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

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Social background

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

Software Developments

Classify objects at pixel level

Latest segmentation models[1]

Hardware Developments

Inexpensive RGBD cameras

Azure Kinect
$399

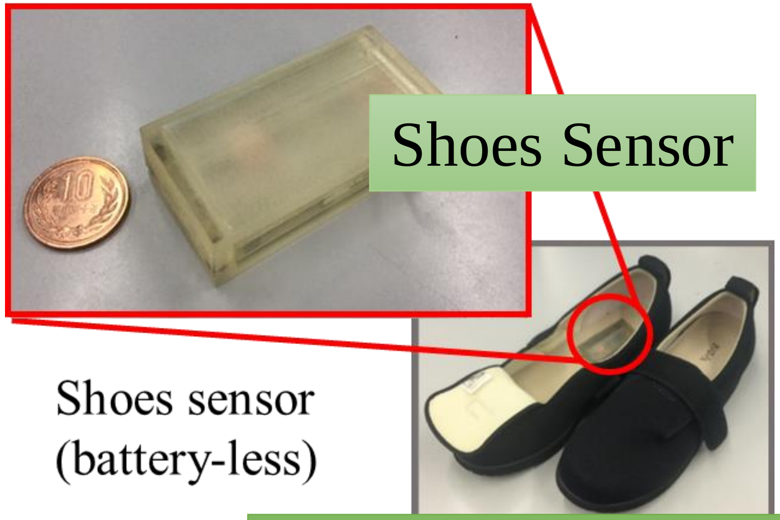
Intel RealSense
$499

3D data of the object

Open a new way of estimating force only by observing deformations

[1] Kirillov et al, Segment Anything., 2023

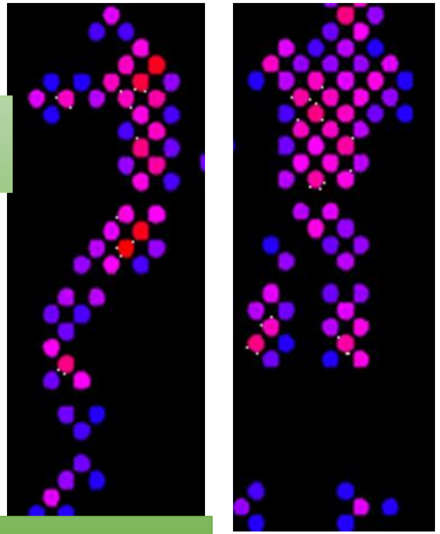
Conventional sensing



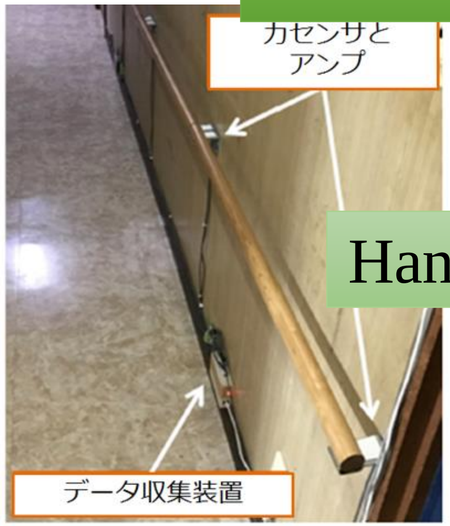
Shoes Sensor

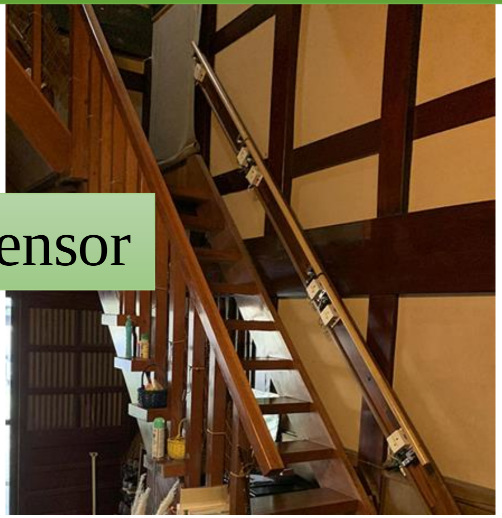
Shoes sensor
(battery-less)

