Simulating Artificial Muscles for Controlling a Robotic Arm with Fluctuation

Max Braun

Osaka University, Yuragi Project, 2007/2008

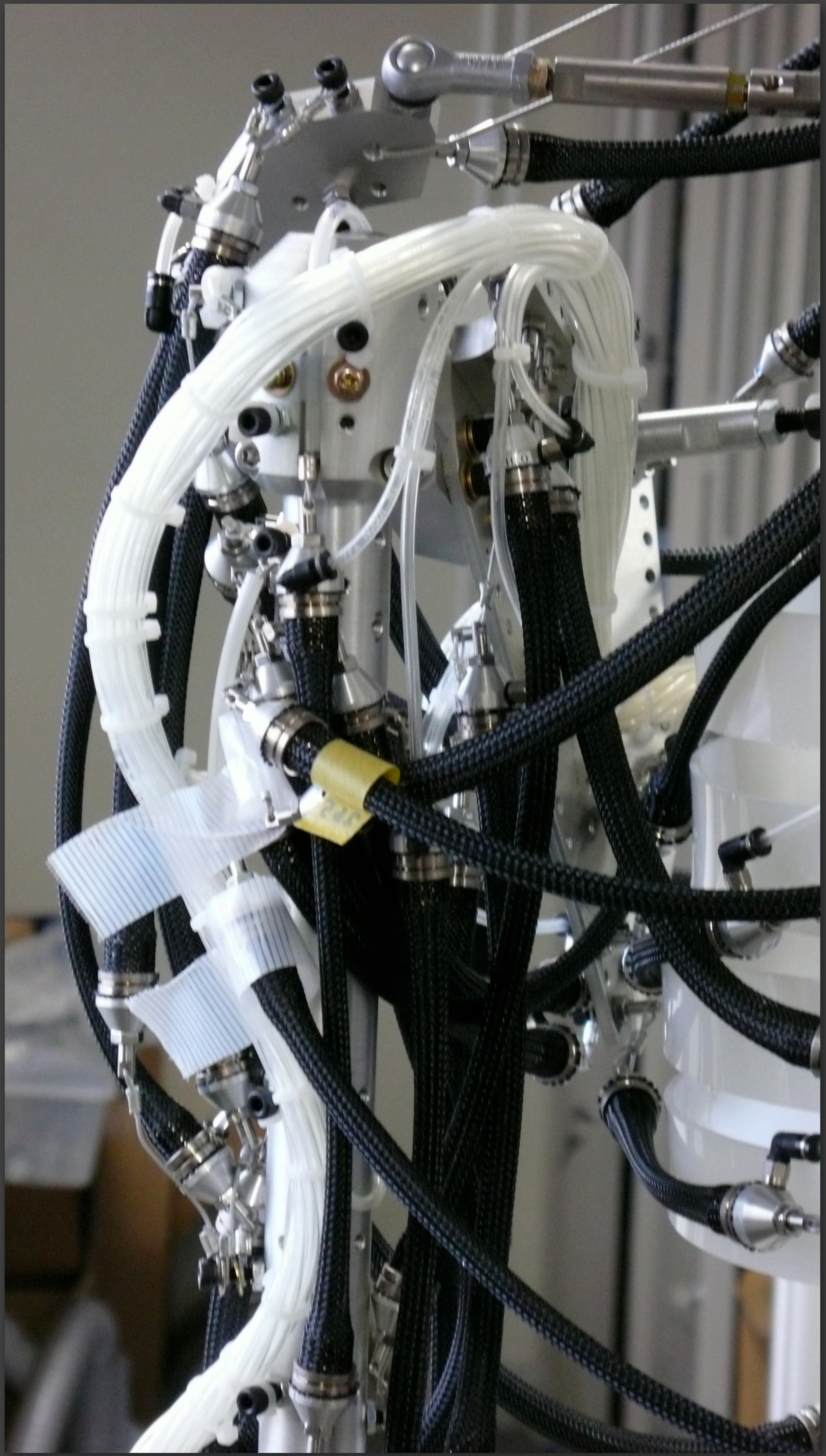
prepare simulator
questions after the presentation

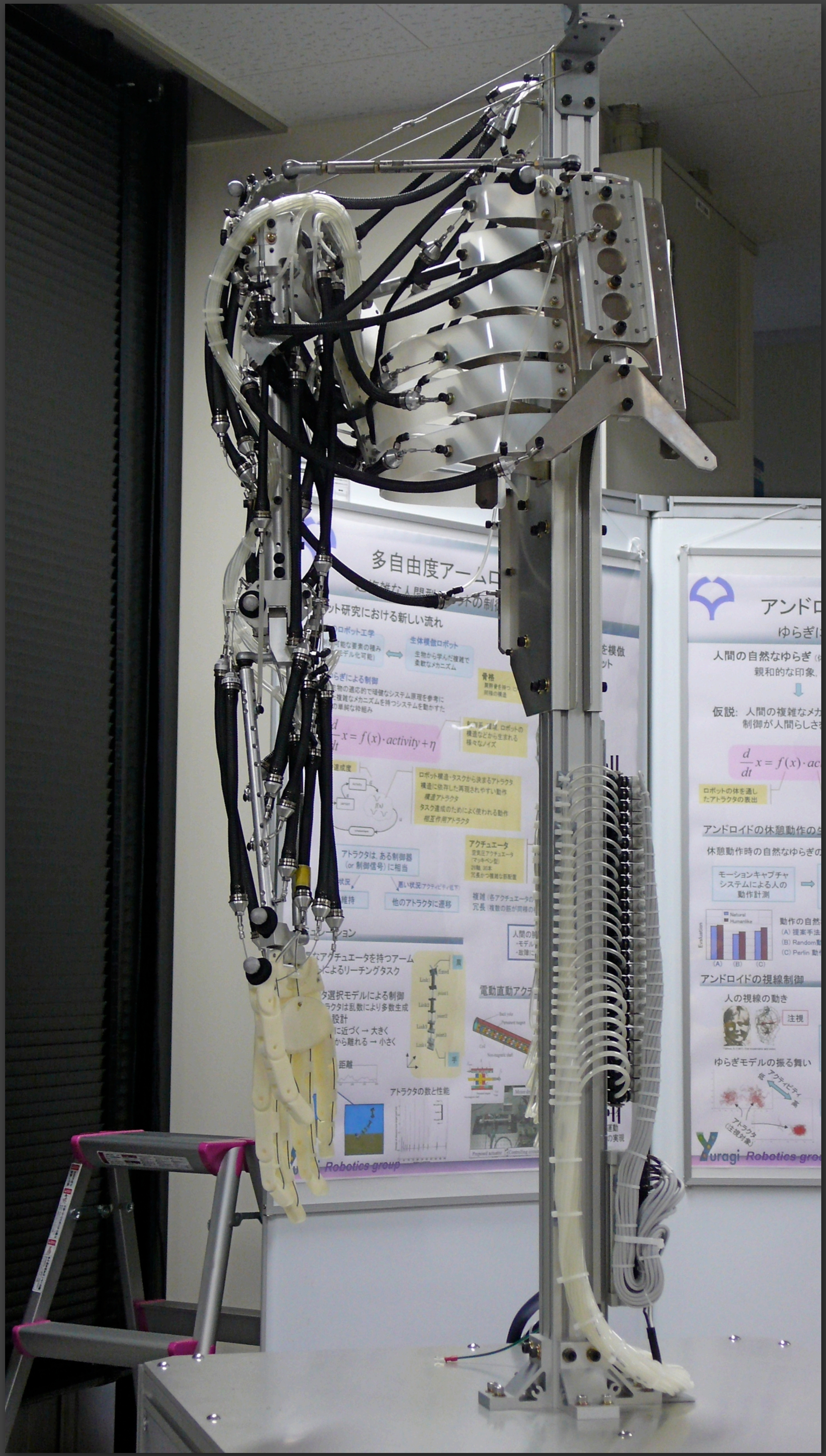
1. *The robotic arm and its artificial muscles*
2. *Simulating artificial muscles*
3. *The simulator software*
4. *Fluctuation and results*

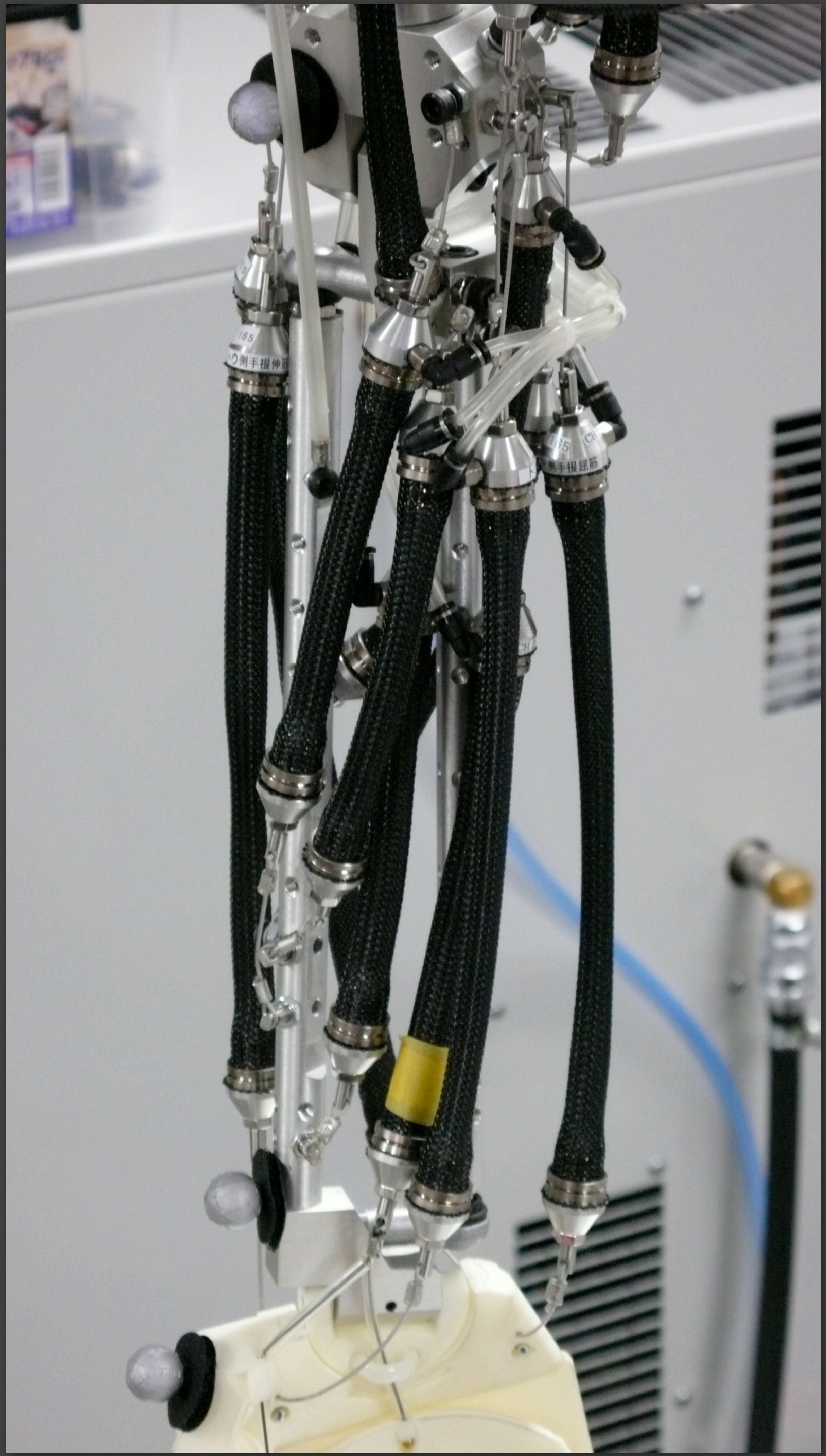
1. structure, hardware
2. model, experiments
3. software engineering
4. Yuragi, IROS paper

1. The robotic arm and its artificial muscles
2. Simulating artificial muscles
3. The simulator software
4. Fluctuation and results

