



Tokyo Tech

# Force Distribution Sensor Based on Externally Observable Three-Dimensional Shape Deformation Information

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Ryuichi Ikeya and Yoshifumi Nishida

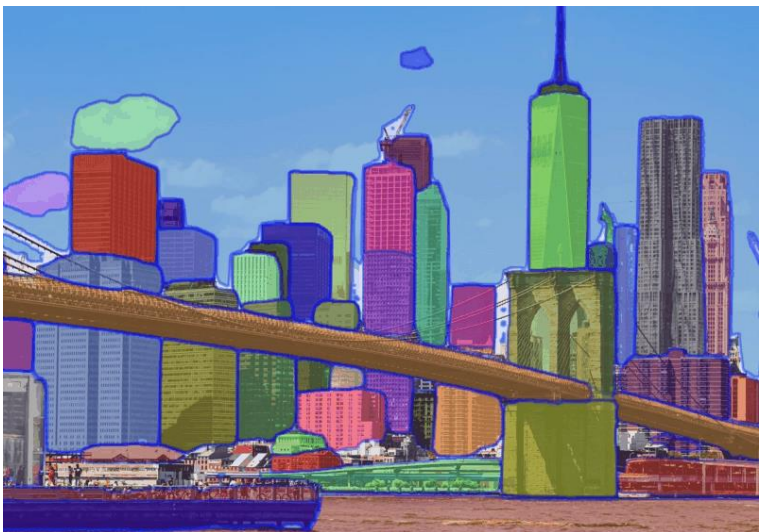
Institute of Science Tokyo

# Technical background

It has become possible to easily extract the shape of an object.

## Software Development

Classification of object at pixel level



Latest segmentation models[1]

## Hardware Development

Inexpensive RGBD cameras



Azure Kinect  
\$399



Intel RealSense  
\$499

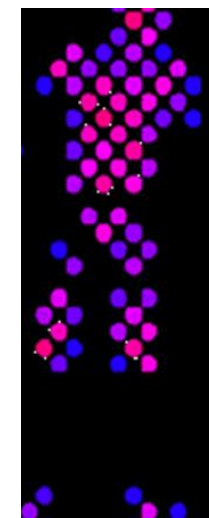
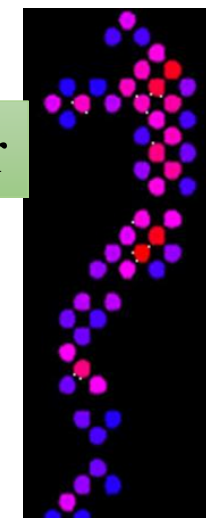
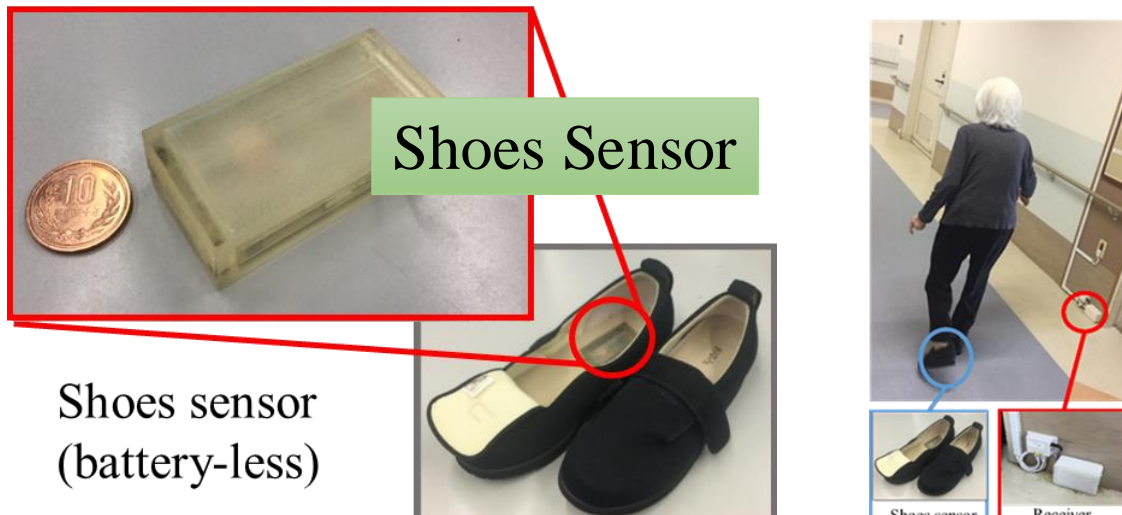


## 3D data of the object

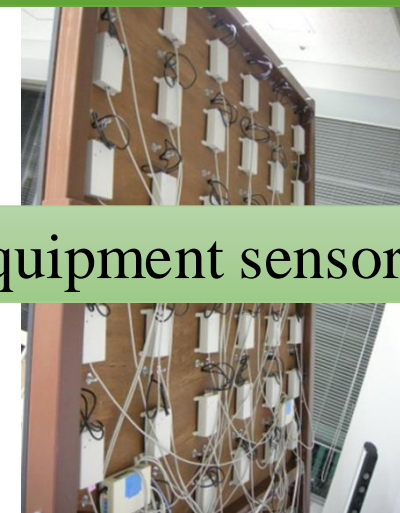


Open a new way of estimating force just by observing deformations.

# Conventional sensing



## Conventional: Sensorization by sensor embedding



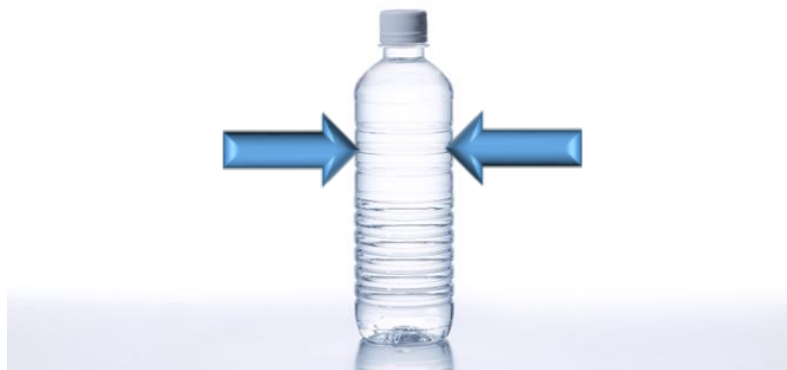


# Future sensing

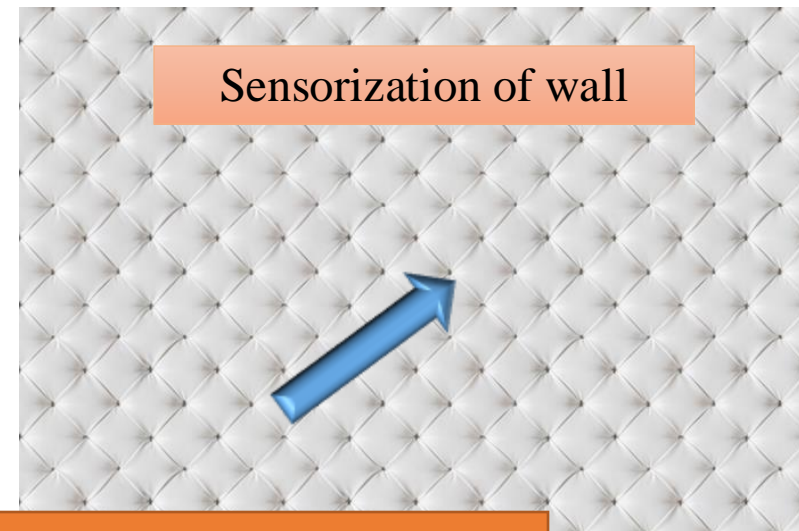
Sensorization of houseplant



Sensorization of PET bottle



Sensorization of wall



Future: Sensorization by deformation observation



Sensorization of sofa and bed



Sensorization of desk

# Previous research

**Vision sensors that estimate forces from images are attracting attention.**

Single-point force estimation from images using an experimentally generated dataset. [1]

- Models can be easily created and inference can be performed in real time.



