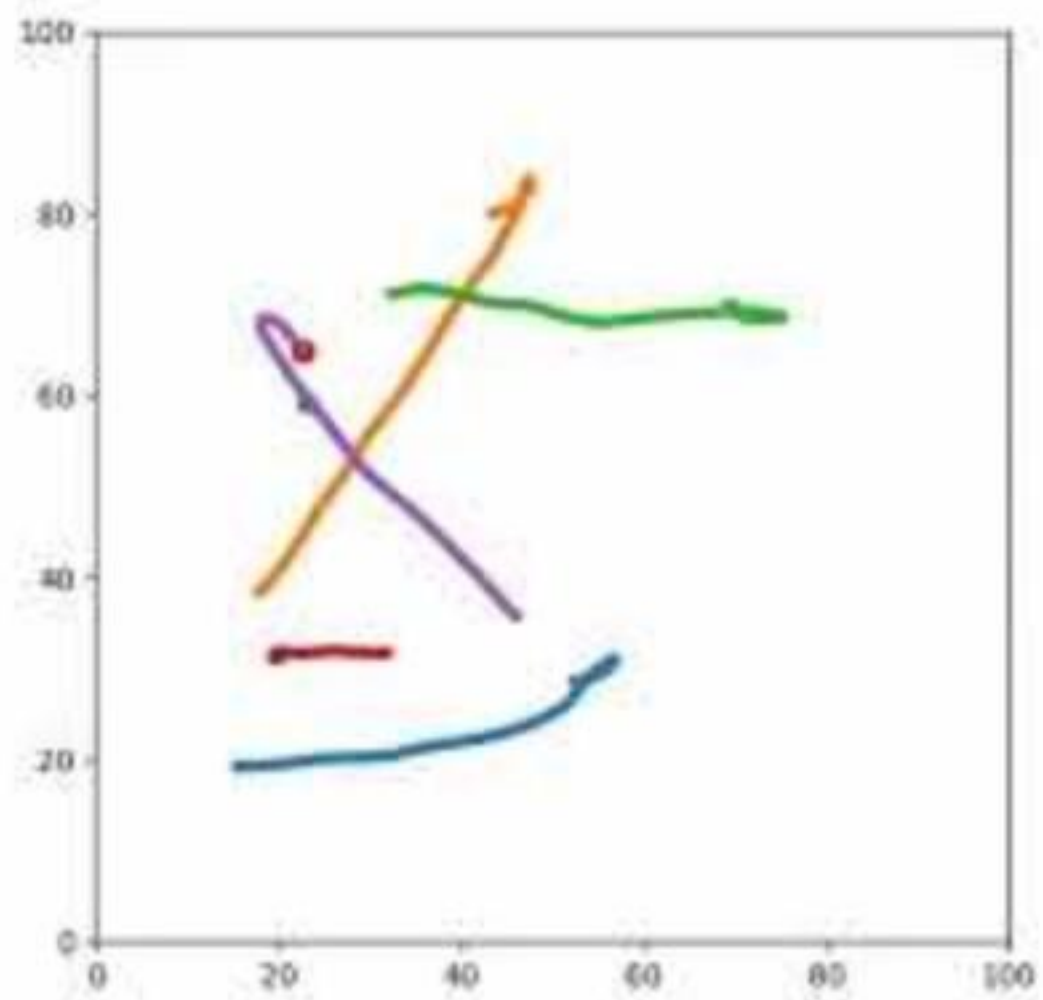
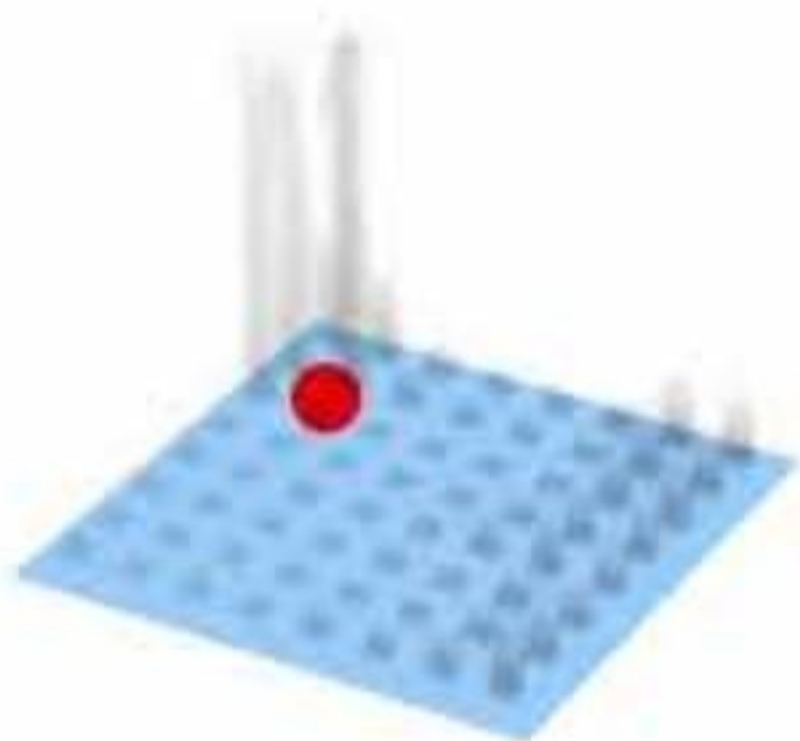
We evaluate the proposed system in three different scenarios: (1) keep the object in place, (2) move the object to a