Bed Sensor

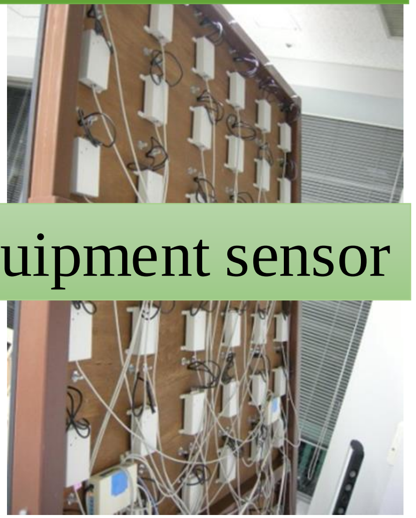


Conventional: Sensorization by sensor embedding





Handrail Sensor

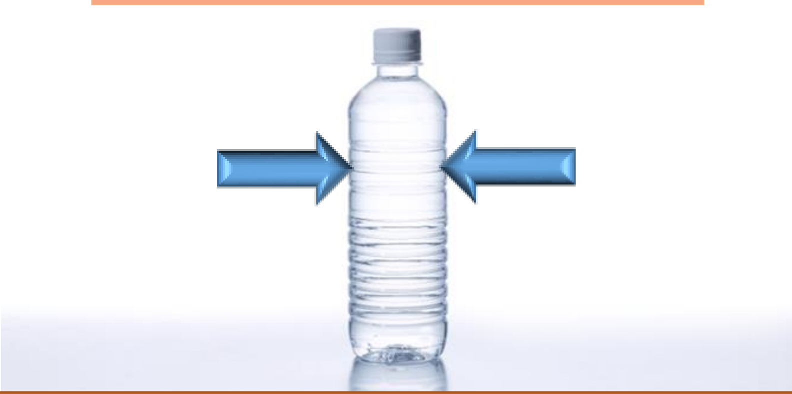


Playground equipment sensor

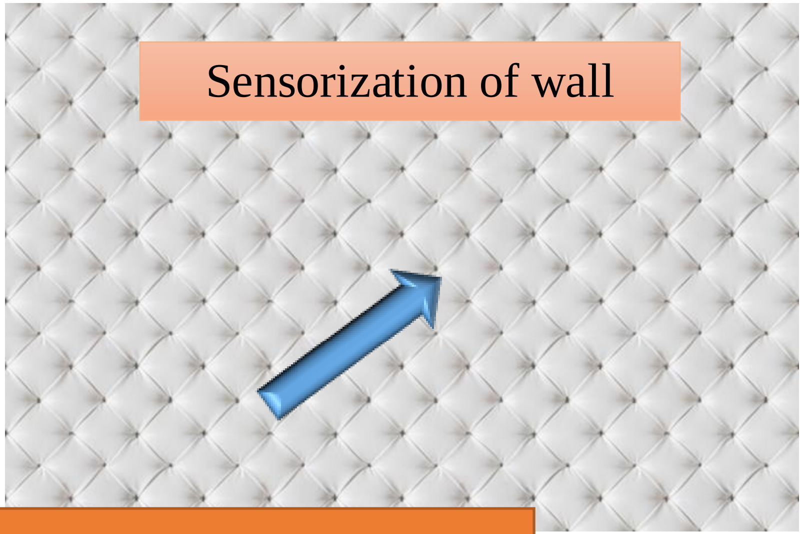
Future sensing

Sensorization of houseplant

Sensorization of PET bottle



Sensorization of wall



Future: Sensorization by deformation observation

Sensorization of sofa and bed

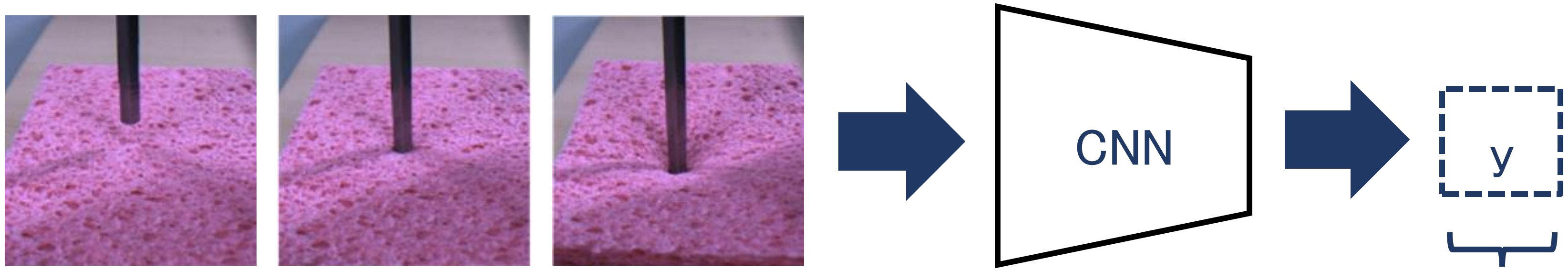
Sensorization of desk

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**



RGB images showing the deformation

Scalar value

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

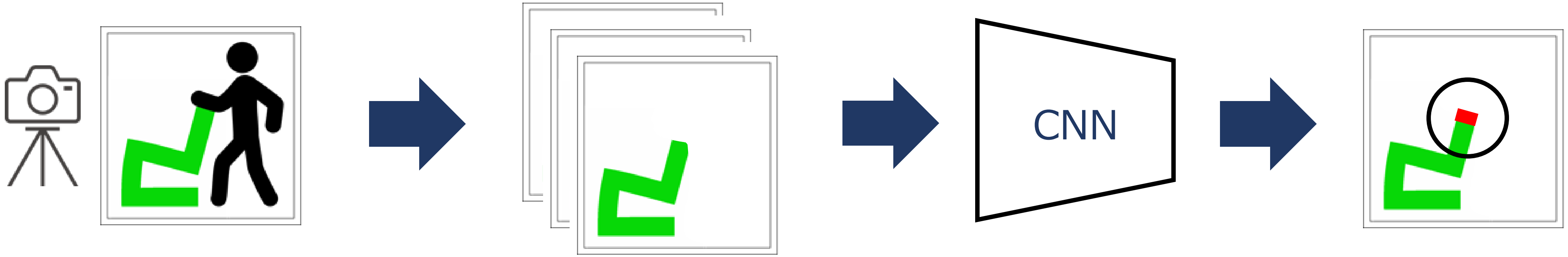
[1] Hwang et al, Inferring Interaction Force from Visual Information without Using Physical Force Sensors., 2017