## Limitations

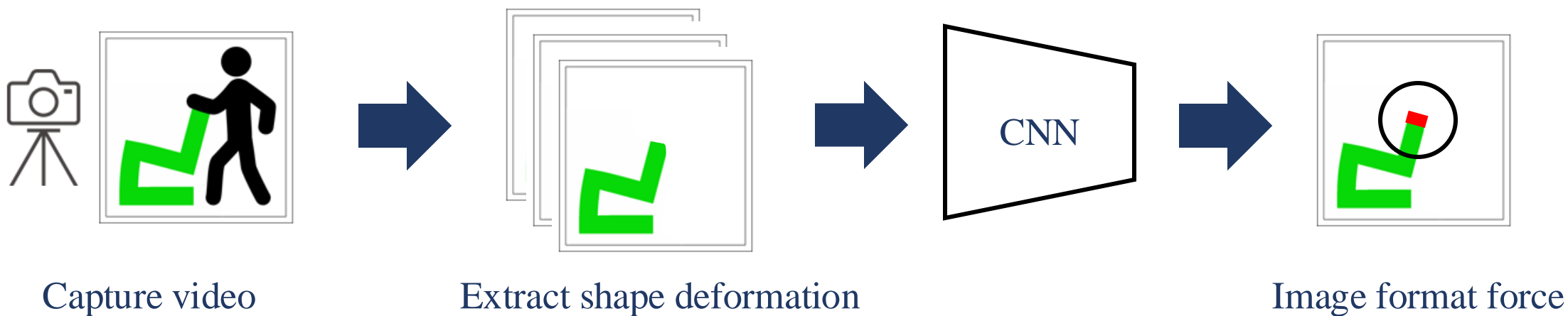
- Not flexible to changes in the experimental environment.
  - Changes in background, changes in lighting, presence of humans.
- Single-point force estimation limits application possibilities.

# Research objective and method

## Objective

- Proposing a new force sensor principle that estimates force distribution just by observing deformation and verifying its feasibility.

## Method

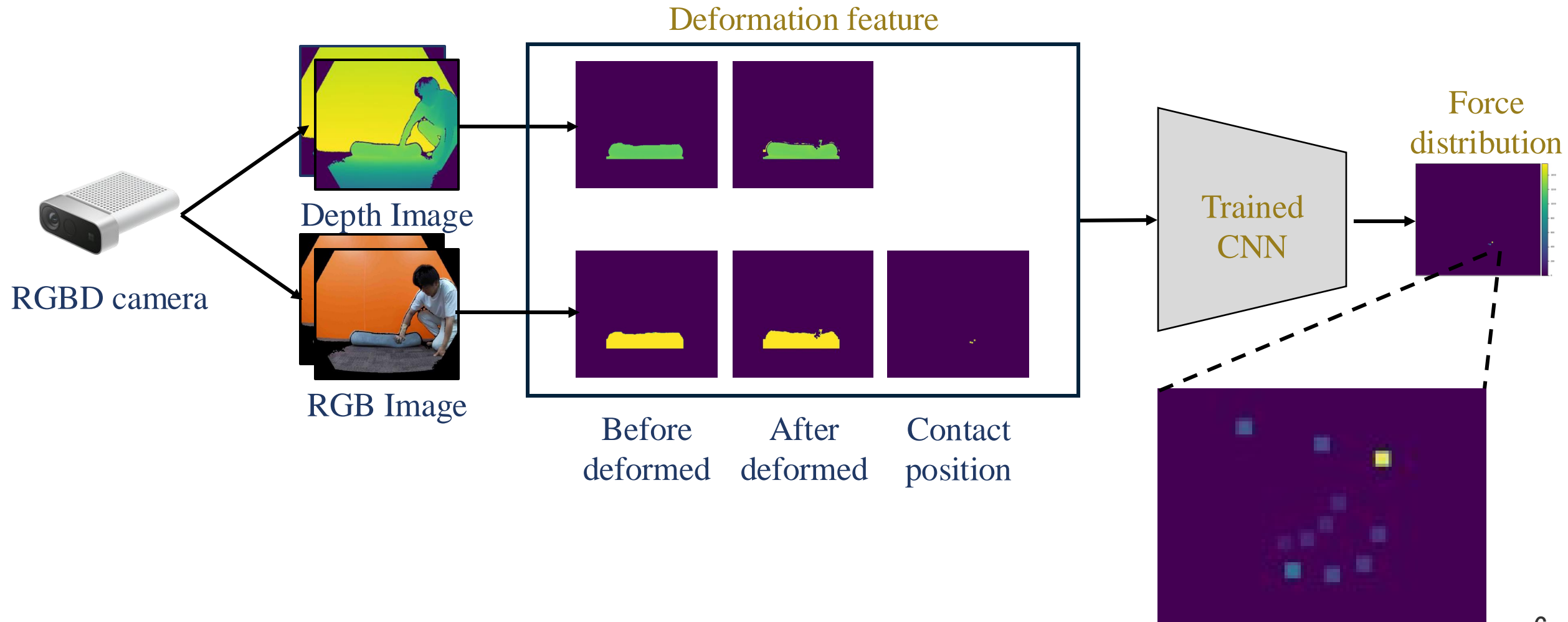


## Novelty

- Flexible to environmental changes by extracting deformation feature.
- Multi-point estimation become possible by expressing force in image format.

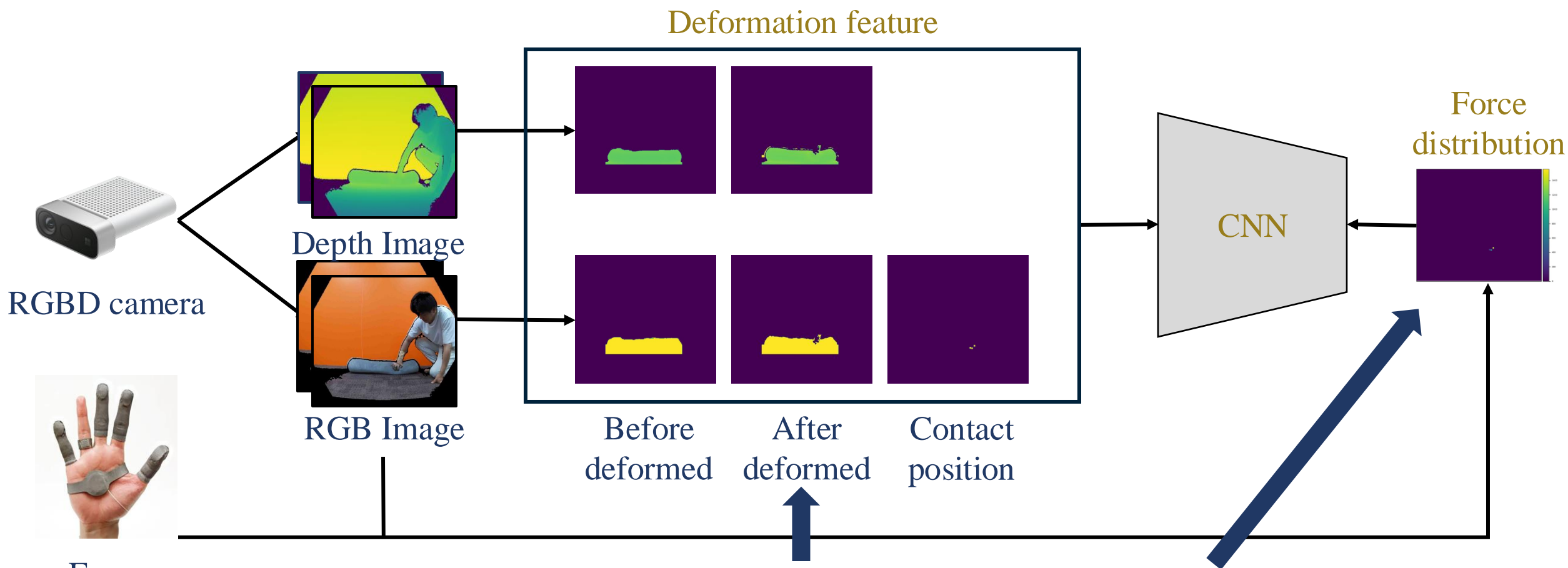
# Details of the proposed method (Inference process)

Deformation feature is extracted from two images and force distribution is inferred using a trained machine learning model (CNN).



# Details of the proposed method (Training process)


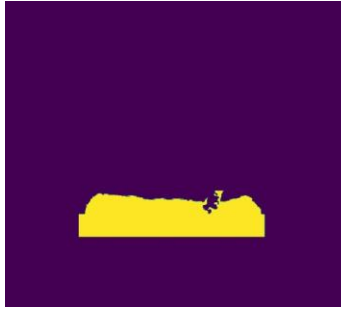
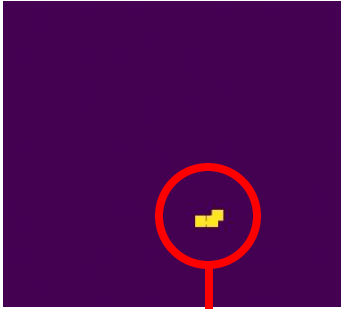

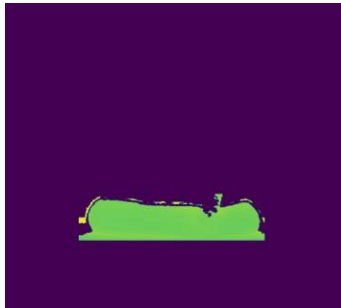
Learns the relationship between deformation feature and force distribution.