desired location, (3) independently control two objects.

#### Hardware Design

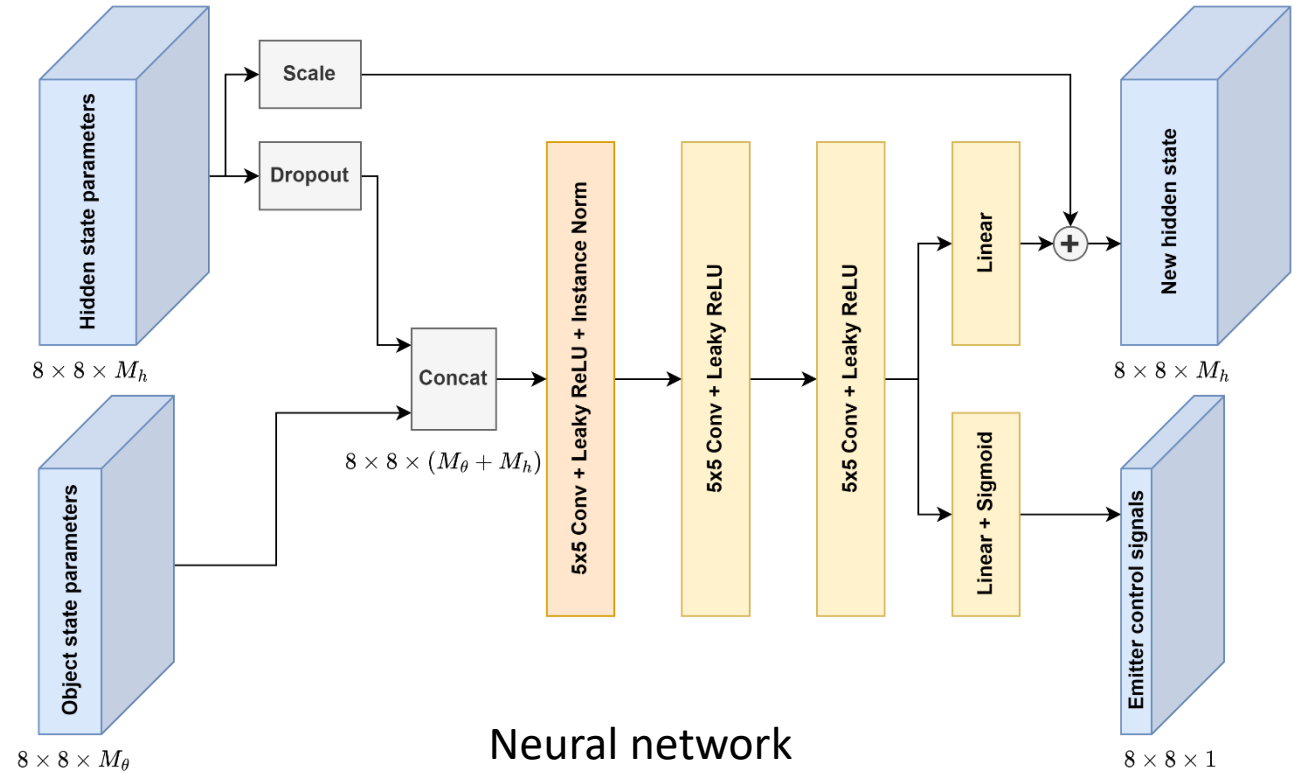
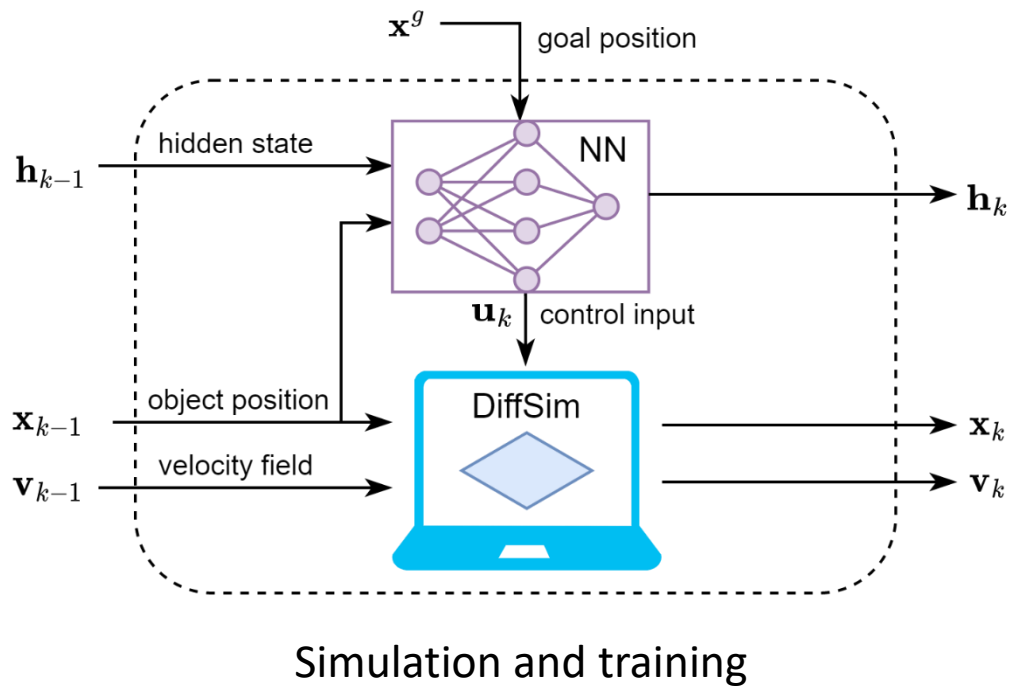
The 80 × 120 cm work surface features 60 outlets with individually controllable nozzles, connected to an air compressor. The top part of the device features a camera that covers the working surface of the device and observes the motion of objects.