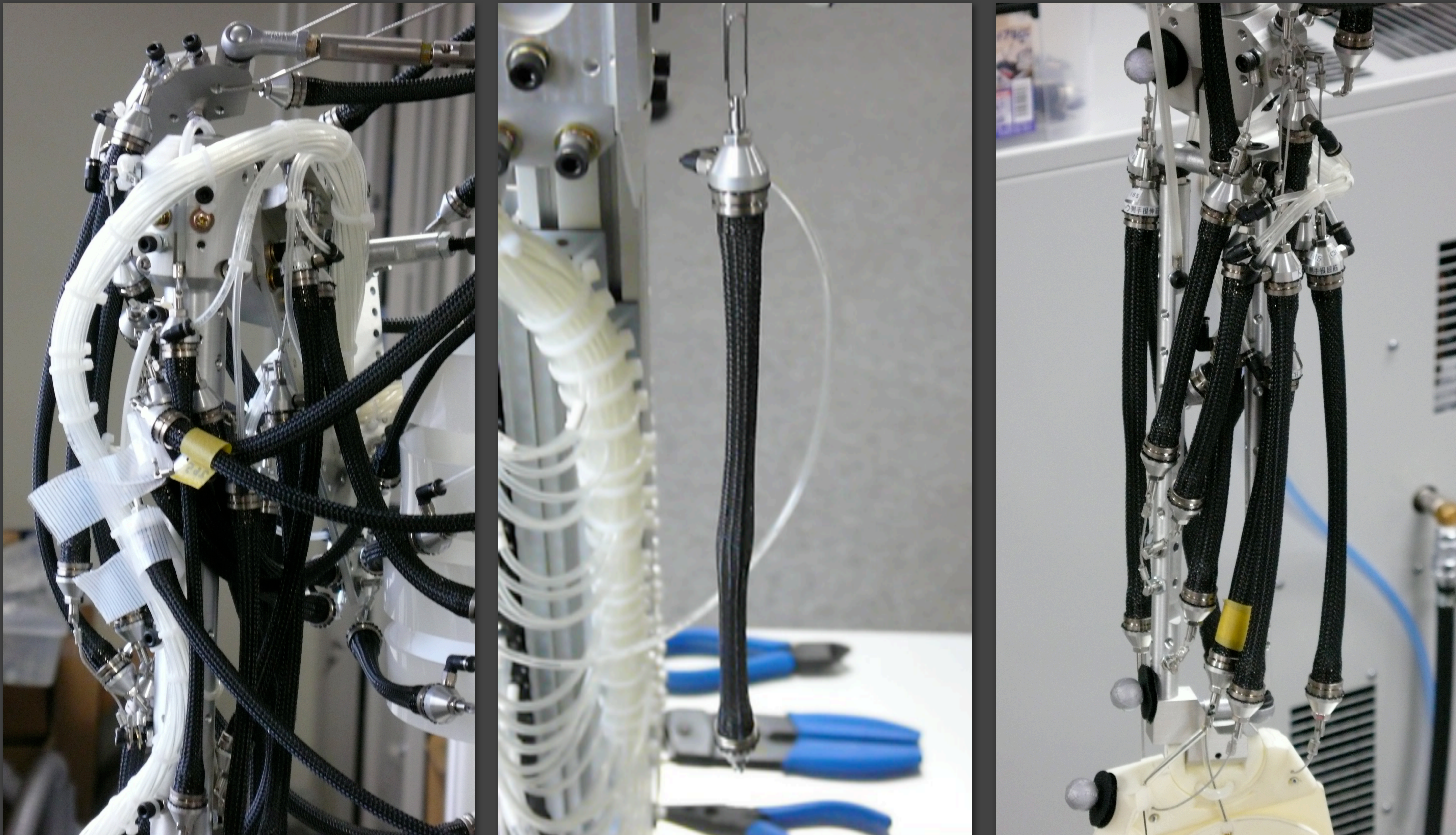
human-like mechanics
detail: 30 pneumatic actuators ("artificial muscles")
behavior: air pressure, flexible







human-like mechanics
detail: 30 pneumatic actuators ("artificial muscles")
behavior: air pressure, flexible

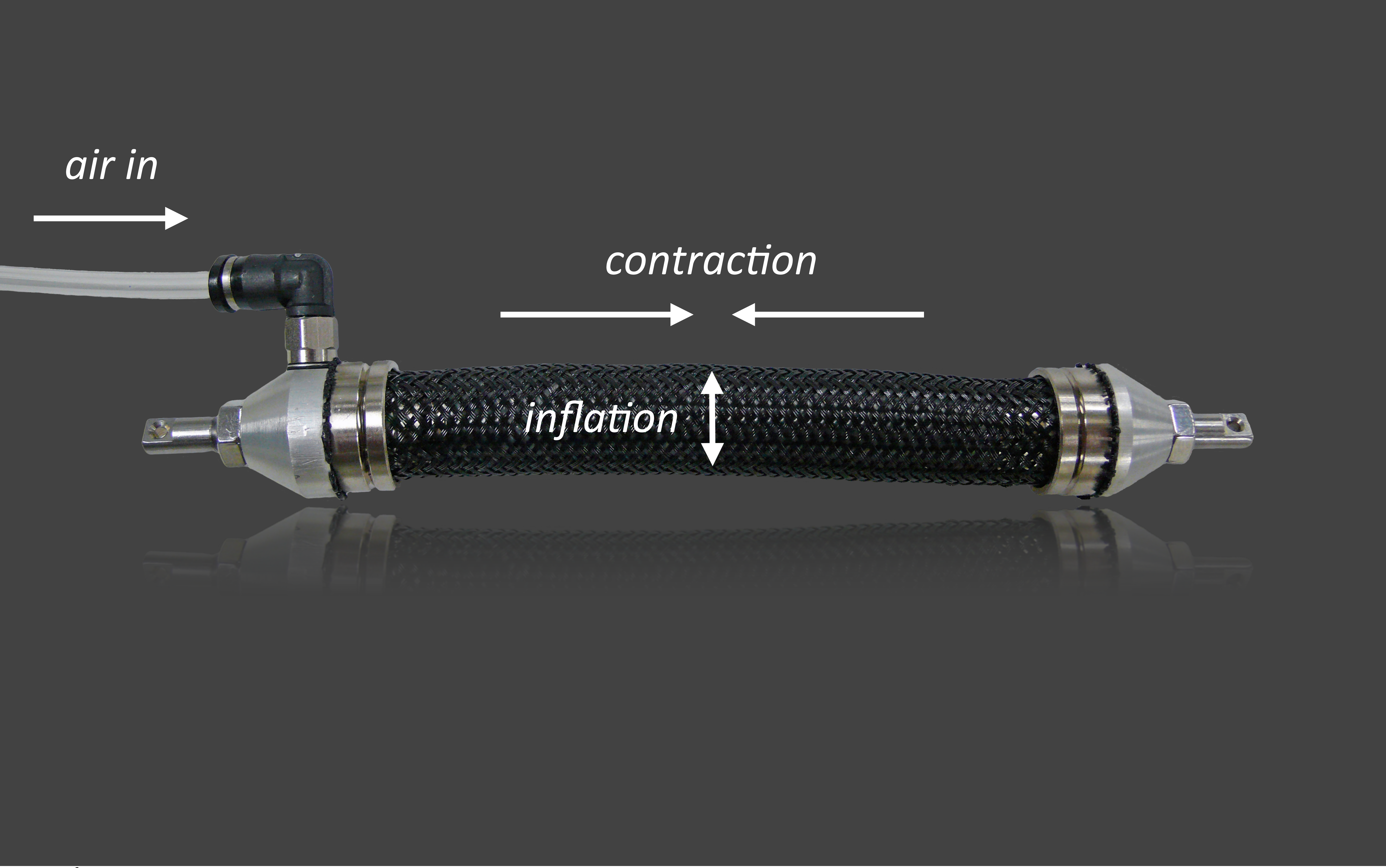


human-like mechanics
detail: 30 pneumatic actuators ("artificial muscles")
behavior: air pressure, flexible

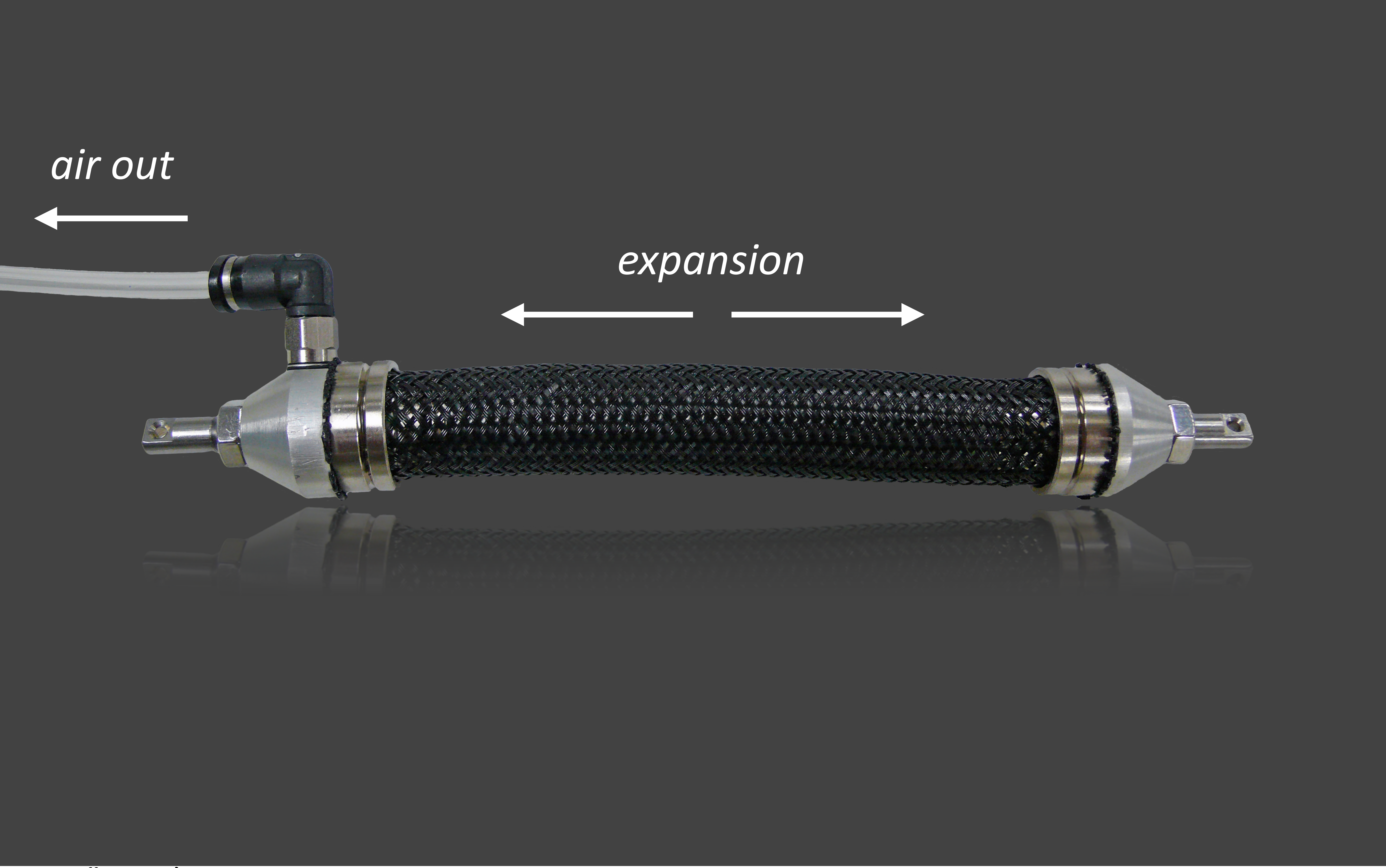
principle
force (pull)

principle
force (pull)

principle
force (pull)



principle
force (pull)