By expressing as image format, machine learning is possible.



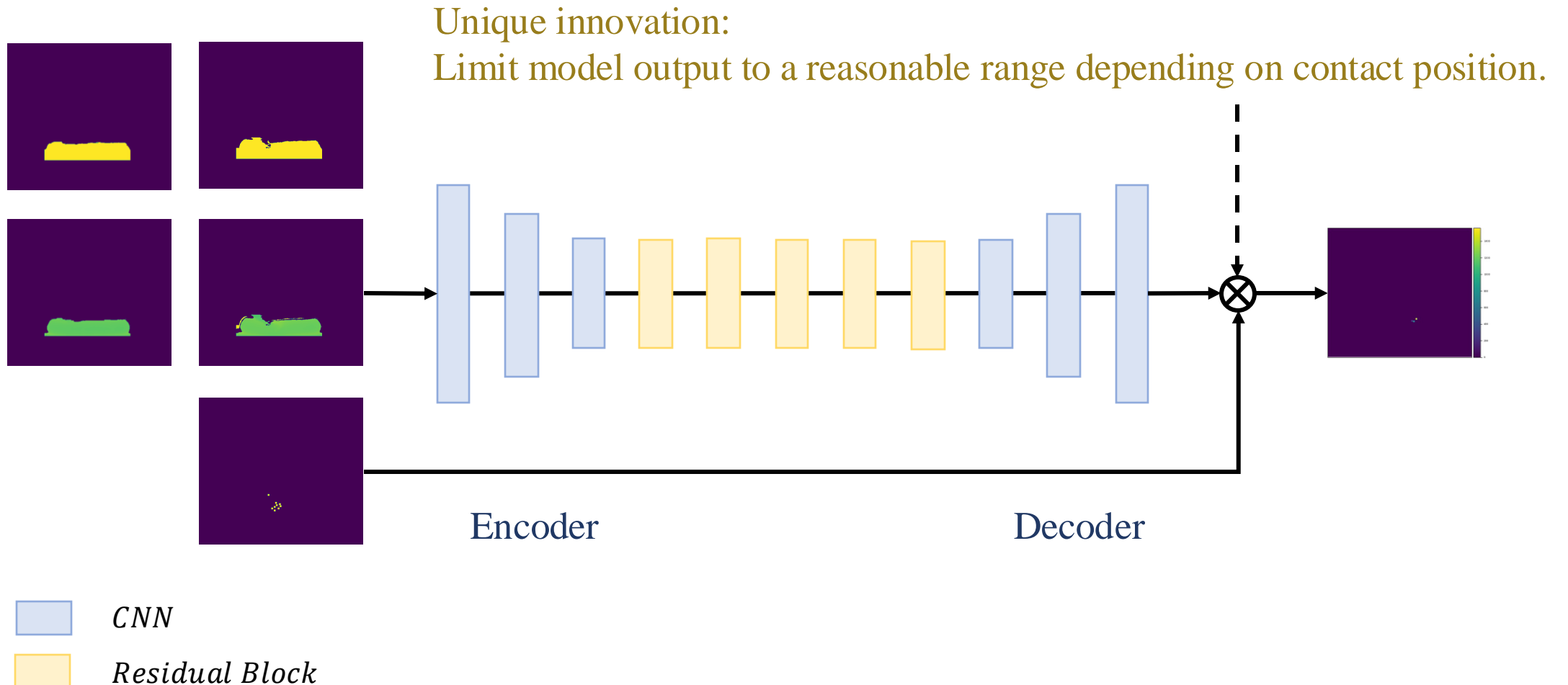
# How to express deformation feature

	Before deformation	After deformation	Contact position
Contour feature Binary image [0 or 1]			
Depth feature Grayscale image [0 to 1]			



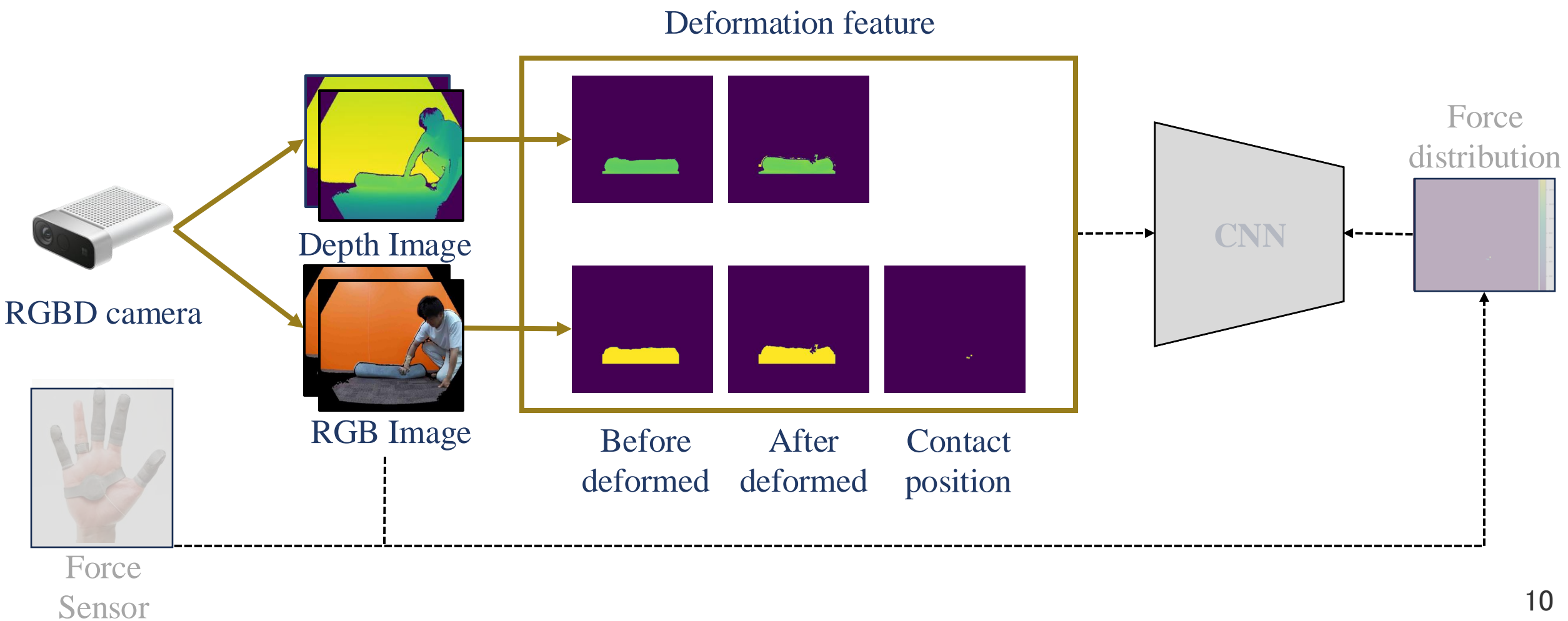
# Machine learning model architecture

A typical encoder-decoder model which is used for tasks with image inputs and output.