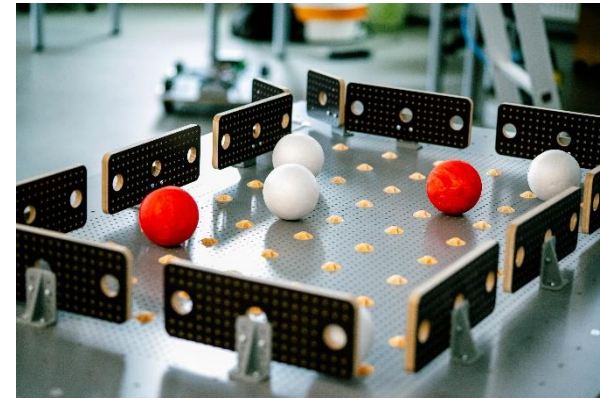
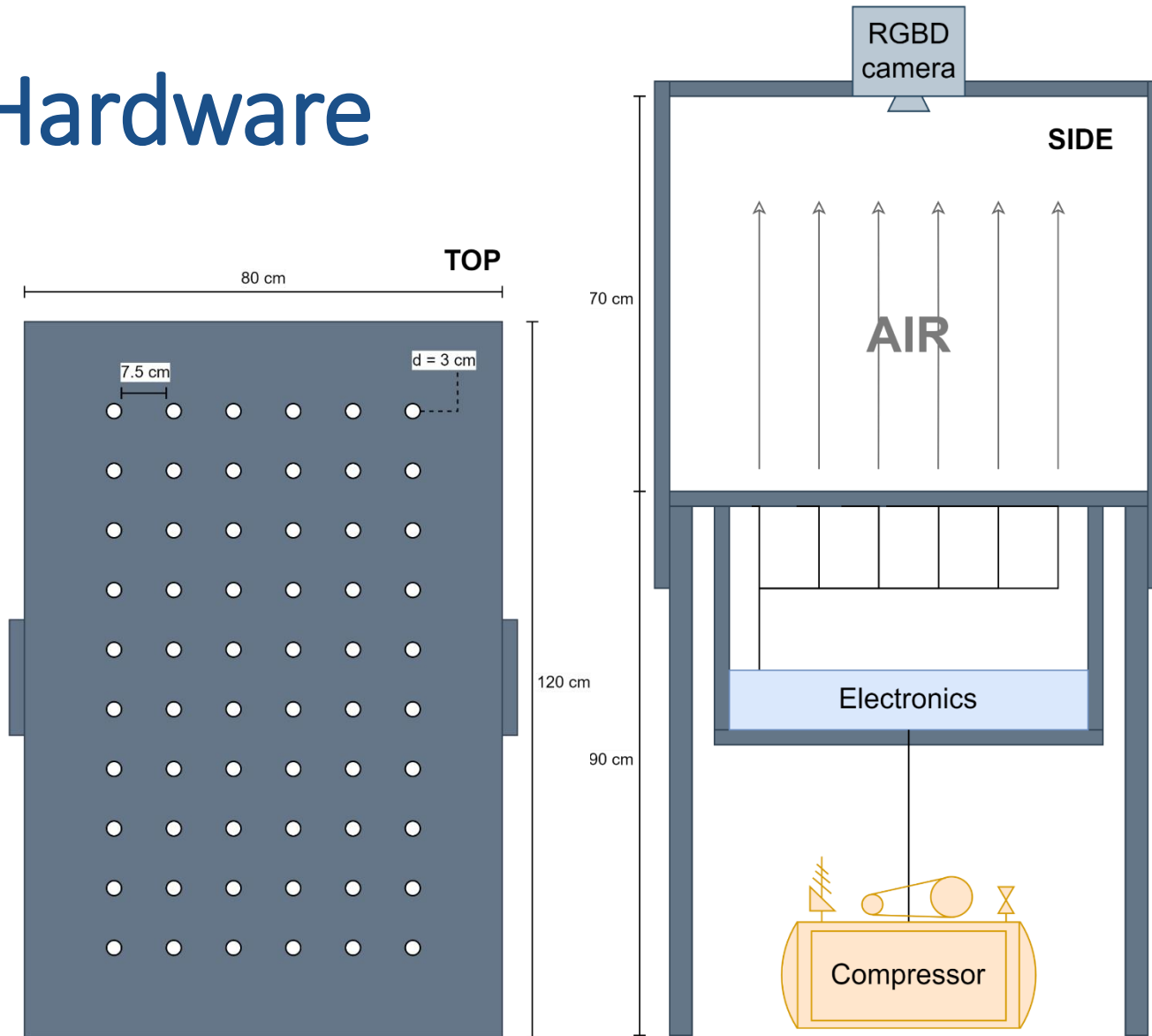
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