Research objective and method

Objective

➢ Proposing a new force sensor principle that estimates force distribution from observable shape deformation information and verifying its feasibility

Method



Capture video | Extract shape deformation | Image format force

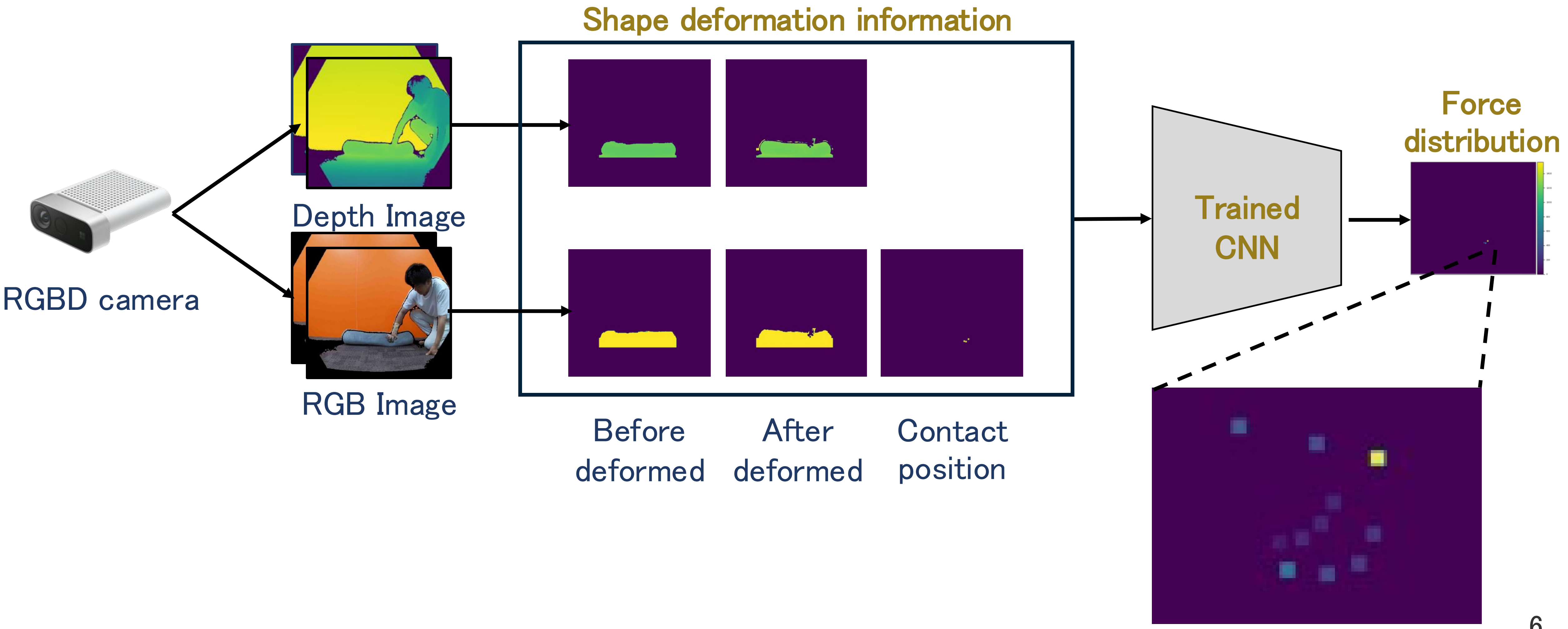
Novelty

➢ Flexible to environmental changes by extracting shape deformation imformation

➢ Expressing force in image format allows for multi-point estimation