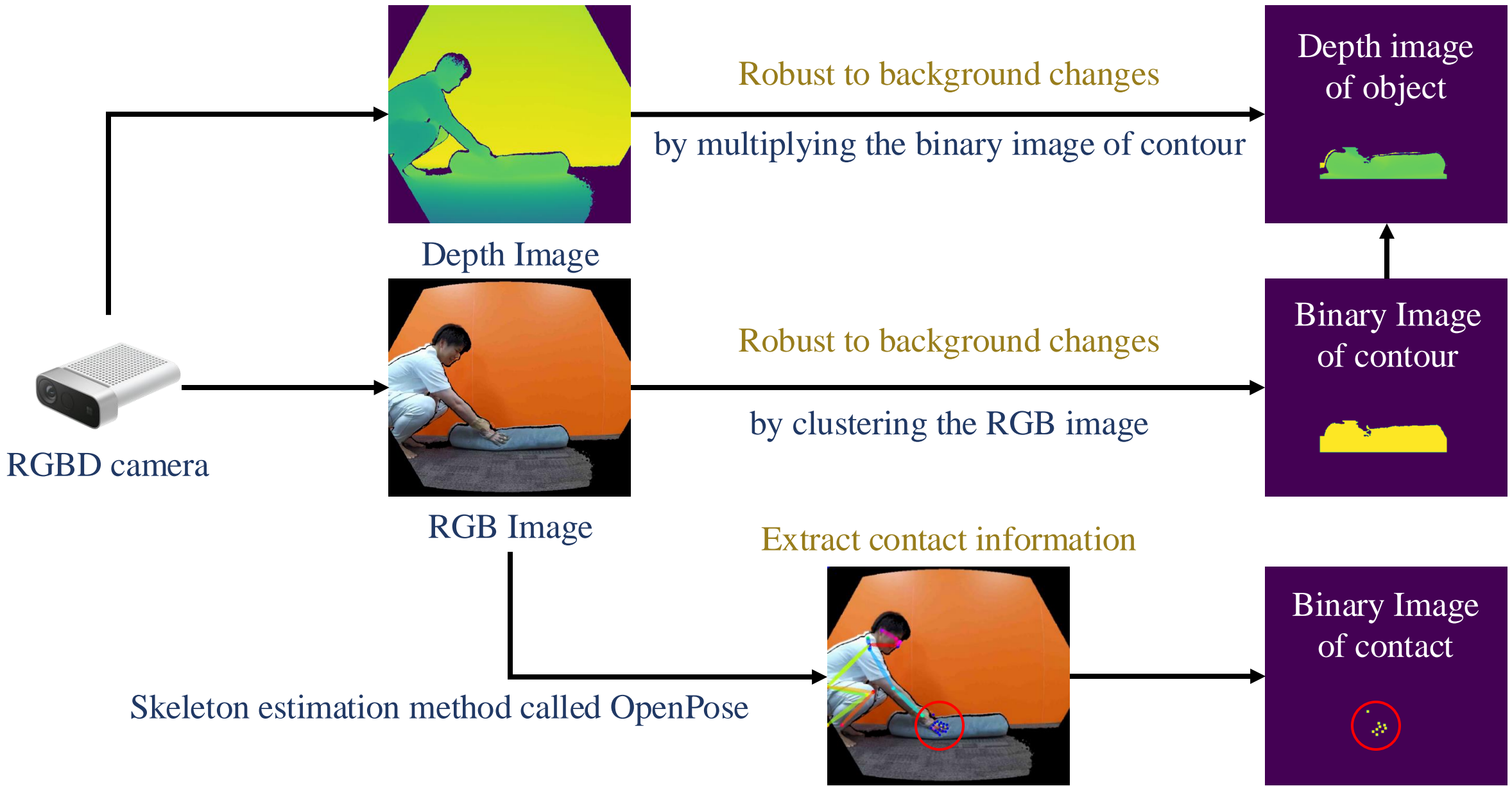


# Creating a Dataset

1. Extracting deformation feature.
2. Creating teacher data using force sensor.



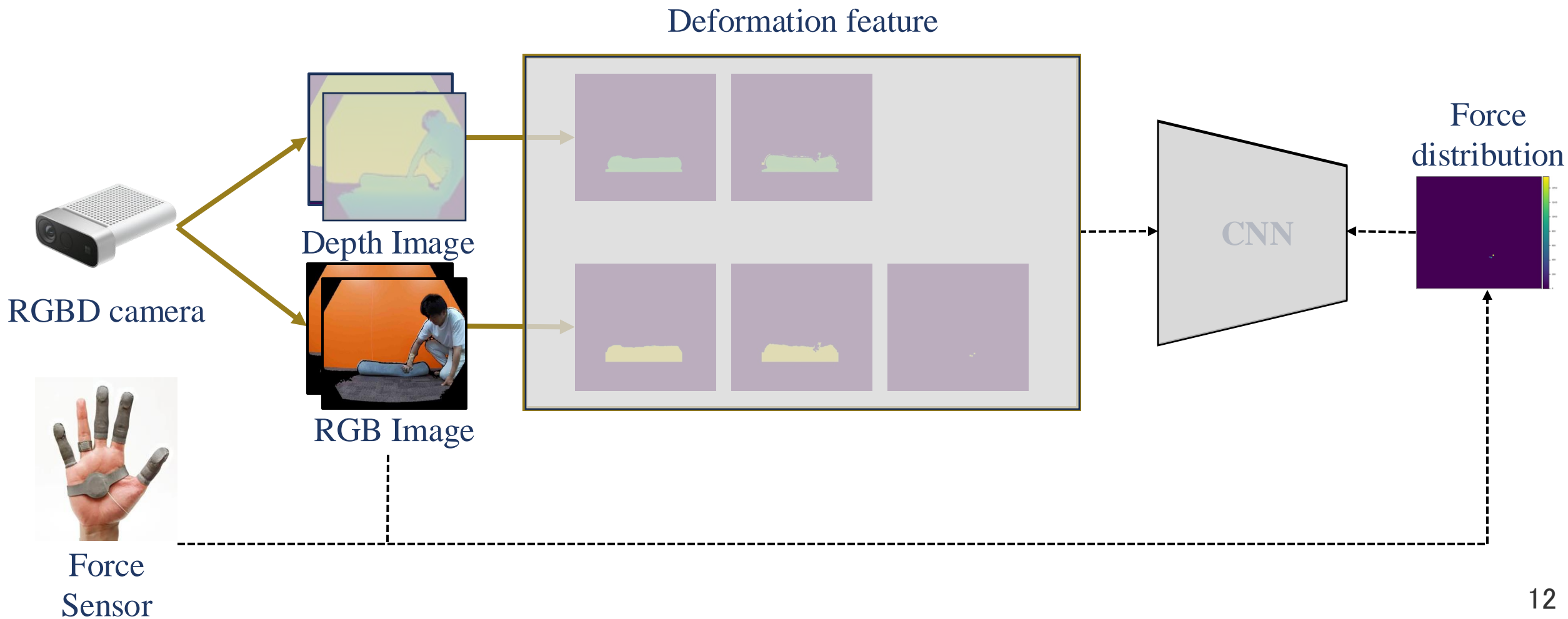
# Overview of extraction of deformation feature by image processing





# Creating a Dataset

1. Extraction of deformation feature.
2. Creating teacher data using force sensor.



# Creating teacher data

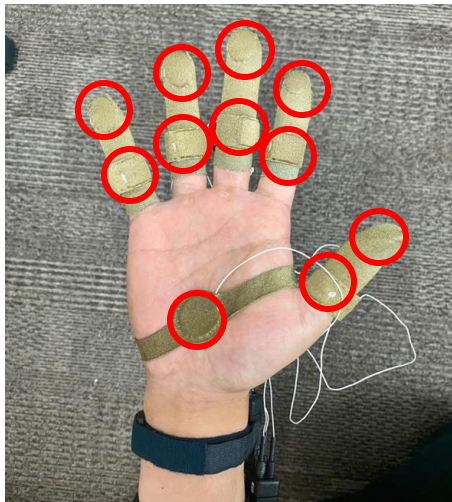


RGB Image

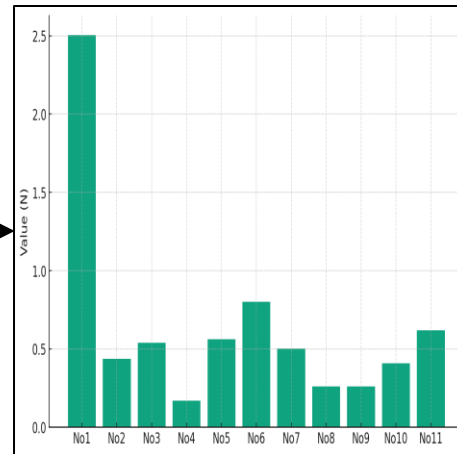
OpenPose



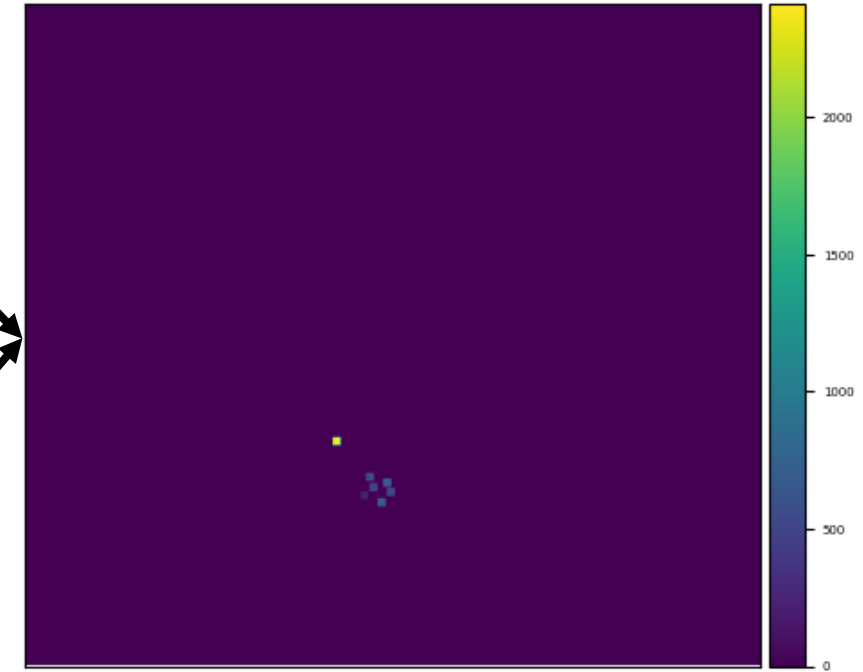
11 representative  
finger skeleton coordinates