practically no push
thus: agonist-antagonist pairs

1. The robotic arm and its artificial muscles

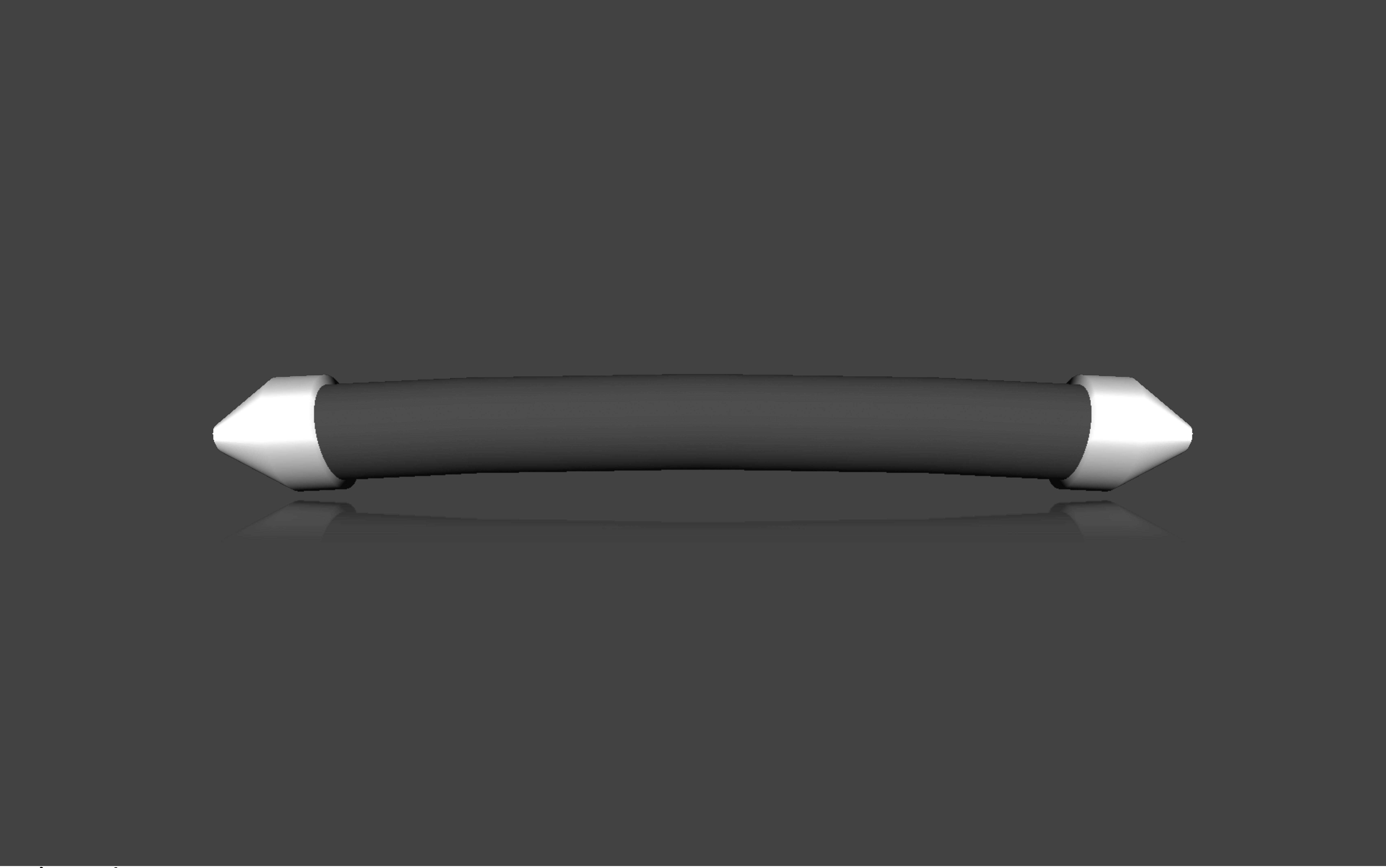
2. Simulating artificial muscles

3. The simulator software

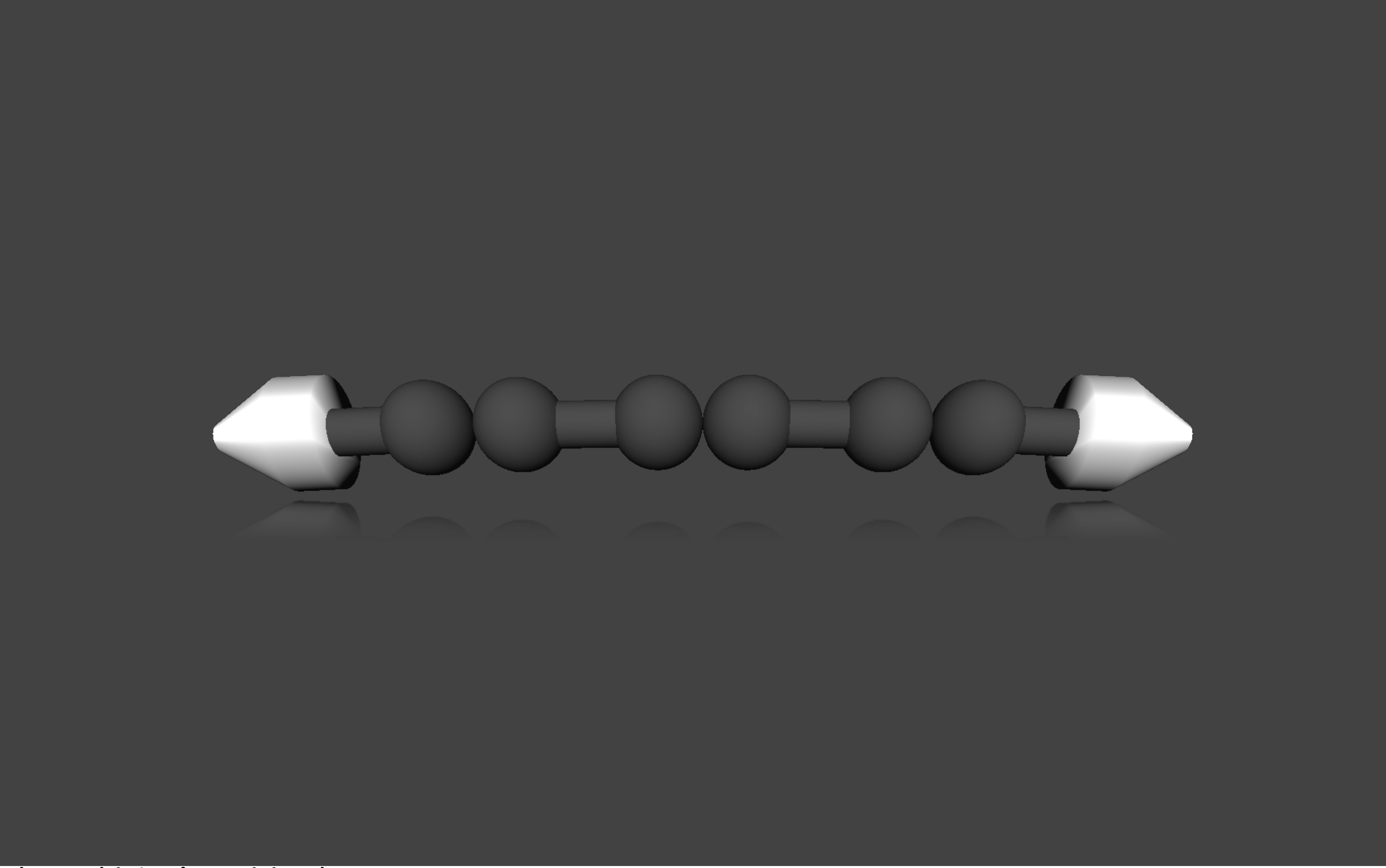
4. Fluctuation and results

the actual muscle and

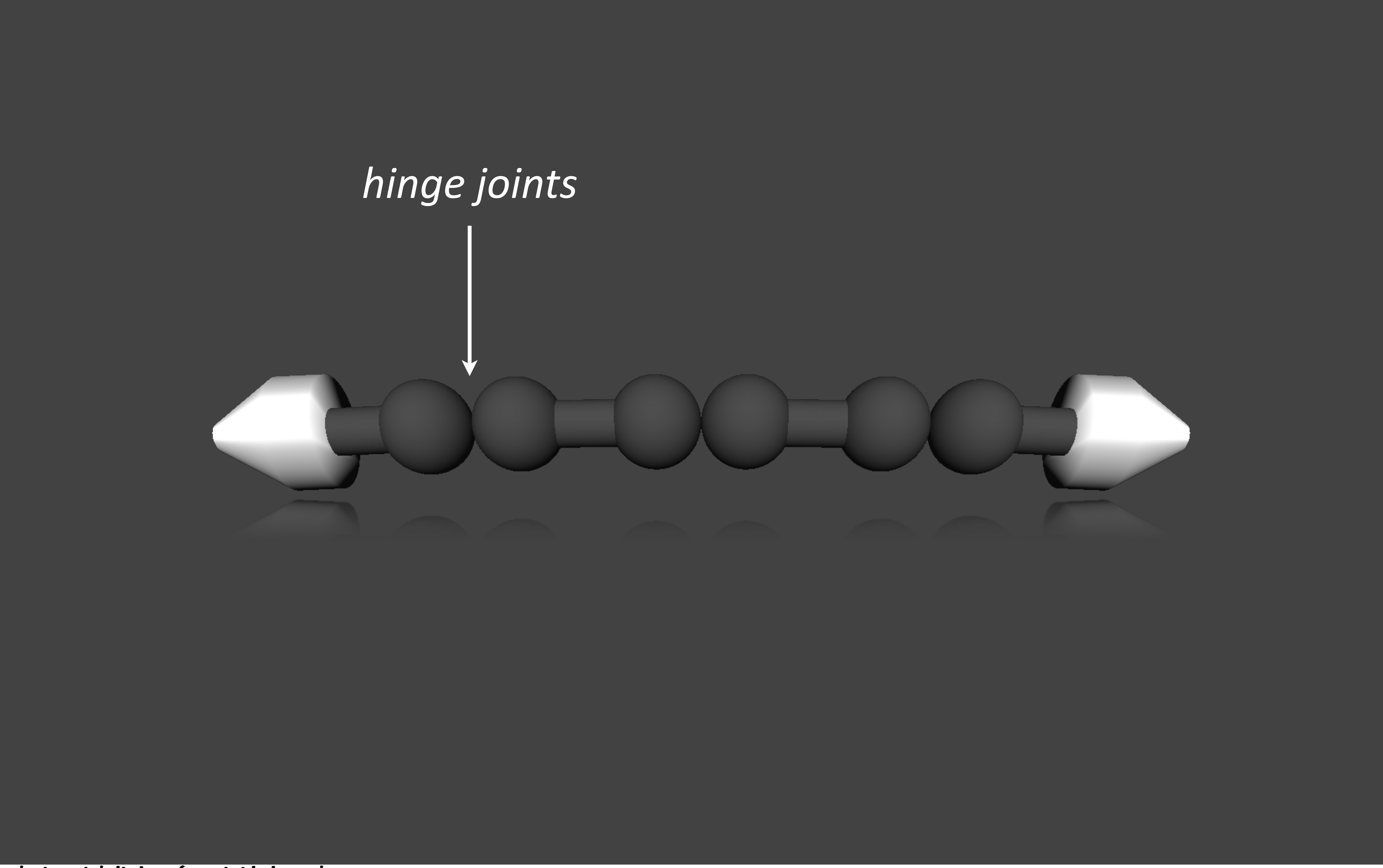
...



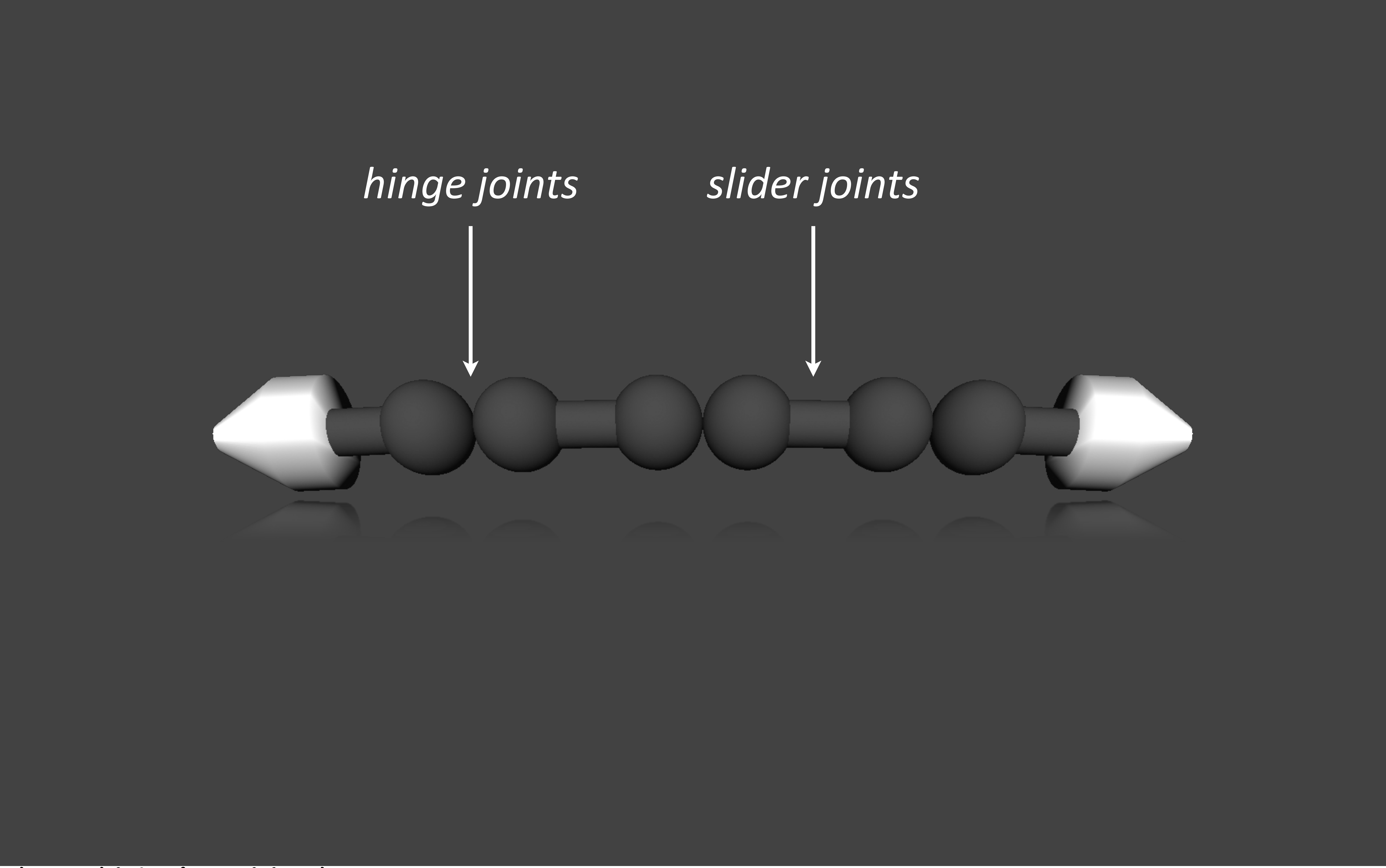
... the model
now: look inside ...