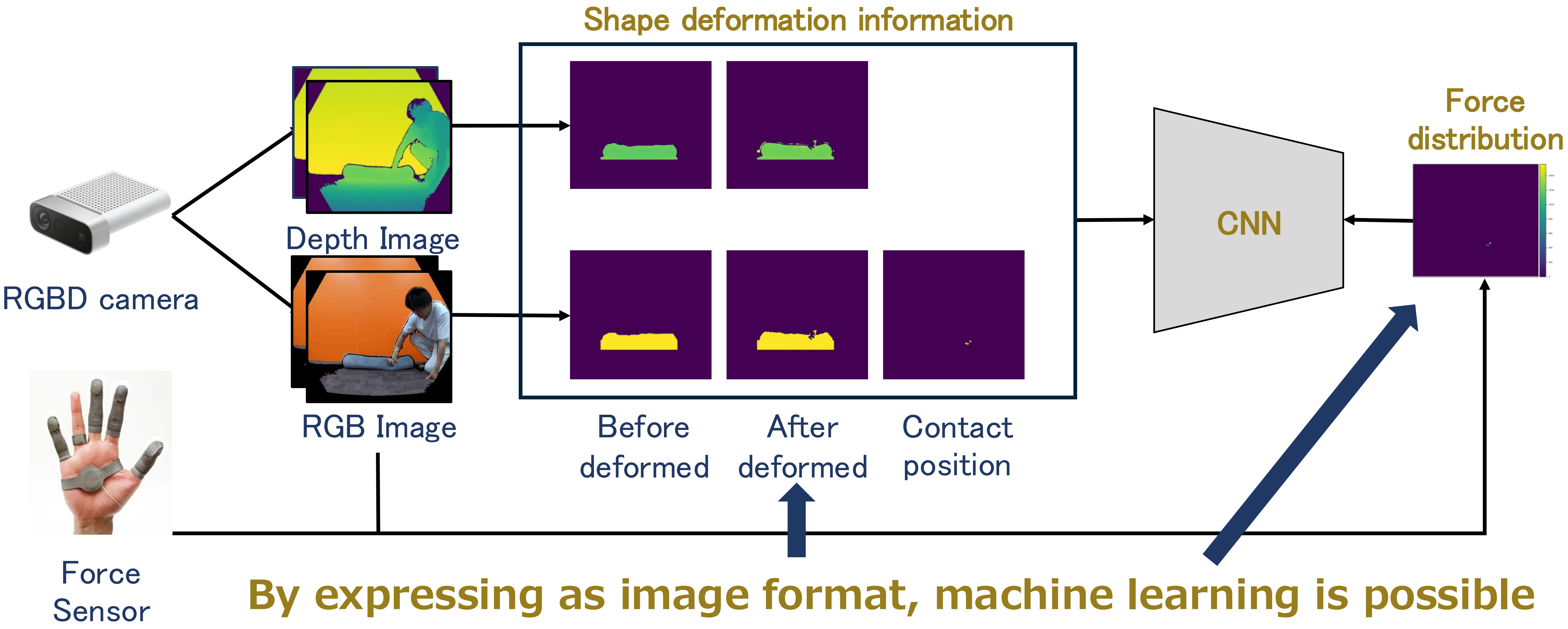
Details of the proposed method (Inference process)

Shape deformation information is extracted from two images and force distribution is inferred using a trained machine learning model (CNN)



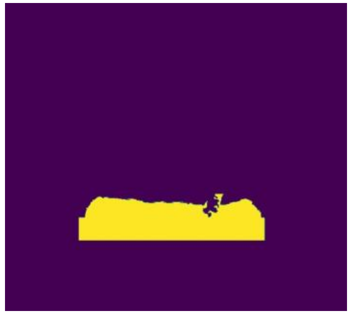
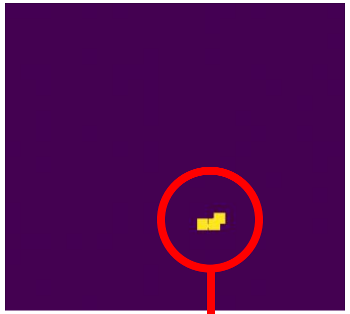
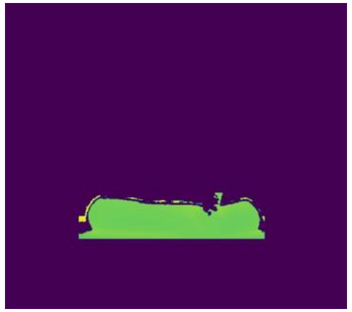
Details of the proposed method (Training process)

Learns the relationship between shape deformation information and force distribution.