Force Sensor

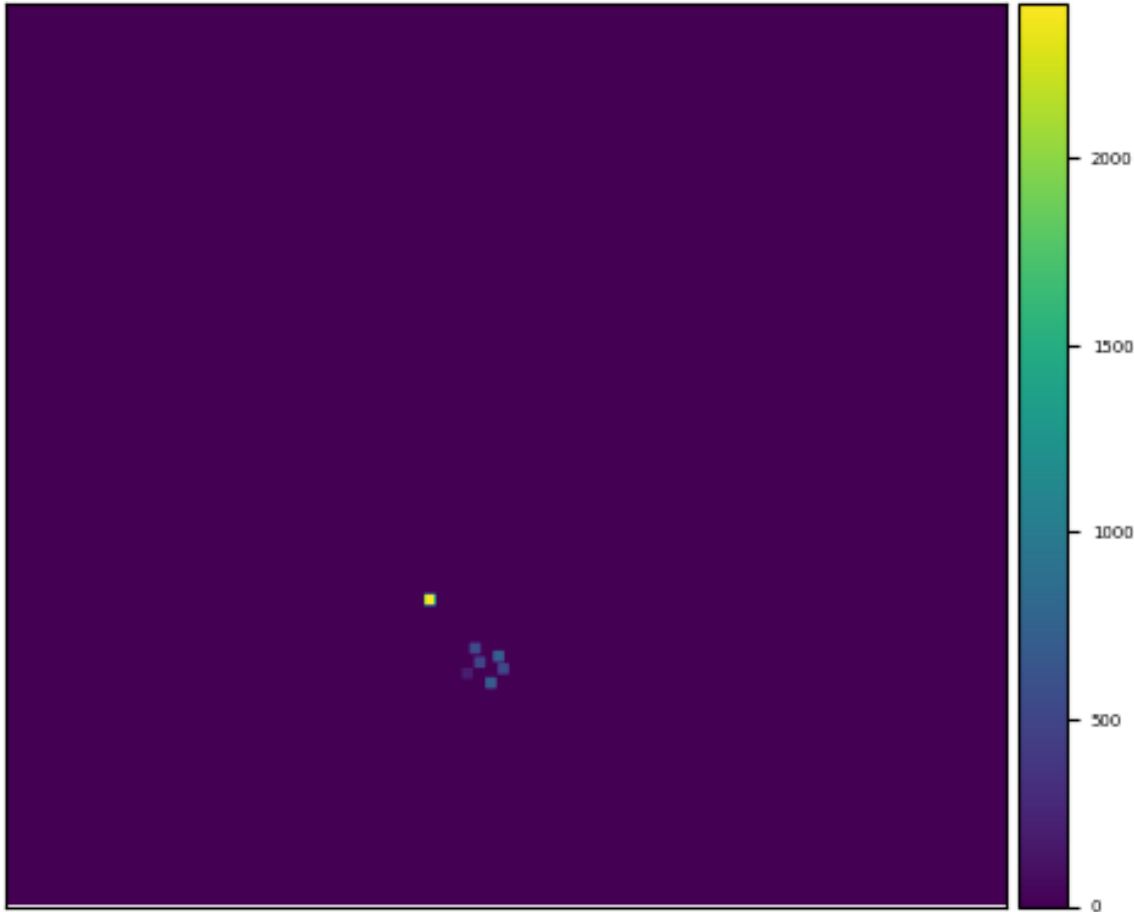


Force sensor values are  
measured at 11 finger skeleton points

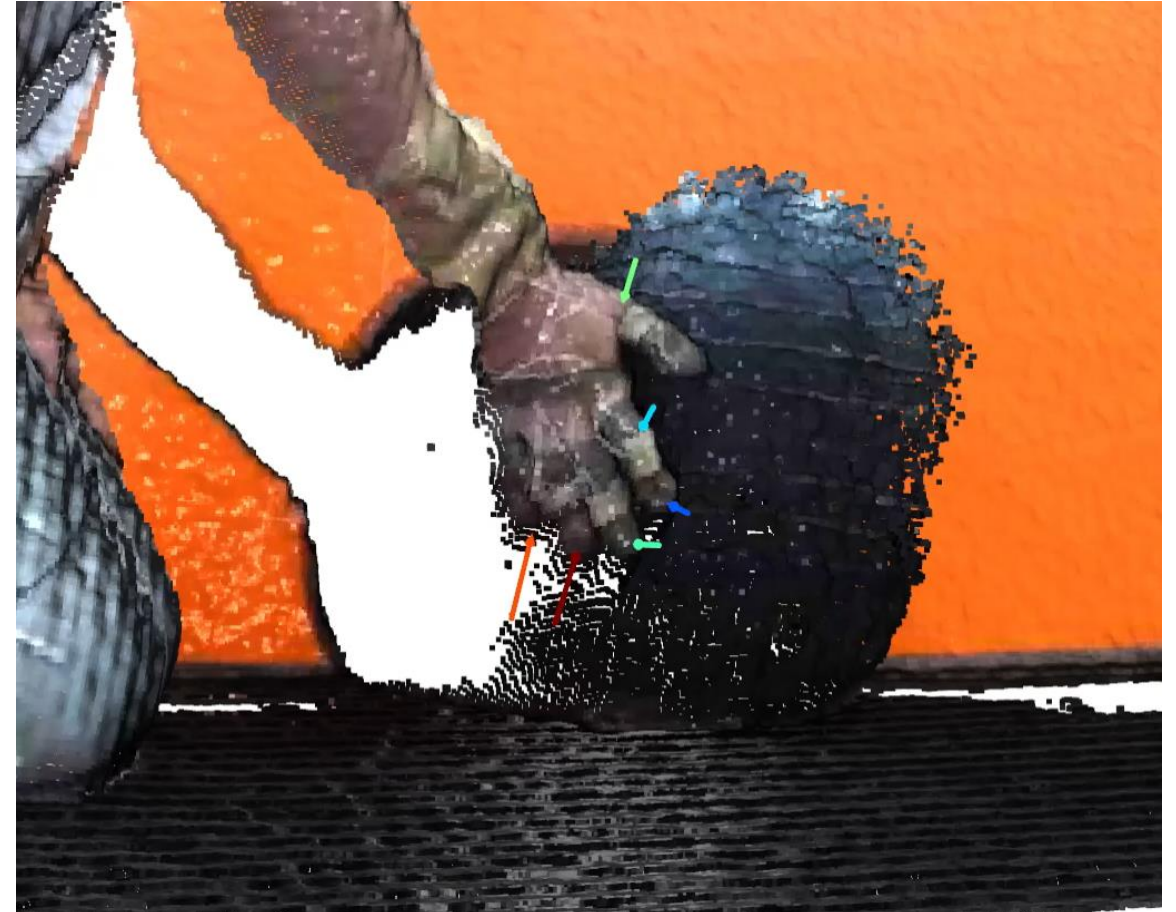


Force sensor values are  
assigned to the corresponding pixel

# Proposal of a 3D visualization system for estimated forces



2D image have poor visibility



Display as vectors on 3D points

# Evaluation on training and test data

## Balance ball



	Error in force distribution of model output		
	Mean Square error( $mN^2$ )	Mean absolute error( $mN$ )	Mean relative error(%)
Training Data	$2.93 \times 10^4$	92.3	11.9
Test Data	$2.13 \times 10^5$	176	17.7