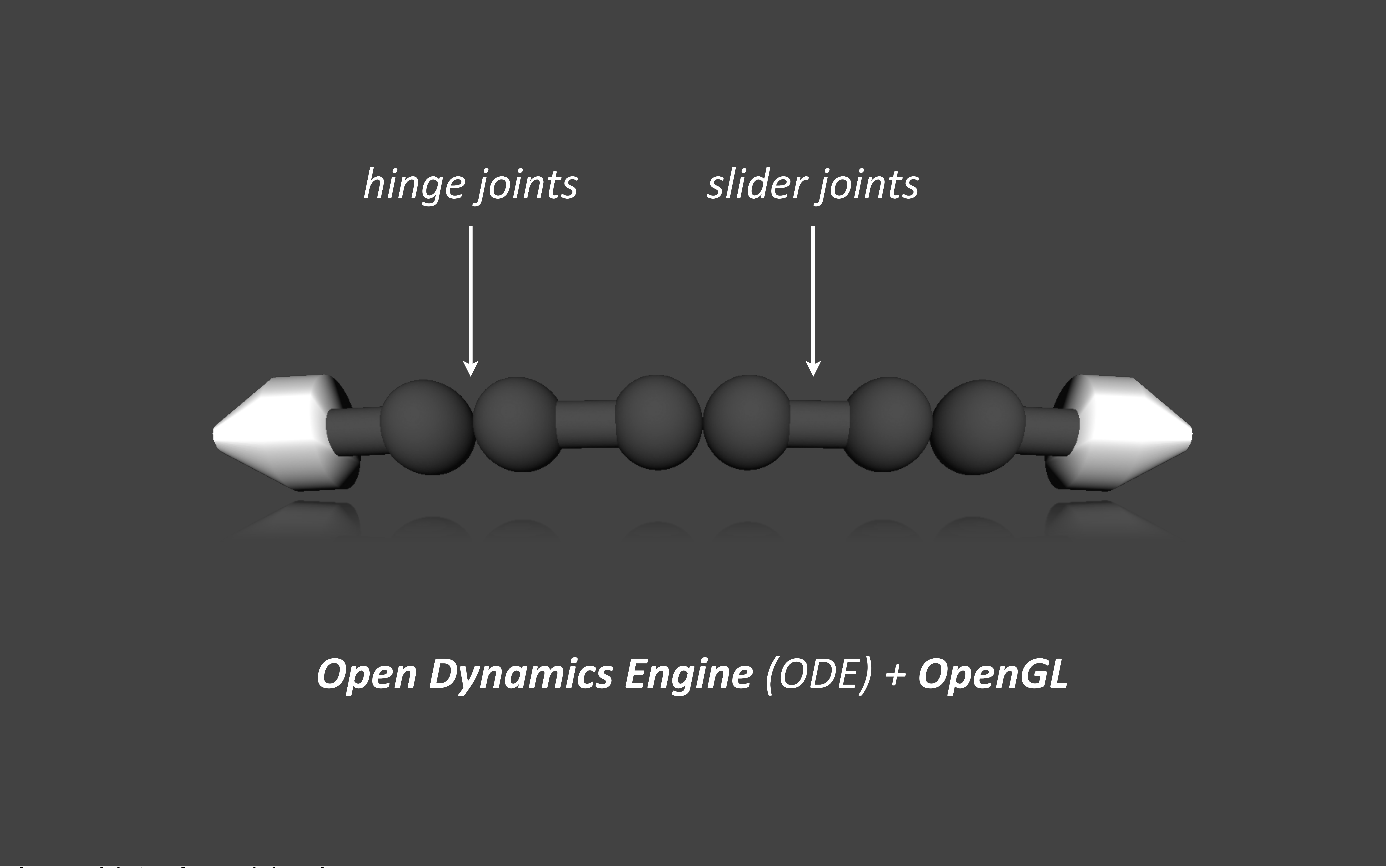
chain with links of variable length
ODE: rigid body dynamics, joints, collision detection, gravity
exert dynamic force on links
but before technical details: demo ...



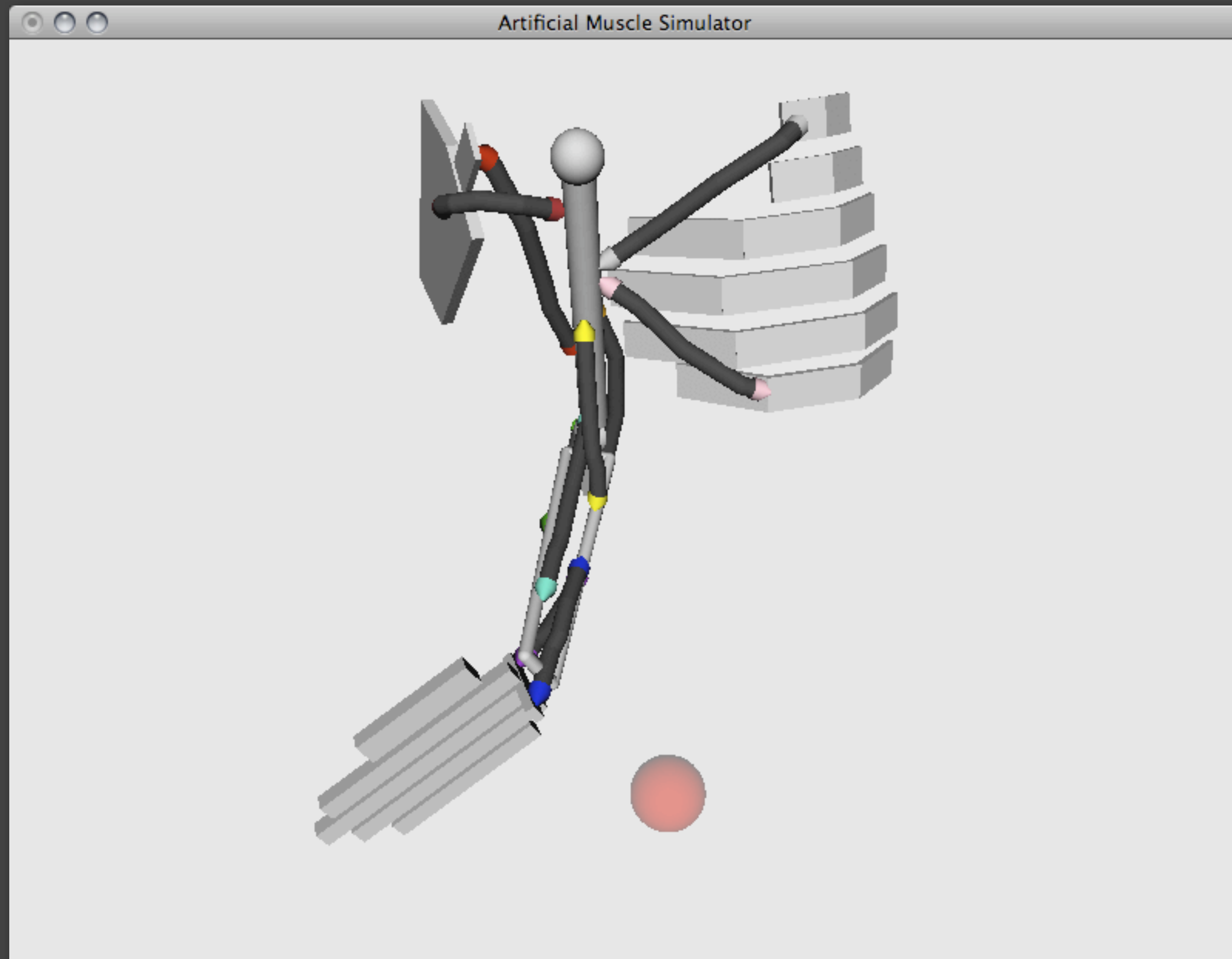
chain with links of variable length
ODE: rigid body dynamics, joints, collision detection, gravity
exert dynamic force on links
but before technical details: demo ...



chain with links of variable length
ODE: rigid body dynamics, joints, collision detection, gravity
exert dynamic force on links
but before technical details: demo ...



chain with links of variable length
ODE: rigid body dynamics, joints, collision detection, gravity
exert dynamic force on links
but before technical details: demo ...



Demo

simplified arm robot running attractor selection model
links (transparency), interaction
now: model in more detail ...

Refining the model

Experiment:

- Set ***air pressure*** (0–255 bit)
- Set ***weight*** (i.e. force, 0–8.7 kg × g)
- Measure ***length*** (e.g. 132–193 mm)

Simulator:

- Take ***air pressure***
- Measure ***length***
- Exert ***force***

experiments -> data -> function -> simulator
photos: different experiment setups
Q: why not measured force directly for given air pressure and length? - A: (tried it, first image) hard to set variable length and have steady setup.

Refining the model

Experiment:

- Set ***air pressure*** (0–255 bit)
- Set ***weight*** (i.e. force, 0–8.7 kg × g)
- Measure ***length*** (e.g. 132–193 mm)

Simulator:

- Take ***air pressure***
- Measure ***length***
- Exert ***force***

experiments -> data -> function -> simulator
photos: different experiment setups
Q: why not measured force directly for given air pressure and length? - A: (tried it, first image) hard to set variable length and have steady setup.

Refining the model

Experiment:

- Set ***air pressure*** (0–255 bit)
- Set ***weight*** (i.e. force, 0–8.7 kg × g)
- Measure ***length*** (e.g. 132–193 mm)

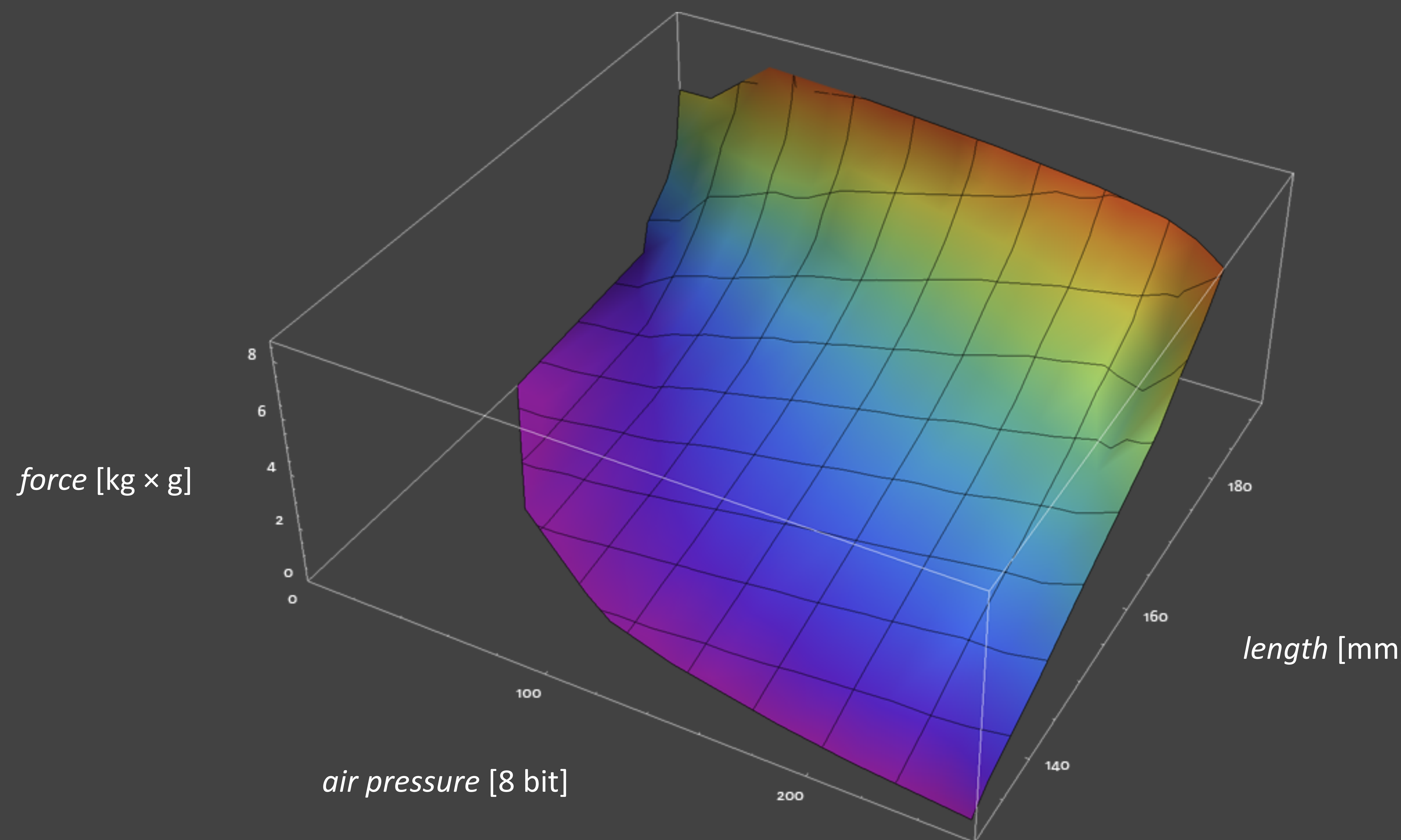
Simulator:

- Take ***air pressure***
- Measure ***length***
- Exert ***force***

experiments -> data -> function -> simulator
photos: different experiment setups
Q: why not measured force directly for given air pressure and length? - A: (tried it, first image) hard to set variable length and have steady setup.