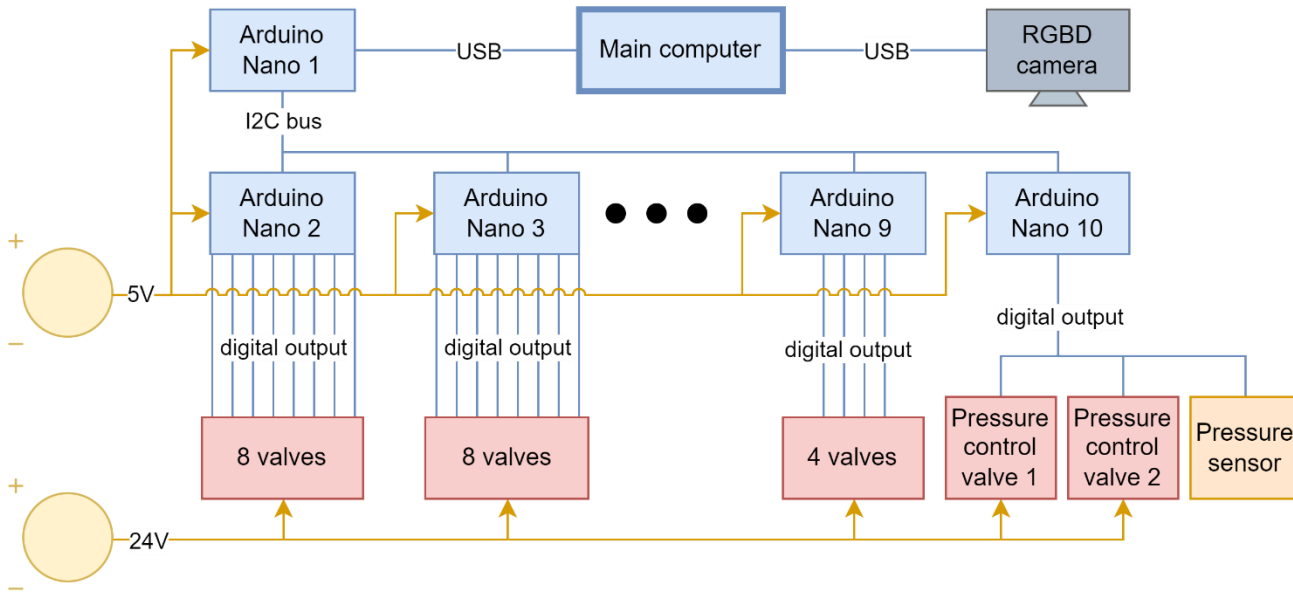
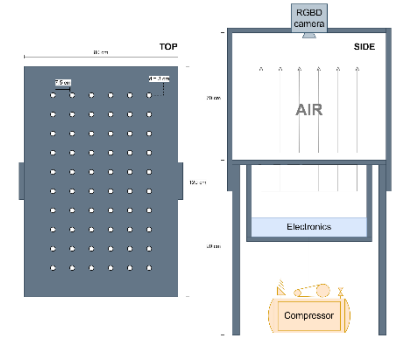
# System architecture



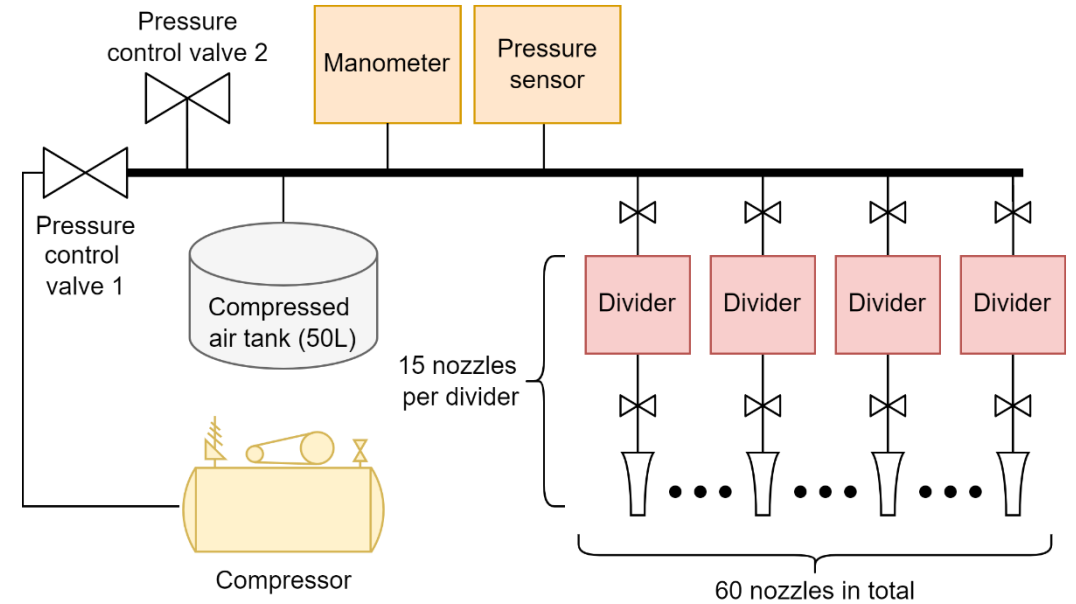