## Cushion

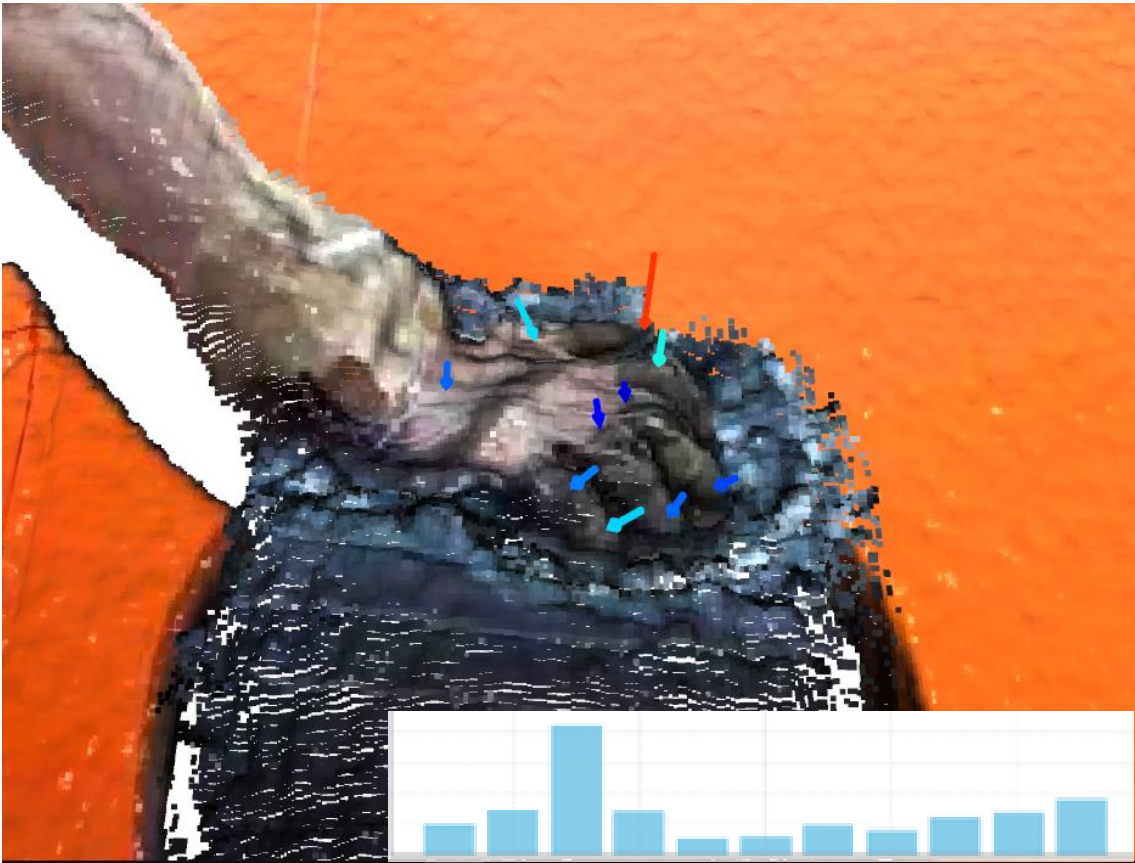


	Mean Square error ( $mN^2$ )	Mean absolute error ( $mN$ )	Mean relative error (%)
Training Data	$1.07 \times 10^4$	71.6	12.3
Test Data	$6.61 \times 10^4$	147	20.3

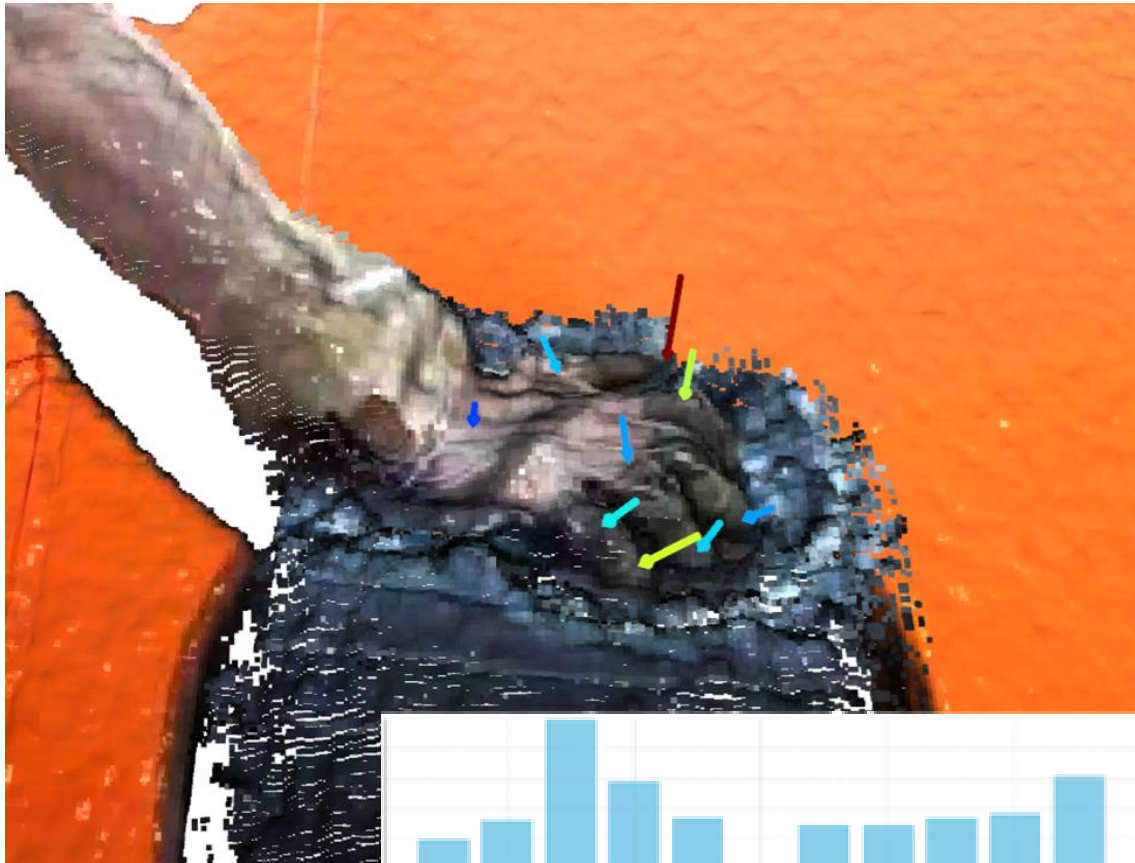


# Visual comparison of model output and ground truth

Example with average error for balance ball.