Measurement

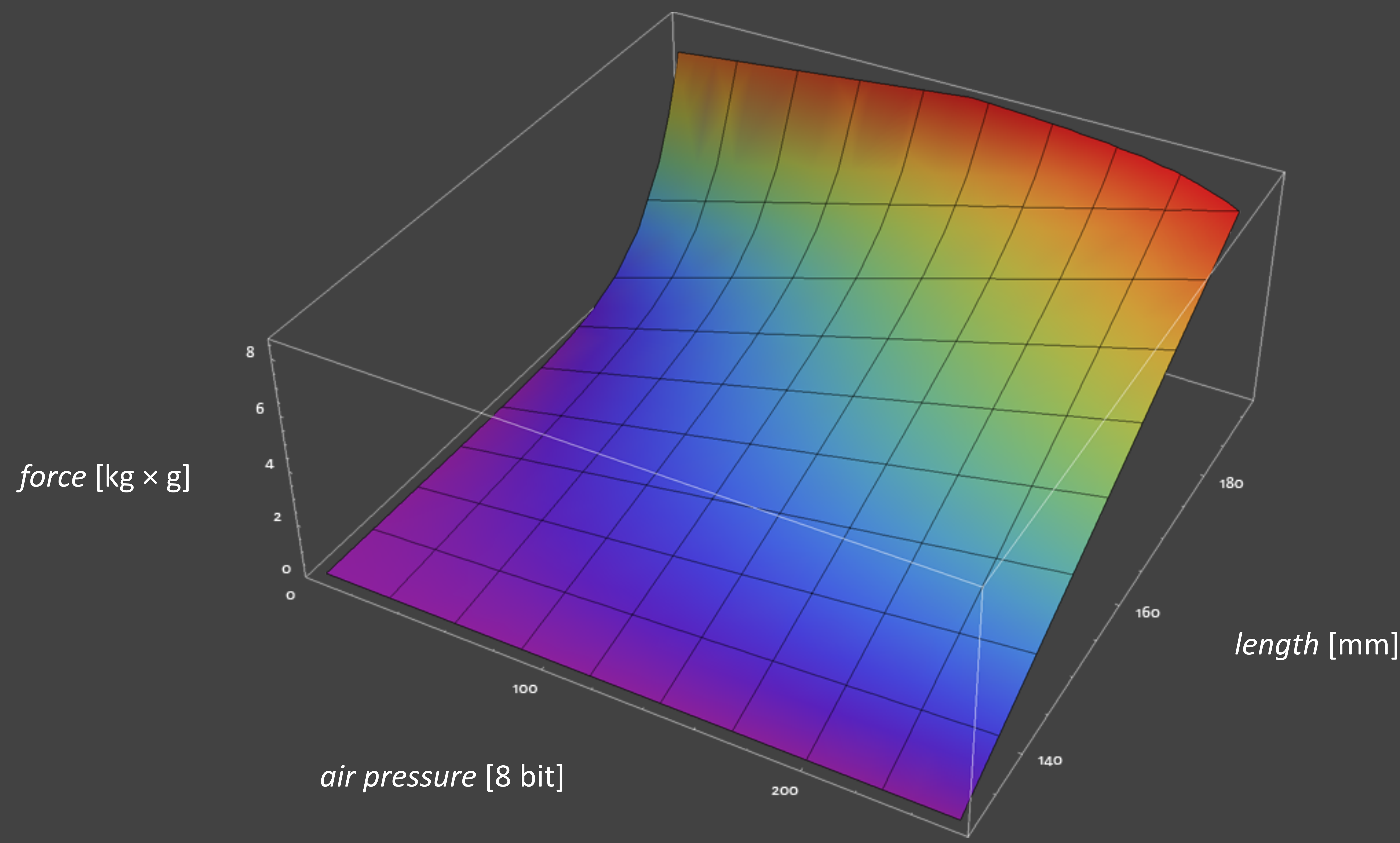
From a *set of data points* to a *functional representation*



inverse
plot

Function fit

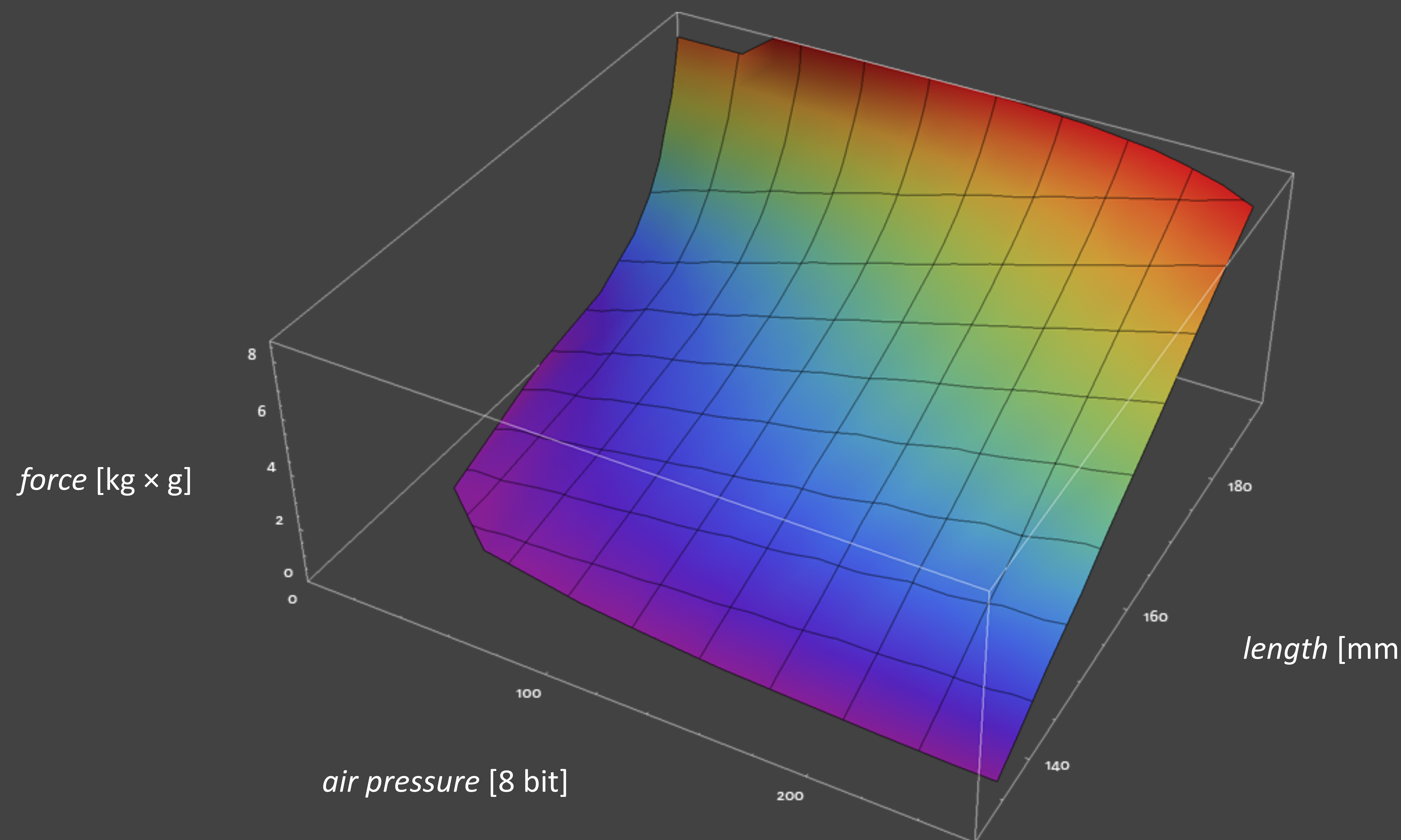
$$F(p,l) = c \cdot \left(\frac{p}{p_{\max}} \cdot \frac{l - l_{\min}}{l_{\max} - l_{\min}} + a \cdot \left(1 - \frac{p}{p_{\max}}\right) \cdot \exp\left(b \cdot \frac{l - l_{\min}}{l_{\max} - l_{\min}}\right)\right)$$



p, pmax: pressure – l, lmin, lmax: length – a, b, c: parameters
linear in length for high pressures and exponential for low pressures, linear interpolation
determine parameters through regression analysis (least squares)
result is a force, exerted on links

Measurement in Simulator

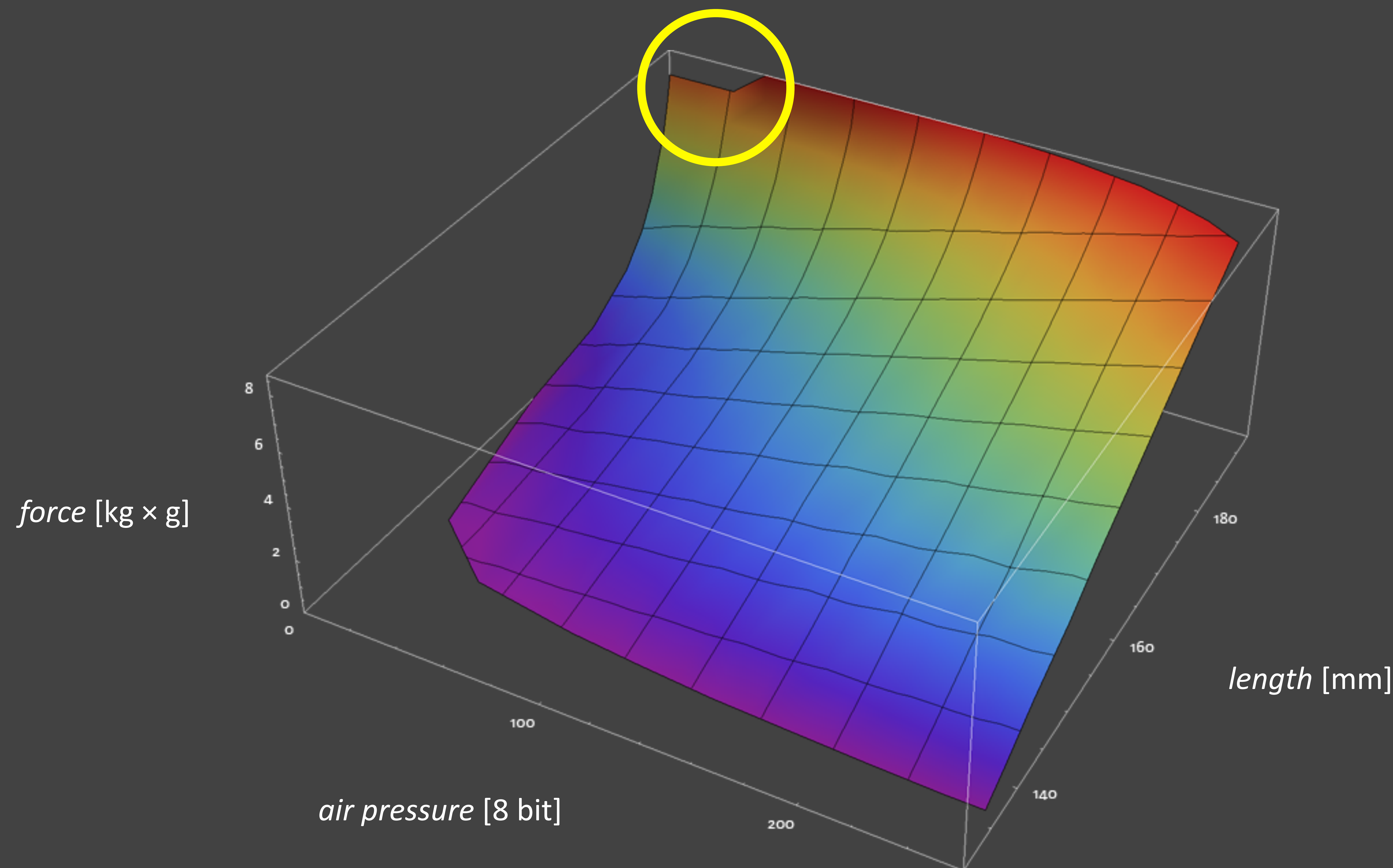
$$\frac{\sum_i (\text{measured}_i - \text{simulated}_i)^2}{\sum_i \text{measured}_i^2} \approx 4.2 \cdot 10^{-4}$$