By expressing as image format, machine learning is possible

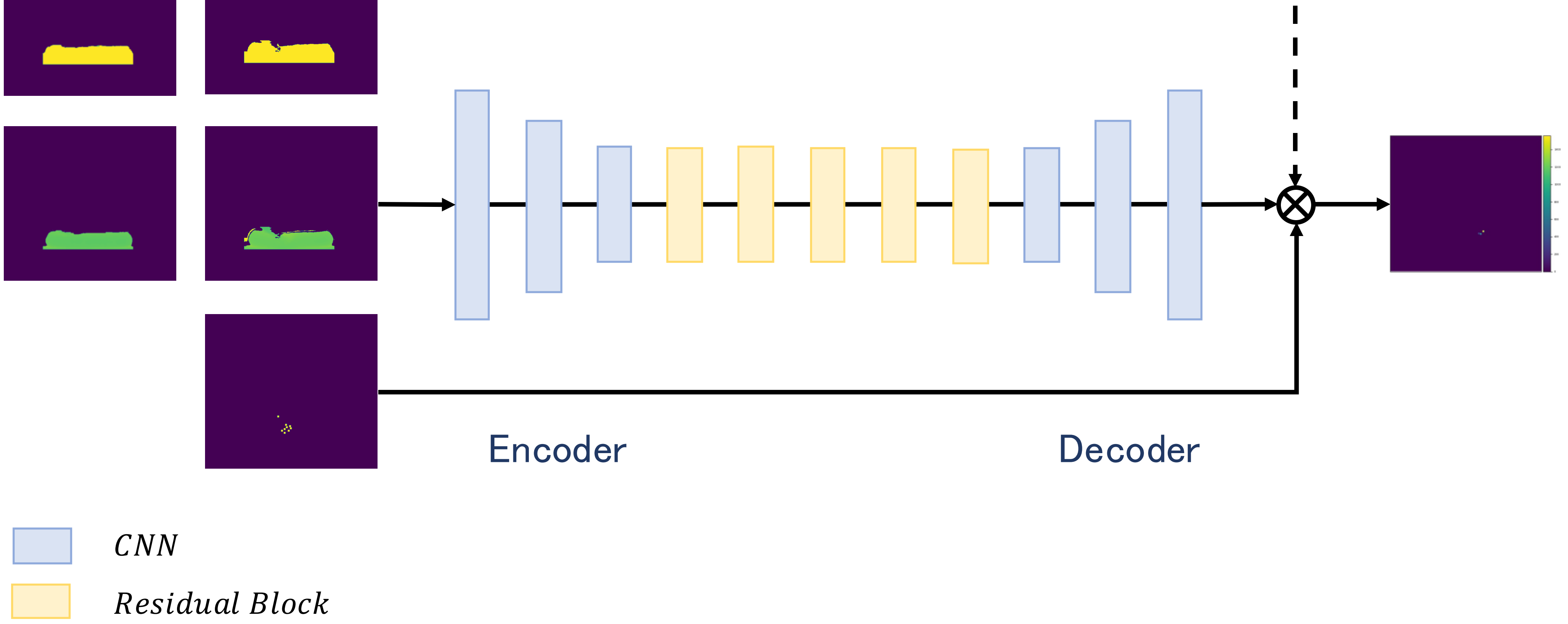
Idea: Expressing shape deformation information

	Before deformed	After deformed	Contact position
Binary image [0 or 1] Object contour			
Binary image [0 to 1] Object depth			

Machine learning model architecture

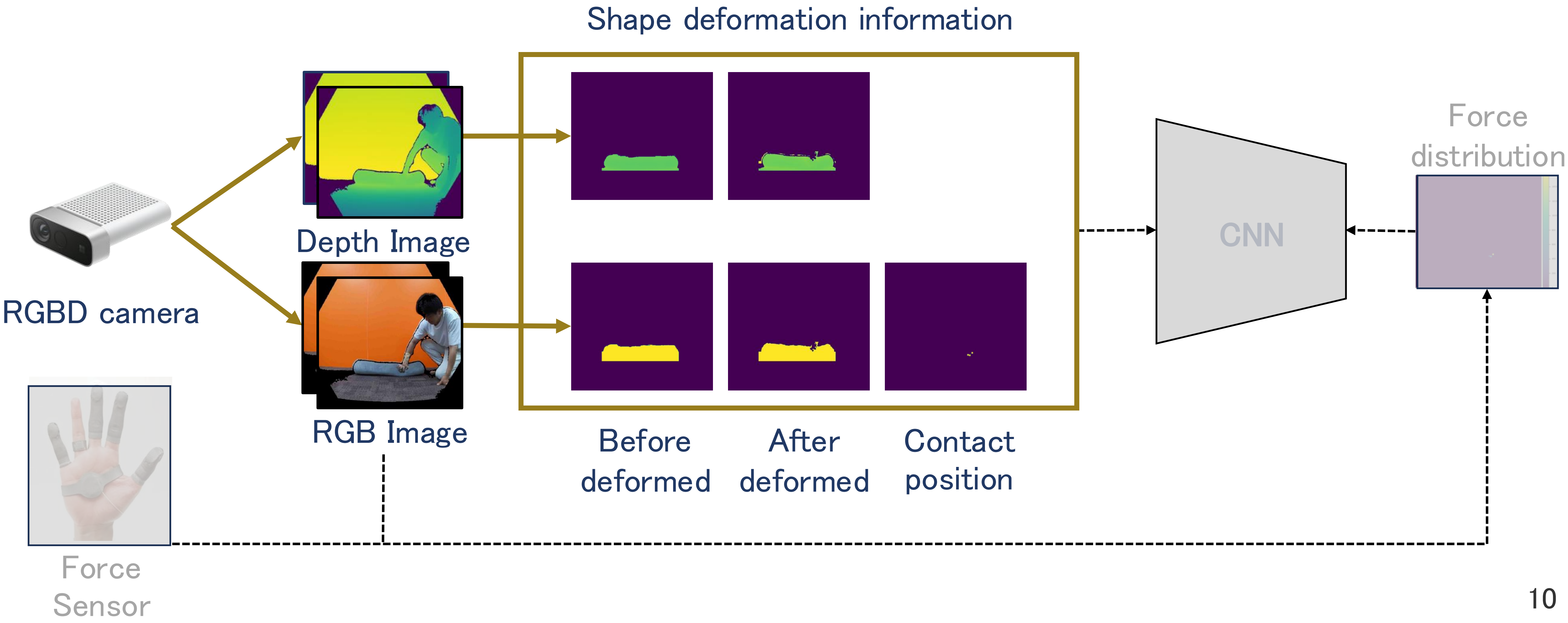
A typical encoder–decoder model which is used for tasks with image inputs and output