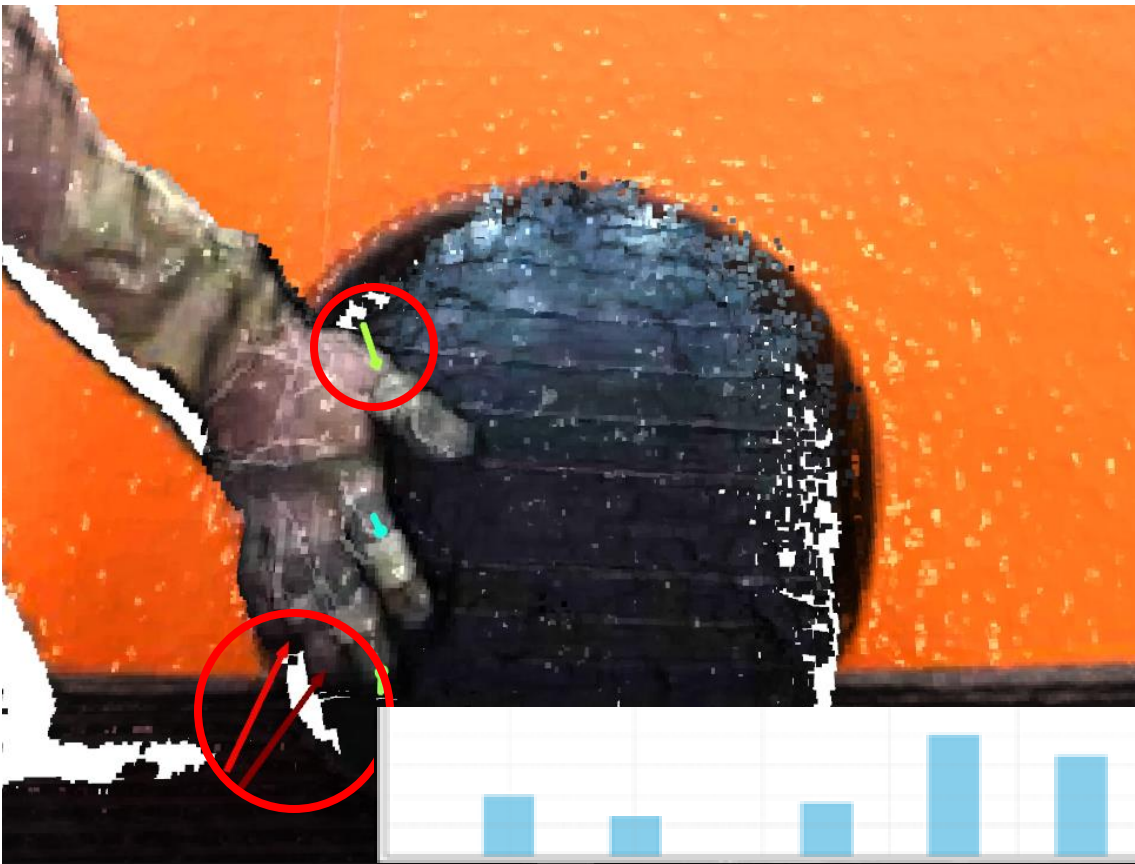
model output



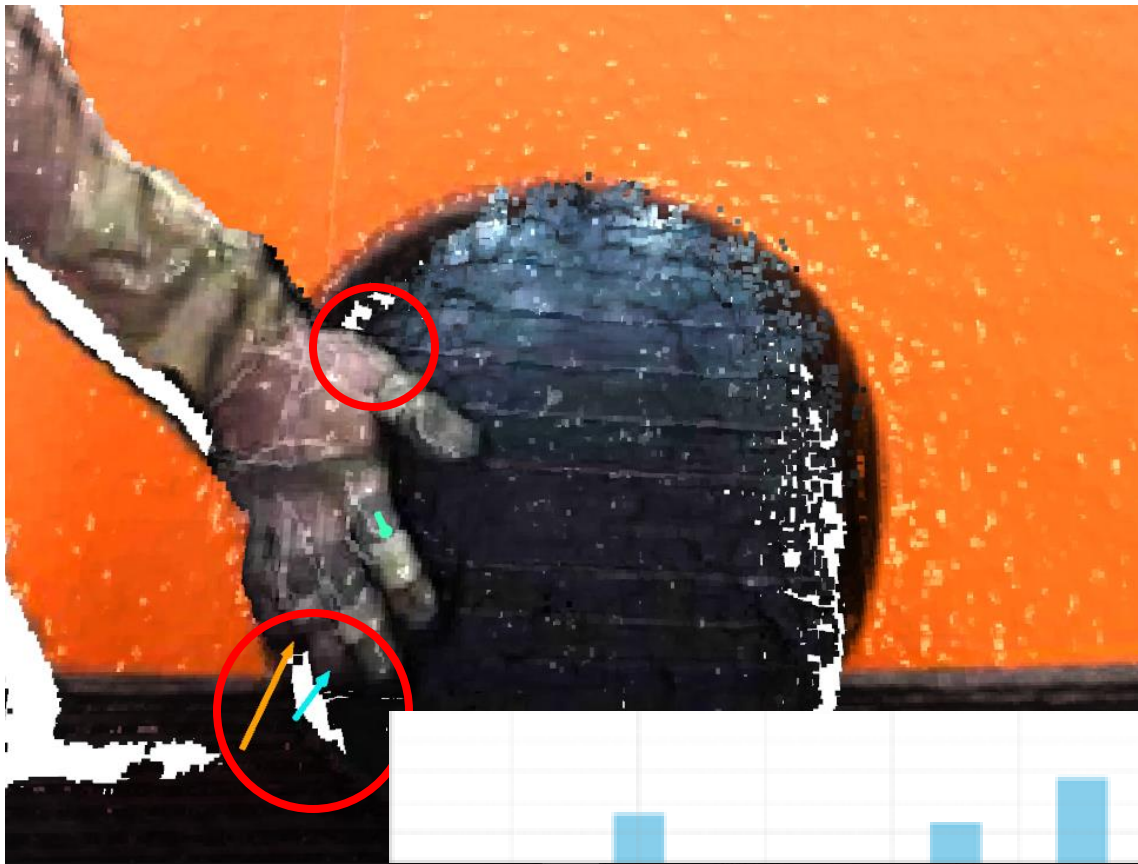
ground truth

# Visual comparison of model output and ground truth

Example with a relatively large error for balance ball.



model output

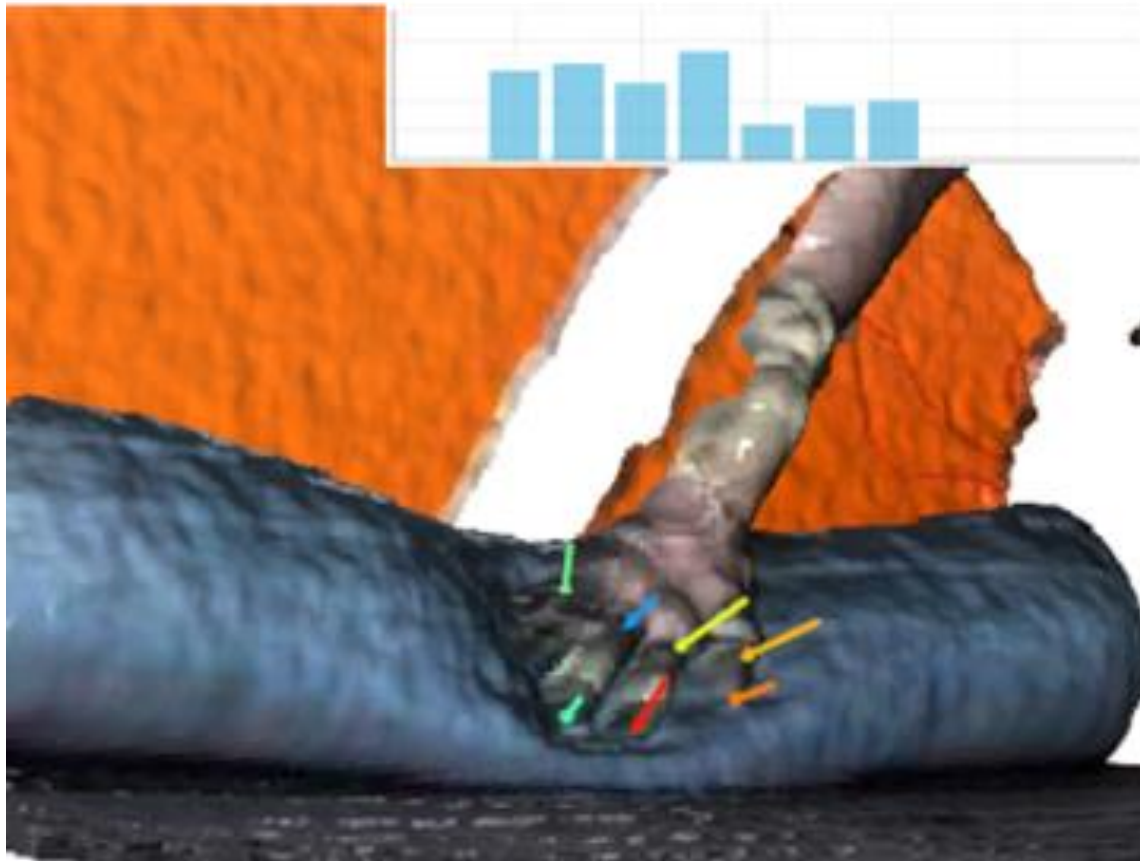


ground truth

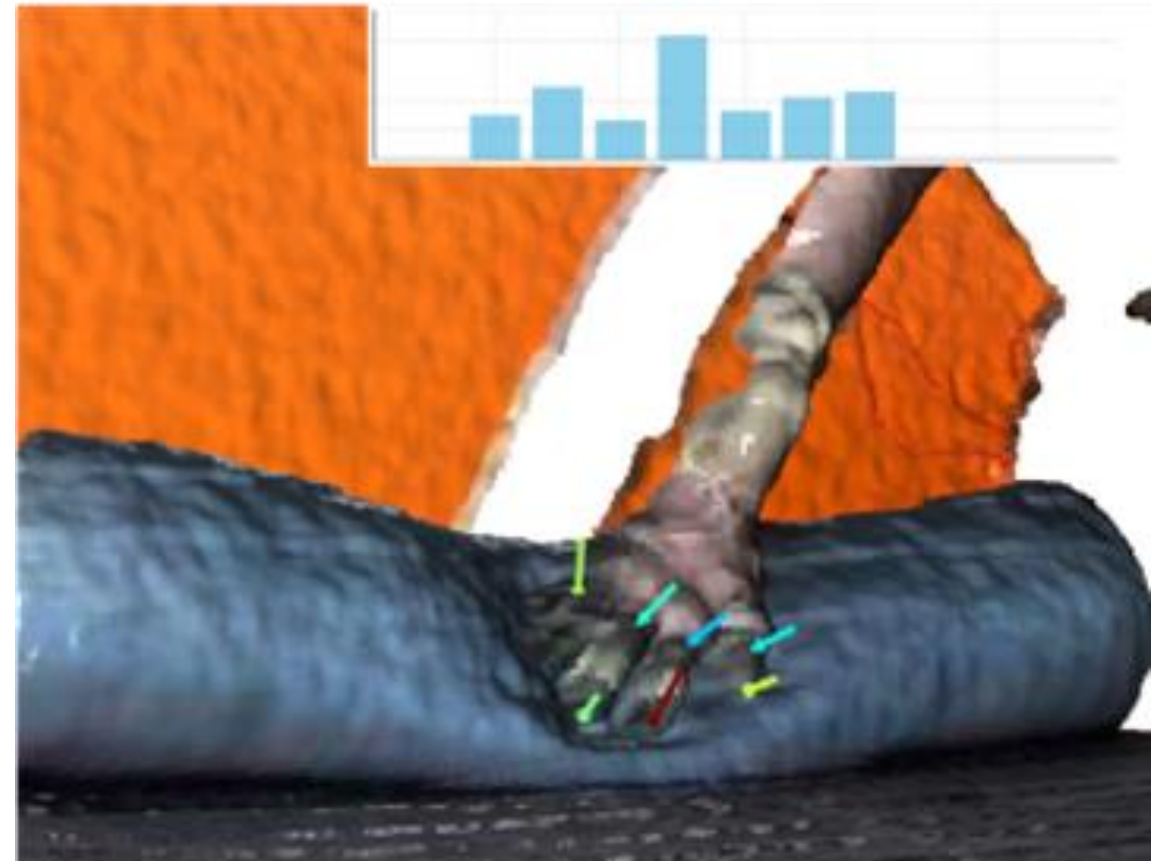


# Visual comparison of model output and ground truth

Example with average error for cushion.