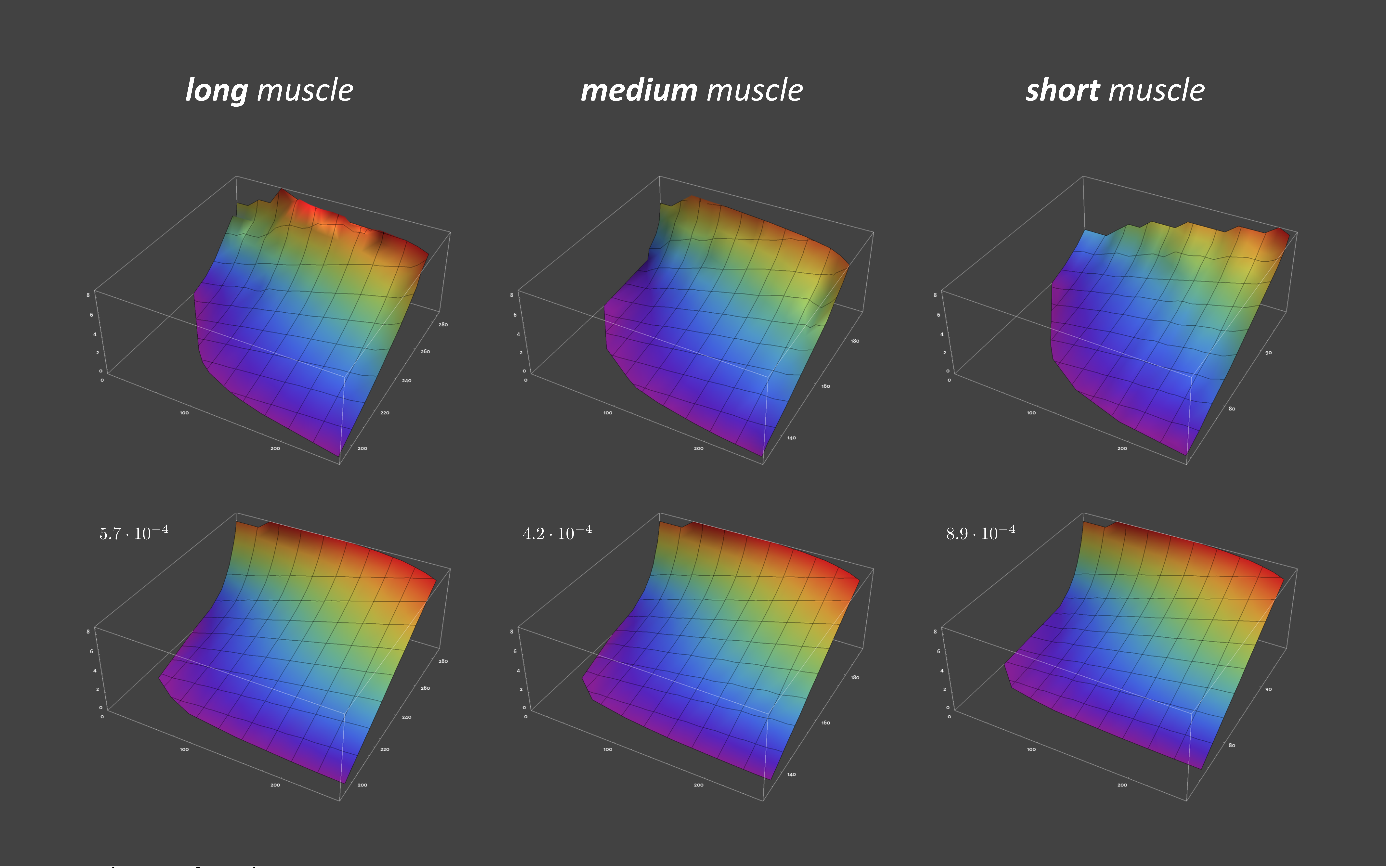
error with respect to original measurement
same kink at low pressure & long length (compare original), reproduced by model

Measurement in Simulator

$$\frac{\sum_i (\text{measured}_i - \text{simulated}_i)^2}{\sum_i \text{measured}_i^2} \approx 4.2 \cdot 10^{-4}$$



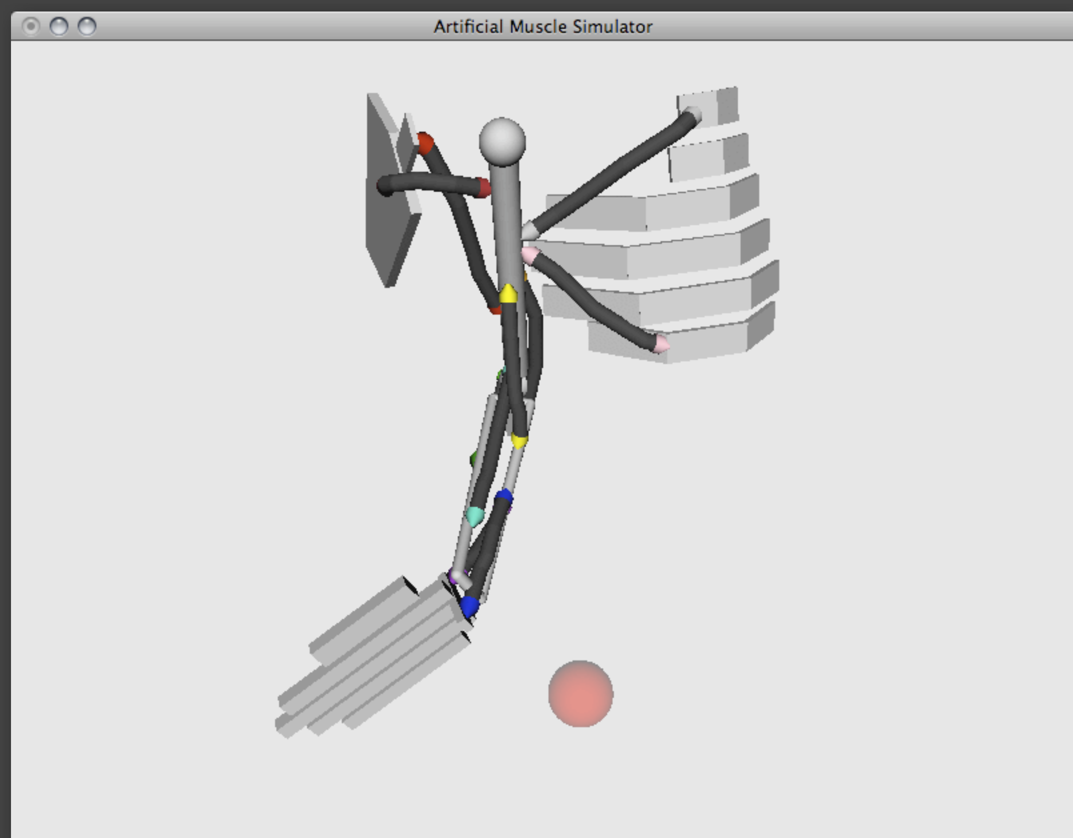
error with respect to original measurement
same kink at low pressure & long length (compare original), reproduced by model

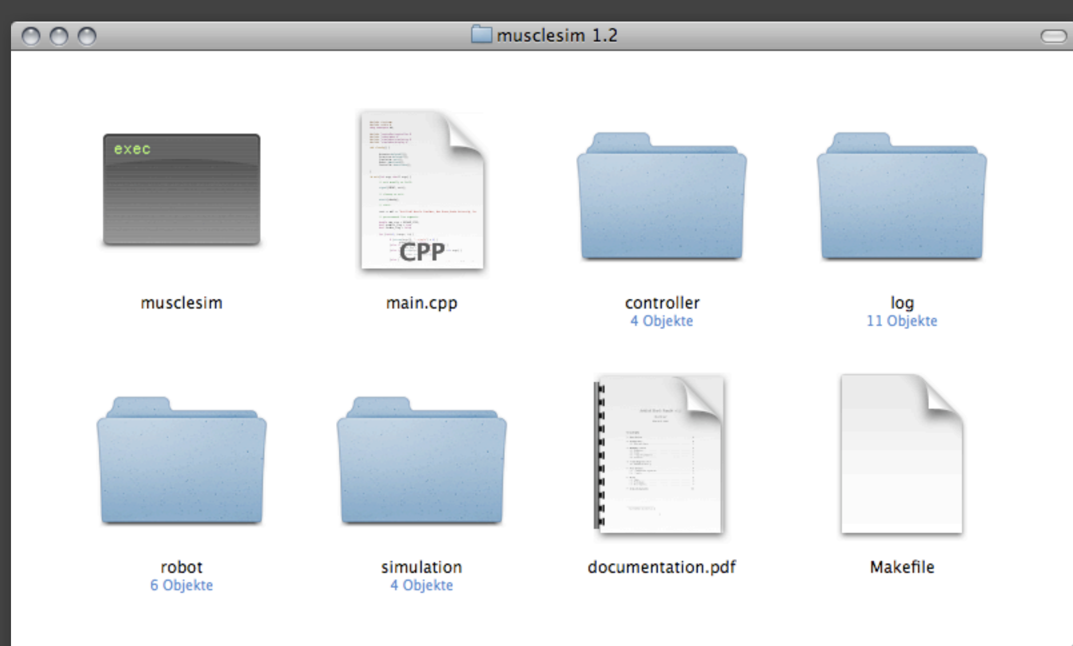


compared 3 types of muscles
top: measurements, bottom: measurements in simulator

1. The robotic arm and its artificial muscles
2. Simulating artificial muscles
3. **The simulator software**
4. Fluctuation and results

Software engineering



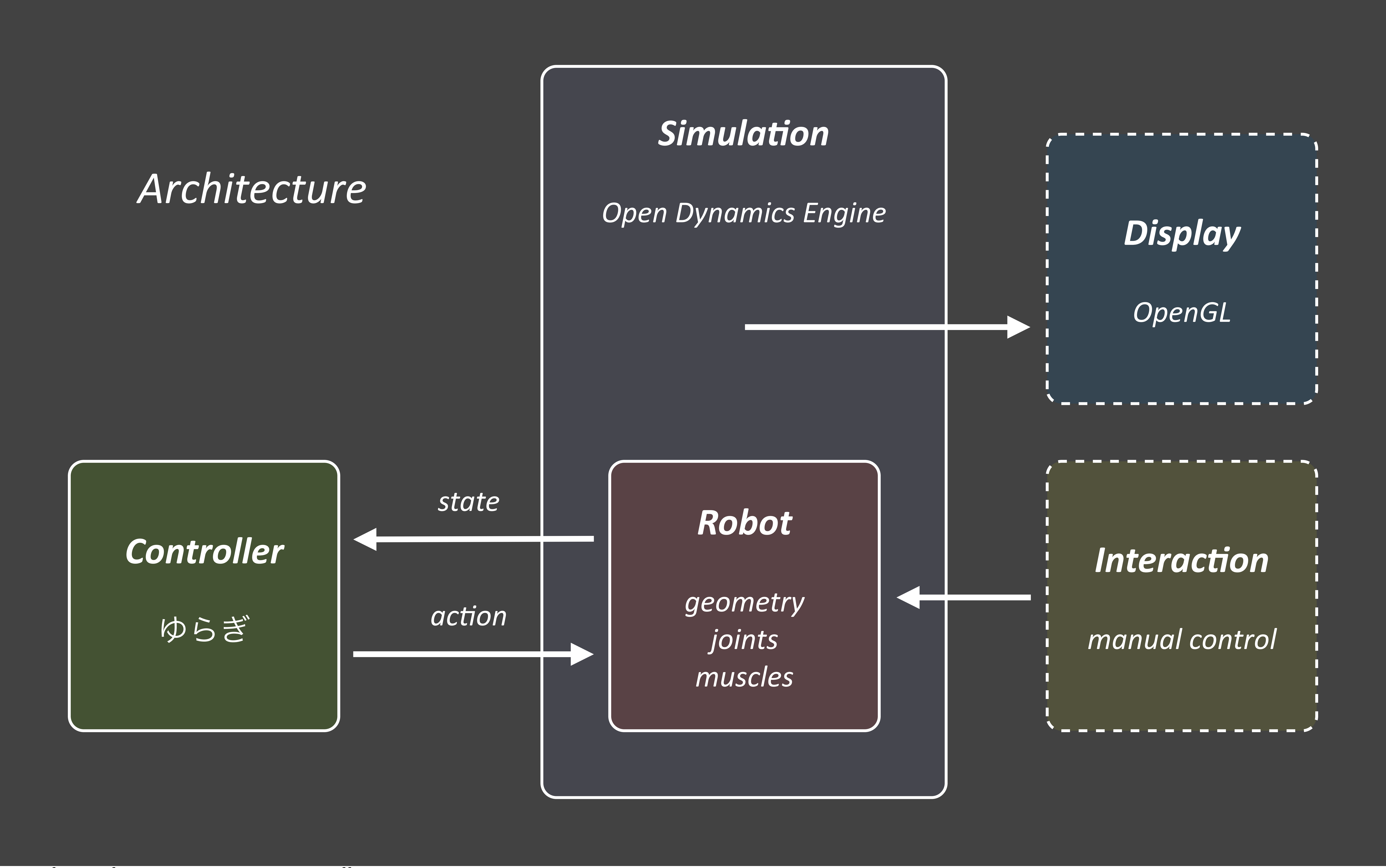


User tasks:

1. ***Build*** a robot
   - Create geometry
   - Connect with joints
   - Place actuators
2. ***Control*** the robot dynamically

Realization:

- Abstraction of ***ODE*** and ***OpenGL***
- Written in ***C++*** (also interface)



simulation loop: robot, state, controller, action
display and interaction: separate and optional

Documentation

Artificial Muscle Simulator 1.2

Max Braun*

March 21, 2008

Contents

*max.braun@ams.eng.osaka-u.ac.jp

1

simulator: reusable, highly customizable
detailed usage: read documentation
now: just one example ...