Idea:
Limit model output to a reasonable range depending on contact position

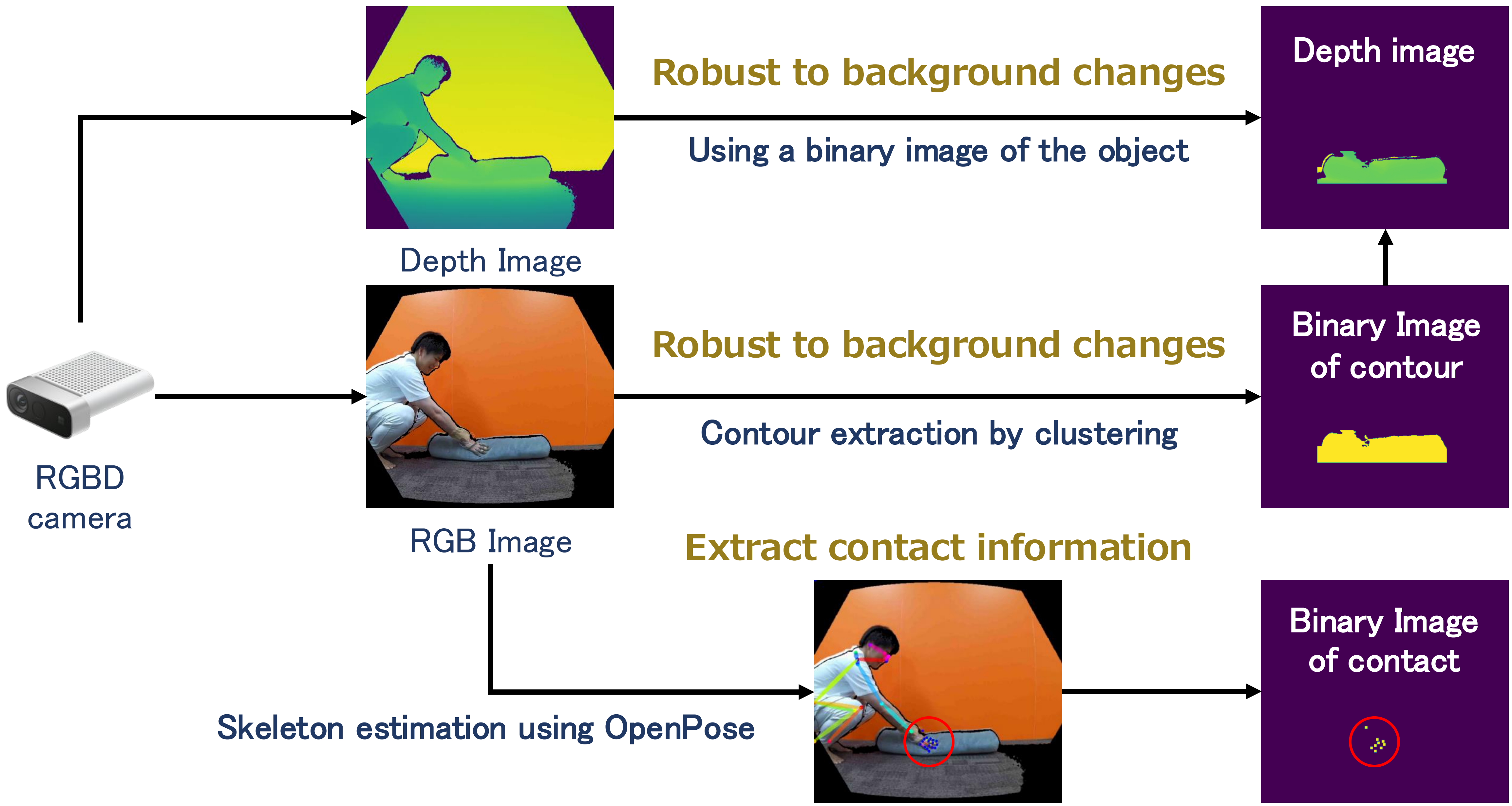


Creating a Dataset

1. **Extraction of shape deformation information using image processing**
2. Creating teacher data using force sensor information