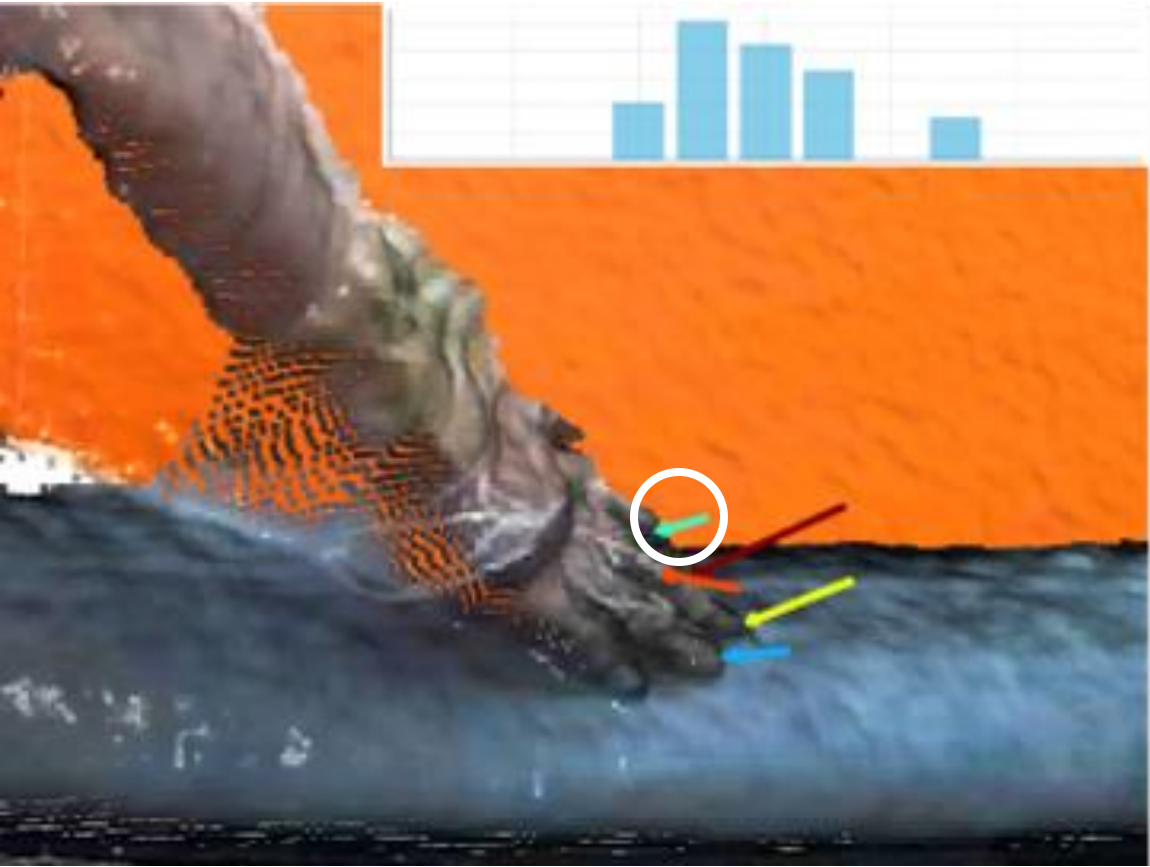
model output



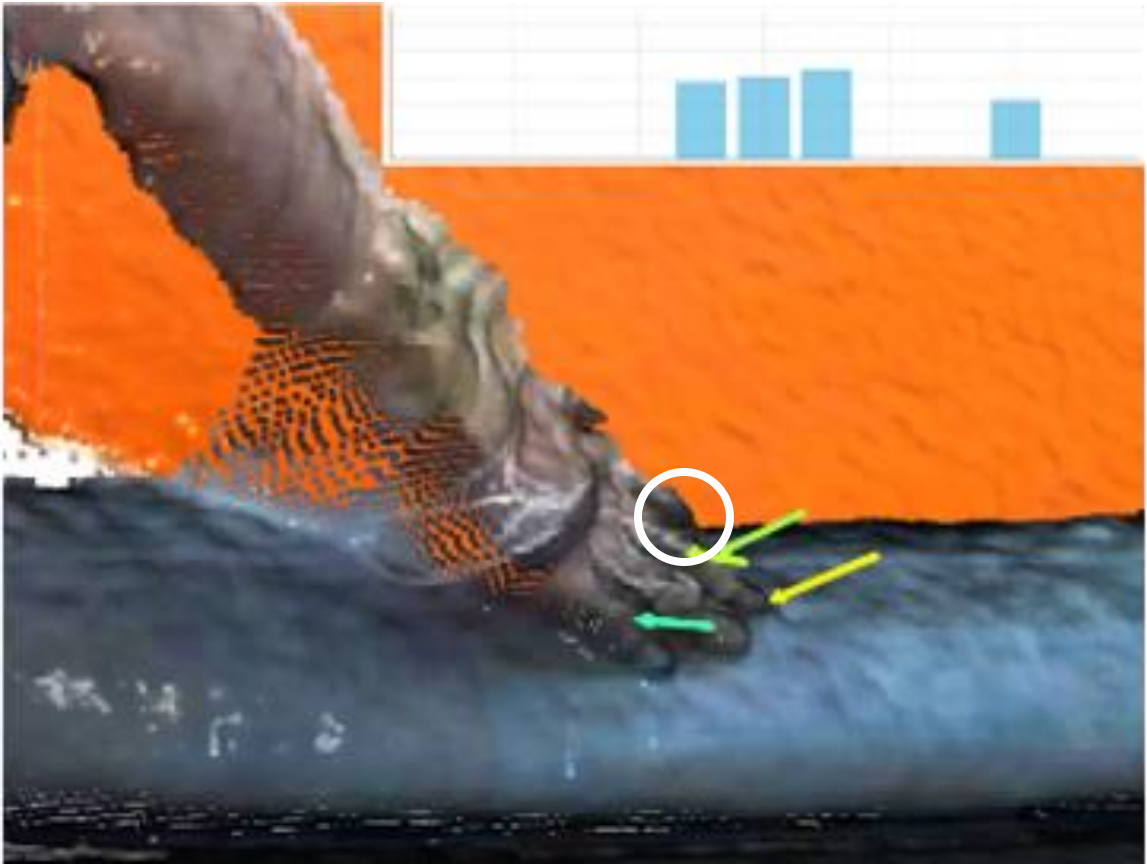
ground truth

# Visual comparison of model output and ground truth

Example with a relatively large error for cushion.



model output



ground truth



# Discussion of error factors

## Image processing noise

- Noise around the contours of shapes.

## Loss of information due to the nature of depth cameras

- Areas with a large incidence angle have some defect.

## Occlusion issues

- Occlusion issues occur behind hands and objects.

## Insufficient accuracy of contact judgment

- cases where a non-touched position is recognized as touched.



contour and depth images



Occlusion Issues



False contact detection

# Conclusions

**We proposed a new force sensor based on deformation feature.**

**Experiments with an integrated system for measuring deformation feature and estimating force distribution.**

- Build a system that can automatically extract data sets using image processing.
- For realistic 3D deformations
  - For the balance ball, the system was able to infer with an error of about 18%.
  - For cushions, the system was able to infer with an error of about 20%.

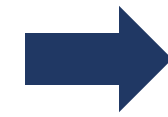
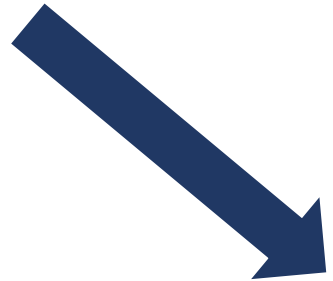
**Discussion of error factors.**

- Present several sources of error.

# Prospects for the future



Turning a chair into a sensor by observing deformation



Turning a bed into a sensor by observing its deformation

## Analysis of physical activity in the elderly

Ayano Nomura, et.al., "Visualization of Body Supporting Force Field of the Elderly in Everyday Environment," Proc. of IEEE International Conference on Sensors, 2022