# Hardware



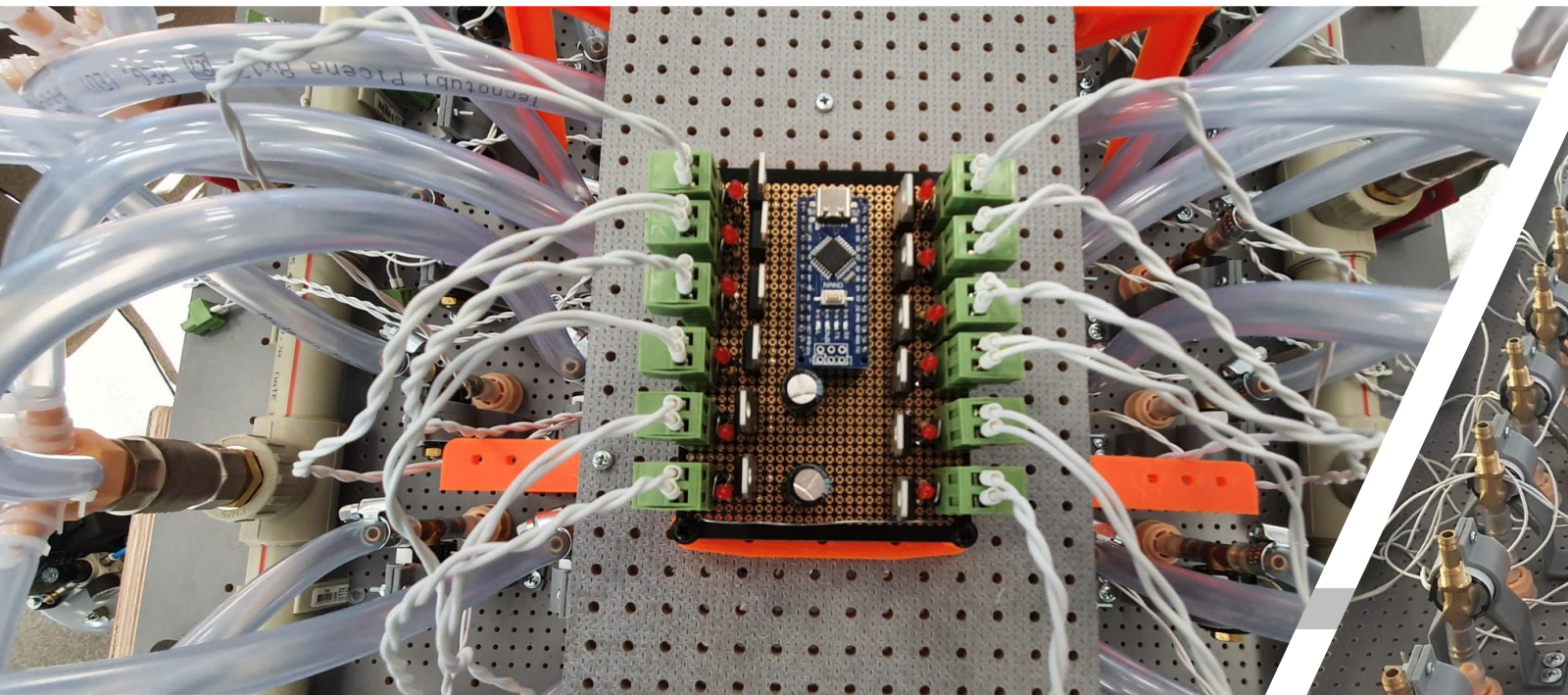
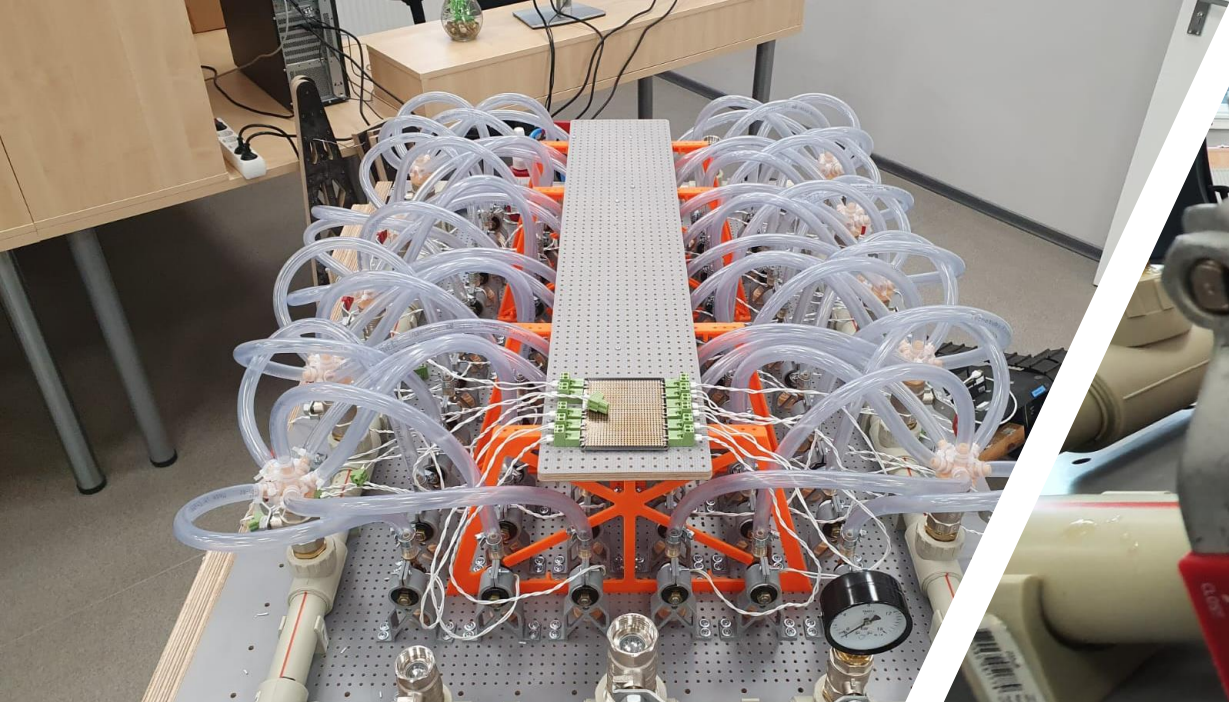
# Hardware architecture