Documentation

7 Acknowledgements

The *Artificial Muscle Simulator* was developed in 2007/2008 by *Max Braun*, a student of computational visualistics at the University of Koblenz-Landau, Koblenz, Germany, during a one-semester stay at the *Yuragi* project[10] of Osaka University, Osaka, Japan, initiated by the Artificial Intelligence Research Group (AGKI)[11] in Koblenz and supported by scholarships from the German Academic Exchange Service (DAAD)[12] and the German National Academic Foundation (Studienstiftung des deutschen Volkes)[13].

References

[1] Smith, R.: Open Dynamics Engine. `http://www.ode.org/`

[2] Smith, R.: ODE User Guide. `http://www.ode.org/ode-latest-userguide.html`

[3] Y. Nakamura, I. Fukuyori, M. Braun, Y. Matsumoto, H. Ishiguro: Control of human-like robotic arm based on biological fluctuation. In IROS, 2008 (submitted)

[10] http://www.yuragi.osaka-u.ac.jp/
[11] http://www.uni-koblenz.de/FB4/Institutes/IFI/AGKI
[12] http://www.daad.de/
[13] http://www.studienstiftung.de/

simulator: reusable, highly customizable
detailed usage: read documentation
now: just one example ...

Code example: a new muscle with its connections

```
dVector3 muscle_start_at = {-223, 360, 0};
dVector3 muscle_start_control = {-293, 410, -40};
dVector3 muscle_end_control = {-280, 360, -100};
dVector3 muscle_end_at = {-230, 360, -120};

Muscle* muscle = new Muscle(
    world, space, // system parameters
    muscle_start_at, // 1st control point
    muscle_start_control, // 2nd control point
    muscle_end_control, // 3rd control point
    muscle_end_at, // 4th control point
    75, // minimum length
    200 // maximum length
);

muscle->connectStartTo(humerus);
muscle->connectEndTo(scapula);
```

Bézier curve: 3rd-degree, 4 control points
muscle specification: control points, minimum length, maximum length

1. The robotic arm and its artificial muscles

2. Simulating artificial muscles

3. The simulator software

4. Fluctuation and results

short introduction to attractor selection model
application of the simulator

Attractor selection model

$$\dot{\mathbf{x}} = a \cdot \nabla P(\mathbf{x}) + \eta$$

state (air pressures)
gradient descent with noise (fluctuation)
potential field P: attractors x_i (Gaussian)
activity: high activity suppresses noise (quality of the external state, average)

Attractor selection model

state change → $$\dot{\mathbf{x}} = a \cdot \nabla P(\mathbf{x}) + \eta$$

state (air pressures)
gradient descent with noise (fluctuation)
potential field P: attractors x_i (Gaussian)
activity: high activity suppresses noise (quality of the external state, average)

Attractor selection model

potential field

$$P(\mathbf{x}) = -\sum_{i=1}^{n} \frac{1}{\sqrt{2\pi\sigma^2}} \exp(-\frac{1}{2\sigma^2}|\mathbf{x} - \mathbf{x}_i|^2)$$

state change

$$\dot{\mathbf{x}} = a \cdot \nabla P(\mathbf{x}) + \eta$$

state (air pressures)
gradient descent with noise (fluctuation)
potential field P: attractors x_i (Gaussian)
activity: high activity suppresses noise (quality of the external state, average)

Attractor selection model

potential field

$$P(\mathbf{x}) = -\sum_{i=1}^{n} \frac{1}{\sqrt{2\pi\sigma^2}} \exp(-\frac{1}{2\sigma^2}|\mathbf{x} - \mathbf{x}_i|^2)$$

state change → $\dot{\mathbf{x}} = a \cdot \nabla P(\mathbf{x}) + \eta$ ← *noise*

state (air pressures)
gradient descent with noise (fluctuation)
potential field P: attractors x_i (Gaussian)
activity: high activity suppresses noise (quality of the external state, average)

Attractor selection model

potential field

$$P(\mathbf{x}) = -\sum_{i=1}^{n} \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2\sigma^2}|\mathbf{x} - \mathbf{x}_i|^2\right)$$

state change

$$\dot{\mathbf{x}} = a \cdot \nabla P(\mathbf{x}) + \eta$$

noise

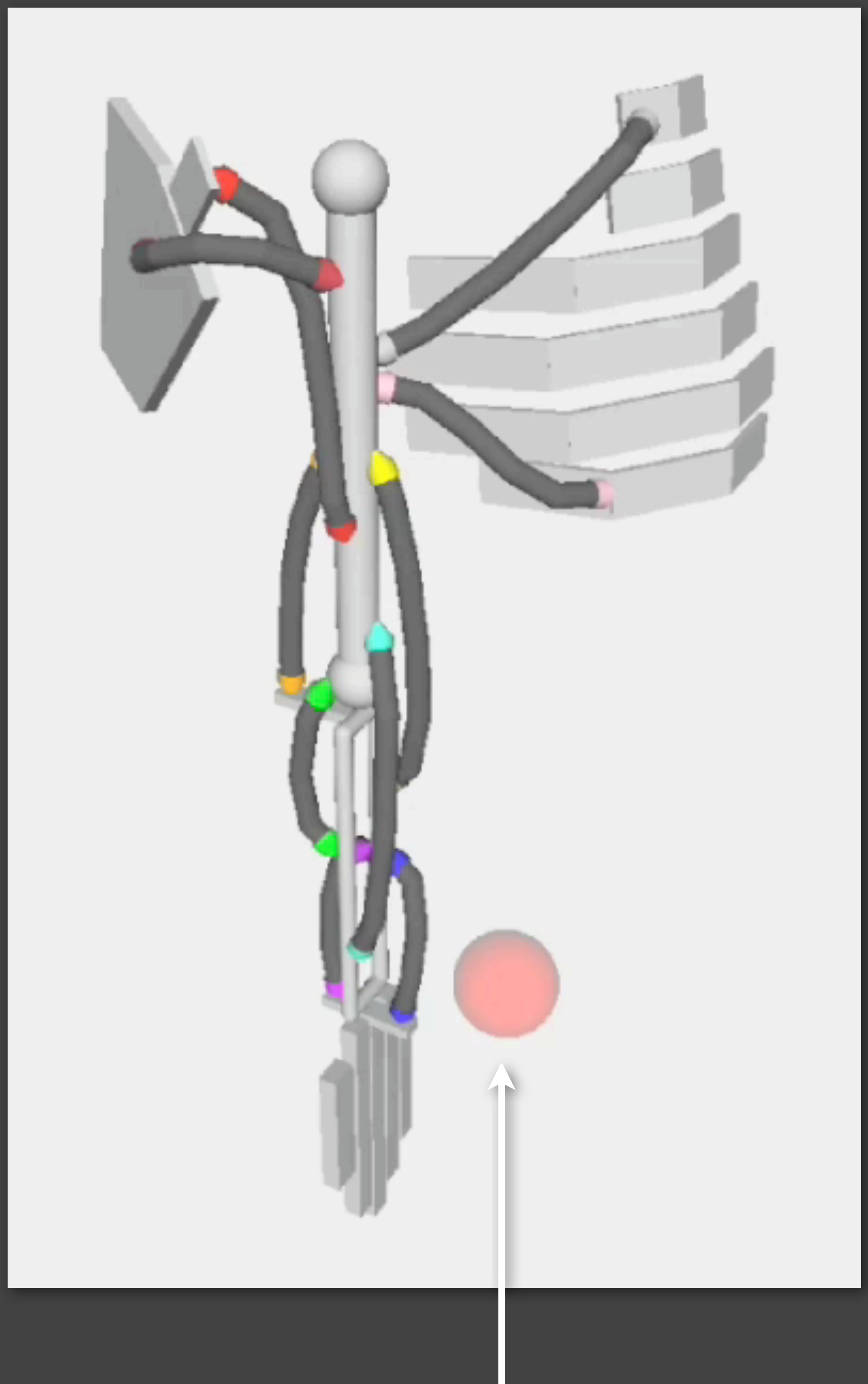
activity

$$a(t) = d(t) - \bar{d}(t-1)$$

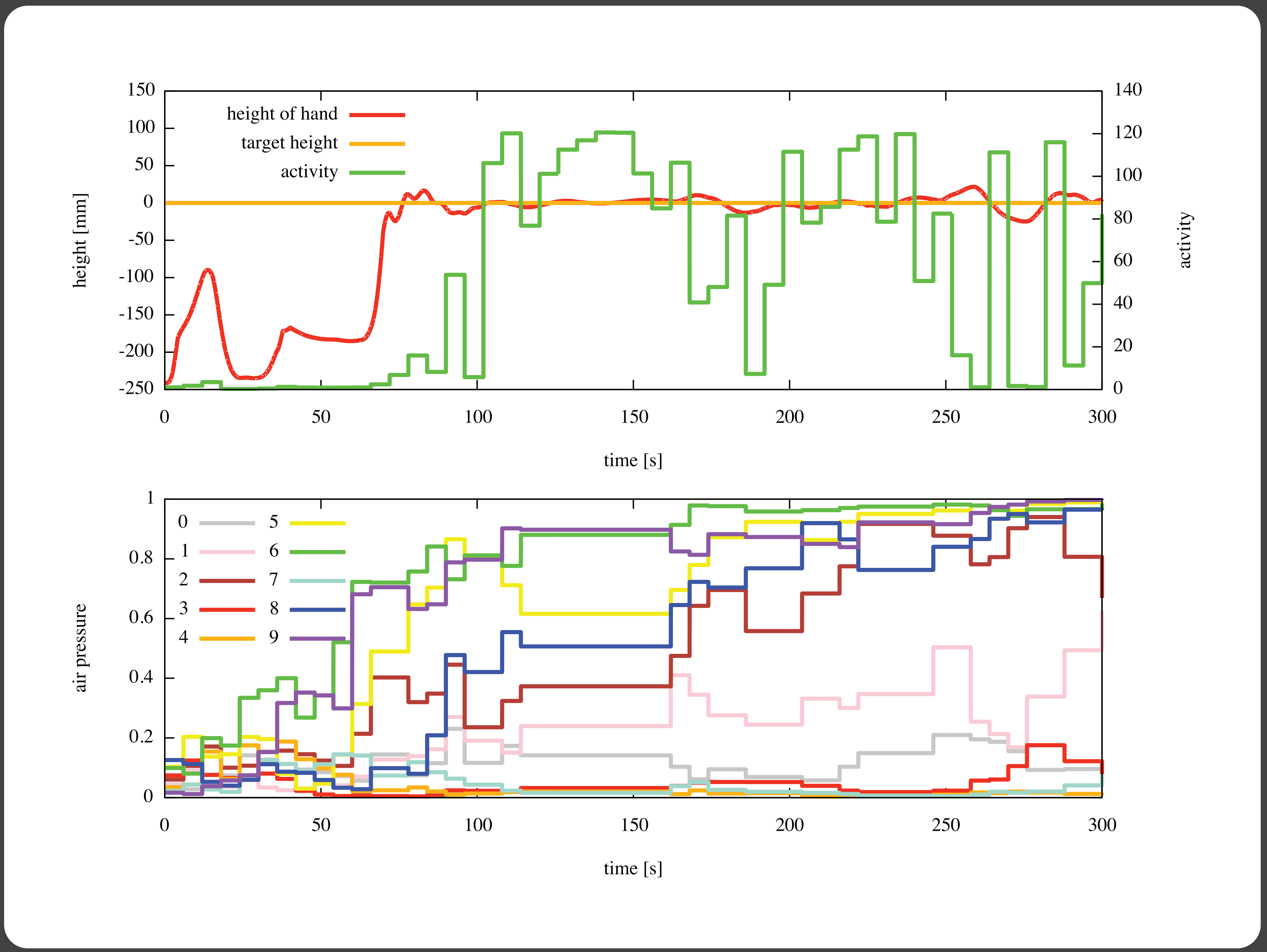
$$d(t) = |\hat{\mathbf{z}} - \mathbf{z}(t)|^{-1}$$

$$\bar{d}(t-1) = \frac{\sum_{\tau=1}^{t-1} \gamma^{\tau} d(t-\tau)}{\sum_{\tau=1}^{t-1} \gamma^{\tau}}$$

state (air pressures)
gradient descent with noise (fluctuation)
potential field P: attractors x_i (Gaussian)
activity: high activity suppresses noise (quality of the external state, average)



target



red dot: target, height reaching task
10 actuators, 400 attractors, 6 seconds delay
upper: height (red), target height (orange), activity (green)
lower: state (corresponding colors)

IROS 2008 submission

Y. Nakamura, I. Fukuyori, M. Braun, Y. Matsumoto, H. Ishiguro:
Control of human-like robotic arm based on biological fluctuation.