Extraction of shape deformation information by image processing



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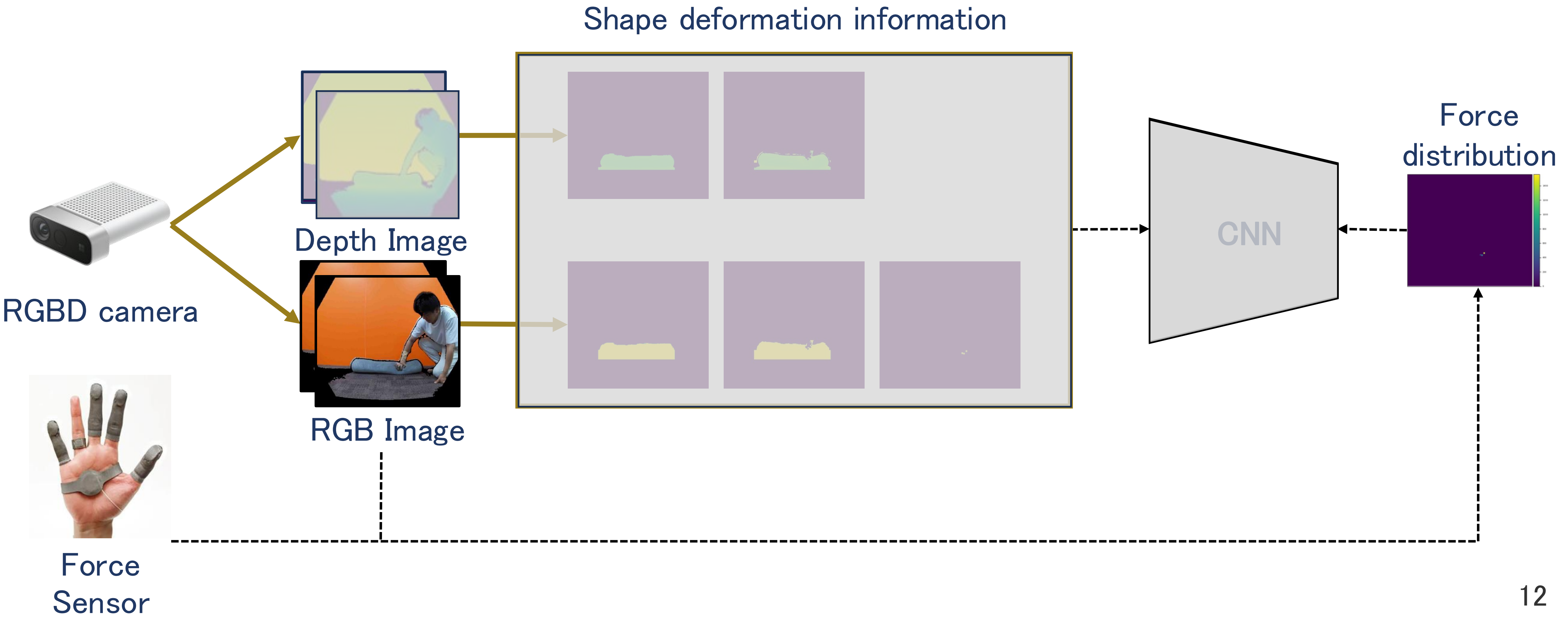
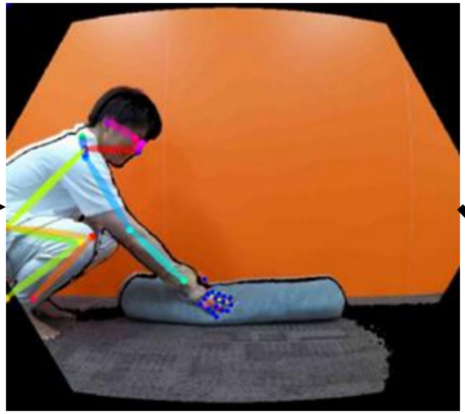