Electronics layout



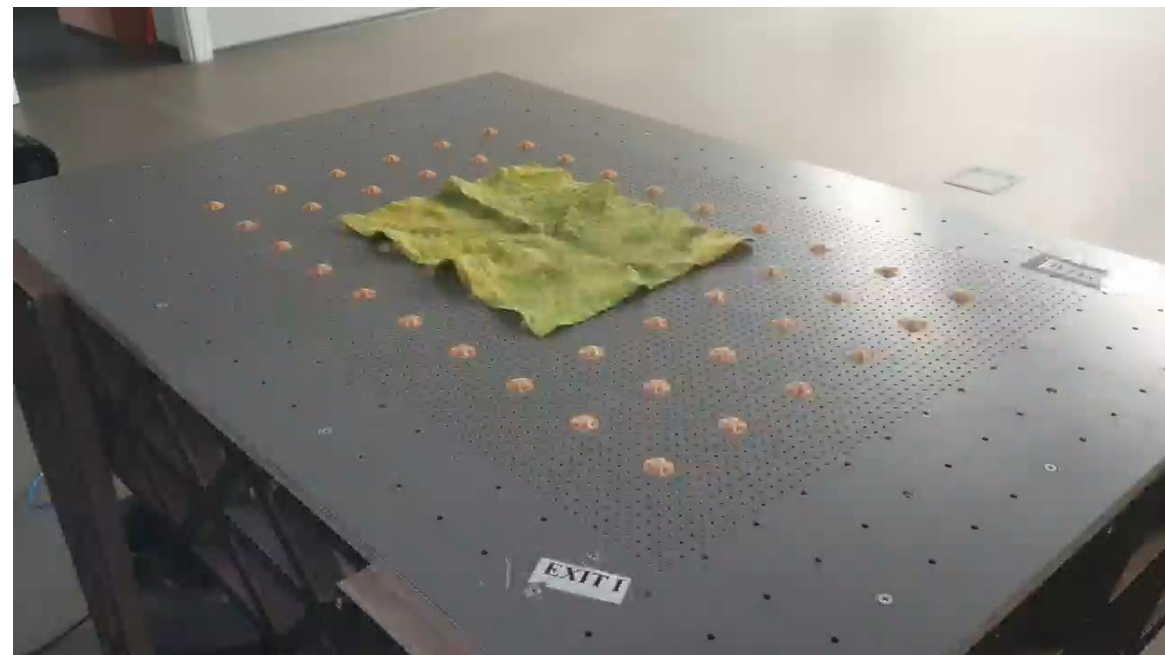
Pneumatics layout



# First prototype



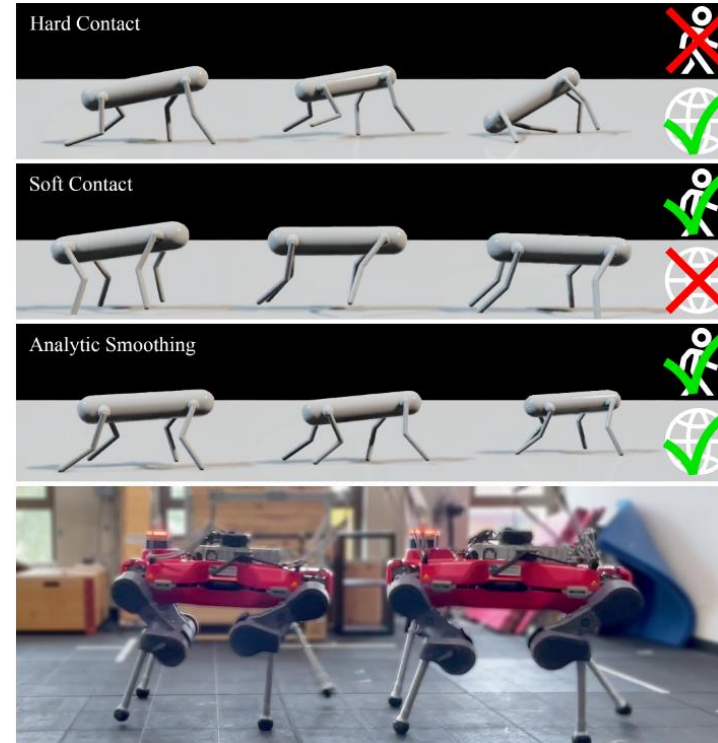
# Current iteration



# Further work: quadrupedal robots



Unitree Go2 quadruped



Bagajo *et al.*, CoRL 2024

# Q&A