Control of human-like robotic arm based on biological fluctuation

Yutaka Nakamura, Ippei Fukuyori, Max Braun, Yoshio Matsumoto, and Hiroshi Ishiguro

***Abstract*— Animals whose bodies have complex structure can work flexible, but controlling a complex system by existing control methods would be difficult because of its complexity. Recent biological studies reveals that animals utilize (or exploit) biological fluctuation to achieve such flexibility. In this paper, we propose a simple but flexible control mechanism inspired by biological adaptation mechanism. We developed a human-like robotic arm and apply our proposed method to the control of the robot. Experimental results show that our proposed method can be applied to the control of a robot with complex structure.**

I. INTRODUCTION

Various robot systems are working in our society, and are indispensable for our lives in these days. However most of them are working at production lines in factories which are designed for robots. In the future, robots are expected to support our daily lives [4], [8], however there is no robots which can work in the real, unstructured environments. In order for the robots to work in our daily lives, they are required to have robustness against various disturbance, flexibility for unknown environments, and utility for performing practical tasks. In order to realize such functions, robots should have large degrees of freedom, and achieve complex motions. Humans and animals have complex mechanical structures, and many robot systems inspired by their structures have been developed[2], [1].

Heretofore various control methods have been studied. The representatives of them are classical control theory which utilizes transfer function, and optimal control theory such as H_∞ control. However the more the complexity of the target system becomes, the harder the modeling of the system becomes. Learning methods such as reinforcement learning can also be utilized for optimization, however the number of necessary trials increases explosively when the complexity of the system increases.[3], [11], [10], [9]. This paper focuses on the problems in which the system is hard to model due to its complexity and fluctuation of the environment, and proposes a simple and robust control method inspired by biological systems. The biological system is known to have a potential to adapts to a new, unknown, and noisy environment. The mechanism of such flexible adaptation is investigated especially in molecular biology, and the importance of the biological fluctuation is made clear[12]. The fluctuation in molecular science is actually a noise due to the heat fluctuation, which is unavoidable and unpredictable. In conventional control for robot systems, such noise should be removed to the maximum extent. However, it is now believed that biological systems do not remove the noise but rather make use of it in order to adapt to the environment.

In this research, we developed a human like robotic arm by imitating the anatomy of human upper limb. Because this robot has similar structure with human and redundant number of artificial muscle actuators like human, so it is expected to work flexible like human arm. However, it is difficult to control this robot by an existing method due to the complexity of its own structure. We propose a novel control method for such a complex robot, inspired by biological fluctuation. This method is expected to handle control problems for complex systems in unknown environment without modeling them.

Section II describes "adaptive attractor selection." Section III describes the proposed control mechanism, and the characteristics and the feasibility of the proposed controller is shown in section IV. In section V, the proposed method is applied to human like robotic arm and show the availability of the proposed method. Section VI concludes the paper.

II. BIOLOGICAL FLUCTUATION

Bacteria can adapt to the environmental changes. For example, even if some important nutrient dramatically decrease, bacteria can handle such crisis by alteration of gene expression. Kashiwagi et al. built a model of this adaptation mechanism based on a biological fluctuation, and explained the behavior of the bacteria. In this model, the gene expression is controlled by a dynamical system with some attractors, and this model is called "attractor selection model"[5].

1) Attractor selection model: The attractor selection model can be represented by Langevin equation as:

$$\tau_x \dot{\mathbf{x}} = f(\mathbf{x}) \times A + \epsilon, \qquad (1)$$

where $\mathbf{x}$ and $f(\mathbf{x})$ are the state and the dynamics of the attractor selection model, and τ_x and ϵ are the time constant and the noise, respectively. This formulation (1) is not the only way to implement the attractor selection model, but it is convenient to explain the behavior of the attractor selection model.

A is a variable called "activity" which indicates the fitness of the state $\mathbf{x}$ to the environment, and controls the behavior of the attractor selection model. That is, $f(\mathbf{x}) \times A$ becomes dominant in (1) when the activity is large, and the state transition approaches deterministic. On the other hand, the noise ϵ becomes dominant in (1) when the activity is small, and the state transition becomes more probabilistic. Because $f(\mathbf{x})$ is designed to have some attractors, the state of the system is entrained into one attractor when the activity is

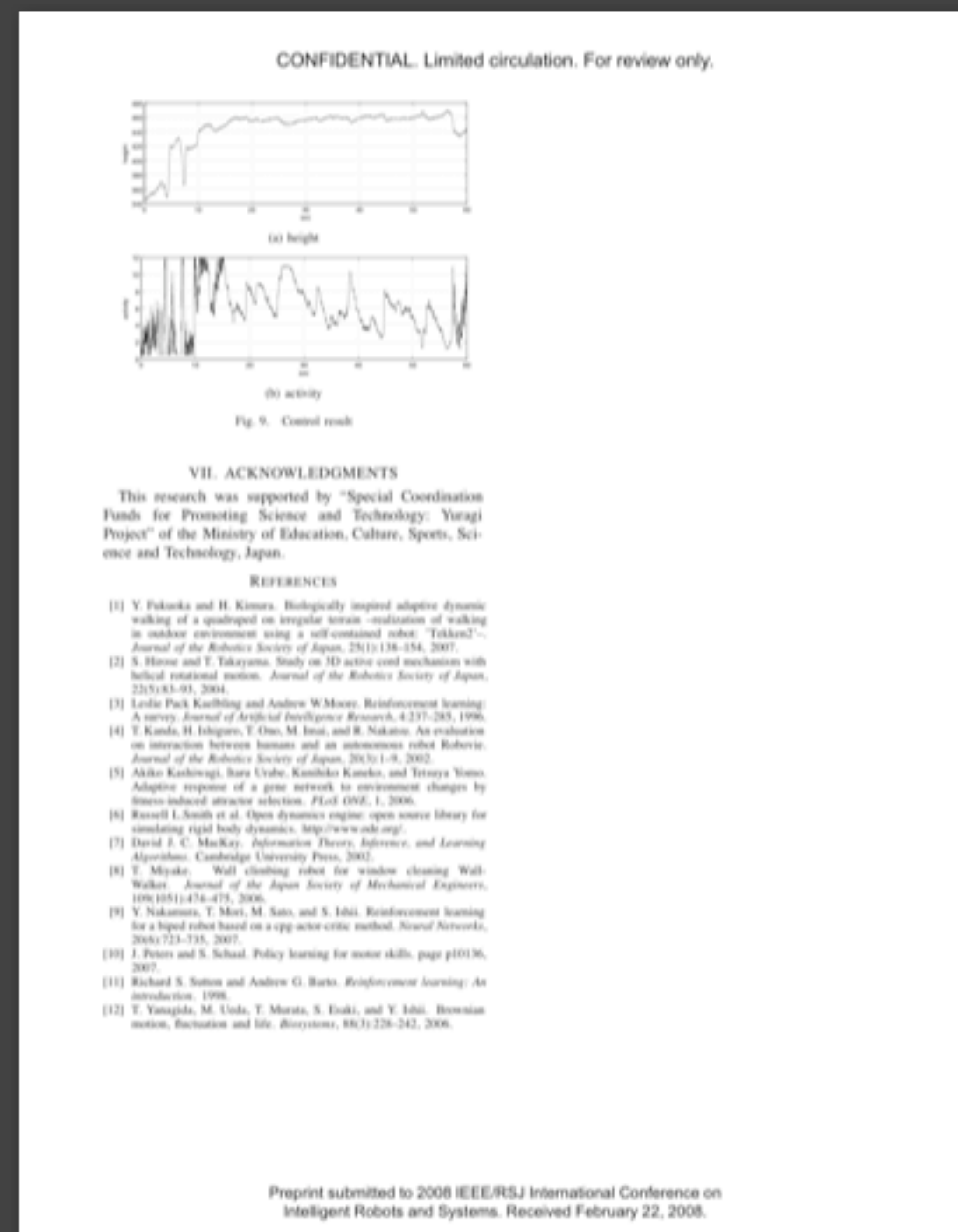
Department of adaptive machine systems, graduate school of engineering, Osaka University, 2-1 Yamada-oka, Suita, Osaka, Japan nakamura@ams.eng.osaka-u.ac.jp

Preprint submitted to 2008 IEEE/RSJ International Conference on Intelligent Robots and Systems. Received February 22, 2008.

attractor selection model, adaptive attractor selection model
results with simulator
results with actual robotic arm
proof of concept

IROS 2008 submission

Y. Nakamura, I. Fukuyori, M. Braun, Y. Matsumoto, H. Ishiguro:
Control of human-like robotic arm based on biological fluctuation.



(a) height

(b) activity

Fig. 9. Control result

VII. ACKNOWLEDGMENTS

This research was supported by "Special Coordination Funds for Promoting Science and Technology: Yuragi Project" of the Ministry of Education, Culture, Sports, Science and Technology, Japan.

REFERENCES

[1] Y. Fukuoka and H. Kimura. Biologically inspired adaptive dynamic walking of a quadruped on irregular terrain -realization of walking in outdoor environment using a self-contained robot: 'Tekken2'-. *Journal of the Robotics Society of Japan*, 25(1):138–154, 2007.
[2] S. Hirose and T. Takayama. Study on 3D active cord mechanism with helical rotational motion. *Journal of the Robotics Society of Japan*, 22(5):83–93, 2004.
[3] Leslie Pack Kaelbling and Andrew W.Moore. Reinforcement learning: A survey. *Journal of Artificial Intelligence Research*, 4:237–285, 1996.
[4] T. Kanda, H. Ishiguro, T. Ono, M. Imai, and R. Nakatsu. An evaluation on interaction between humans and an autonomous robot Robovie. *Journal of the Robotics Society of Japan*, 20(3):1–9, 2002.
[5] Akiko Kashiwagi, Itaru Urabe, Kunihiko Kaneko, and Tetsuya Yomo. Adaptive response of a gene network to environment changes by fitness-induced attractor selection. *PLoS ONE*, 1, 2006.
[6] Russell L.Smith et al. Open dynamics engine: open source library for simulating rigid body dynamics. *http://www.ode.org/*.
[7] David J. C. MacKay. *Information Theory, Inference, and Learning Algorithms*. Cambridge University Press, 2002.
[8] T. Miyake. Wall climbing robot for window cleaning Wall-Walker. *Journal of the Japan Society of Mechanical Engineers*, 109(1051):474–475, 2006.
[9] Y. Nakamura, T. Mori, M. Sato, and S. Ishii. Reinforcement learning for a biped robot based on a cpg-actor-critic method. *Neural Networks*, 20(6):723–735, 2007.
[10] J. Peters and S. Schaal. Policy learning for motor skills. page p10136, 2007.
[11] Richard S. Sutton and Andrew G. Barto. *Reinforcement learning: An introduction*. 1998.
[12] T. Yanagida, M. Ueda, T. Murata, S. Esaki, and Y. Ishii. Brownian motion, fluctuation and life. *Biosystems*, 88(3):228–242, 2006.

Preprint submitted to 2008 IEEE/RSJ International Conference on Intelligent Robots and Systems. Received February 22, 2008.

attractor selection model, adaptive attractor selection model
results with simulator
results with actual robotic arm
proof of concept

大阪大学　“ゆらぎ”プロジェクト

以上です。ありがとうございました。