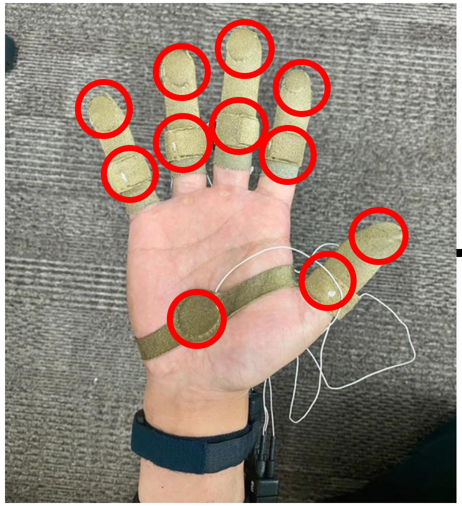
Creating teacher data

RGB Image

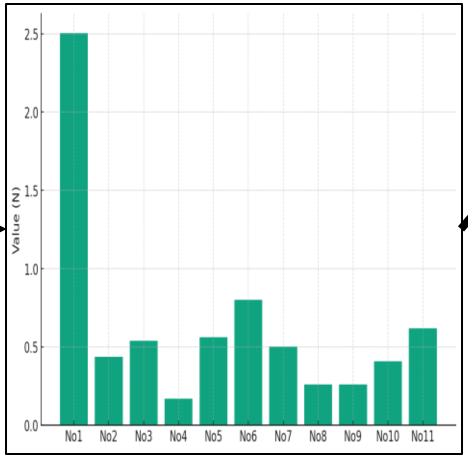
OpenPose



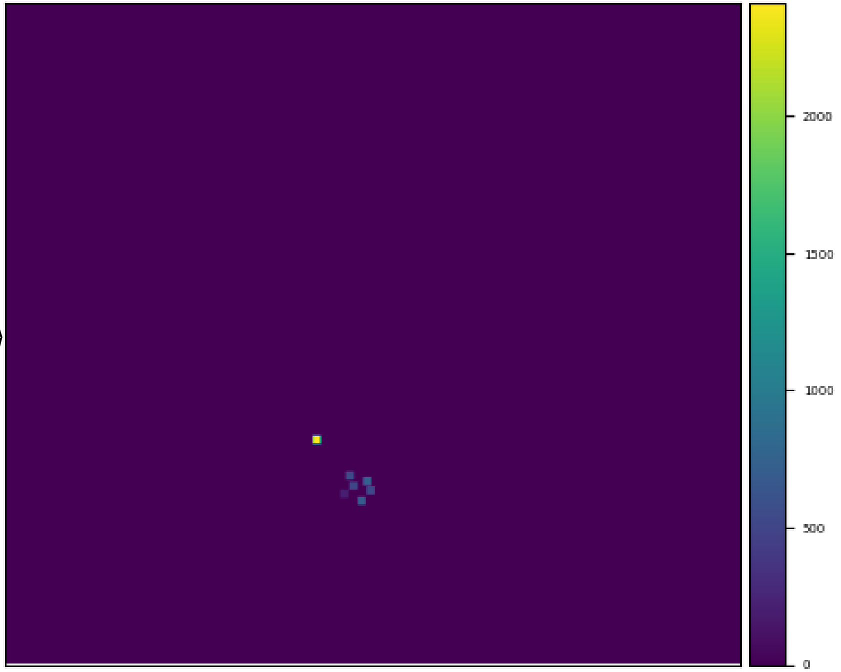
Finger Skeleton Coordinates



Force Sensor

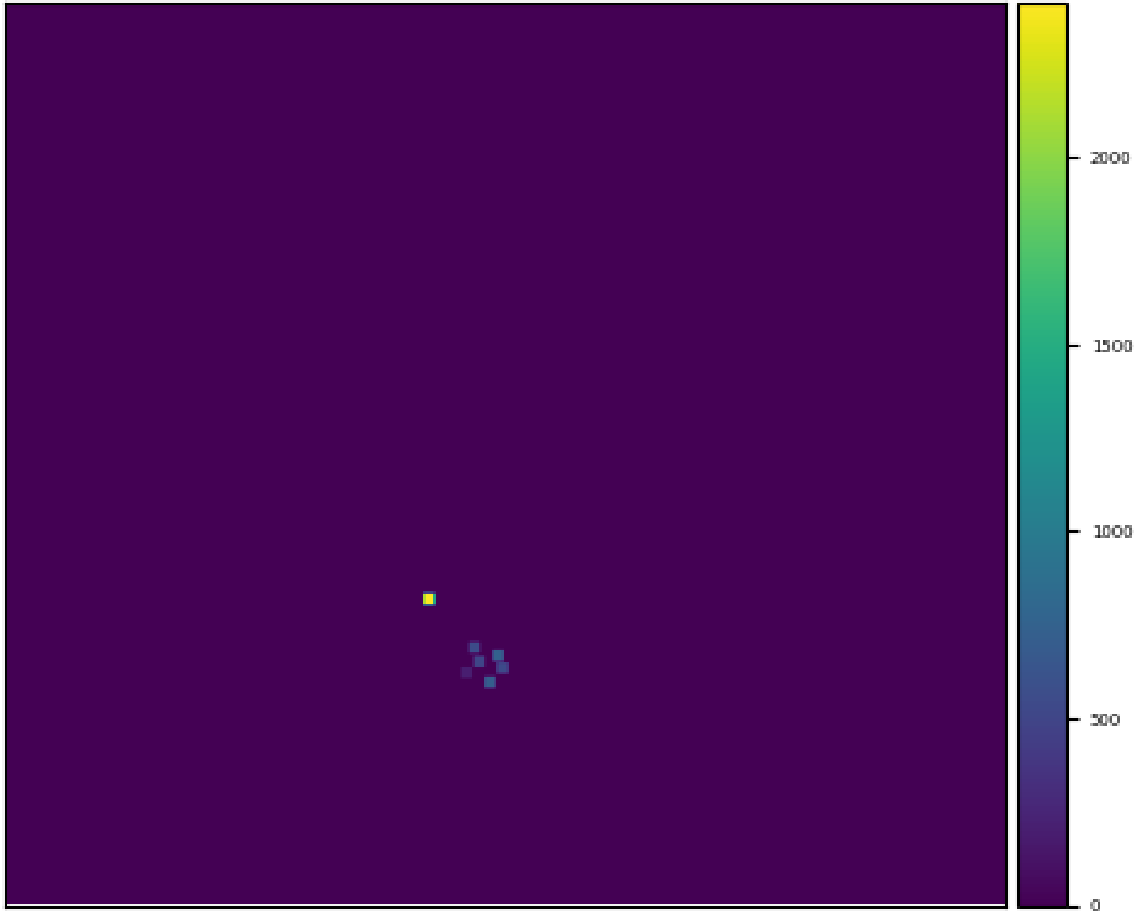


Force sensor values attached to 11 finger skeleton points



Assign the force sensor value to finger skeletal coordinates

Proposal of a 3D visualization system for estimated forces



Visibility is poor in 2D images

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	2.93×10^4	92.3	11.9
Test Data	2.13×10^5	176	17.7

Cushion

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

[Balance Ball] Visual comparison of model output and ground truth

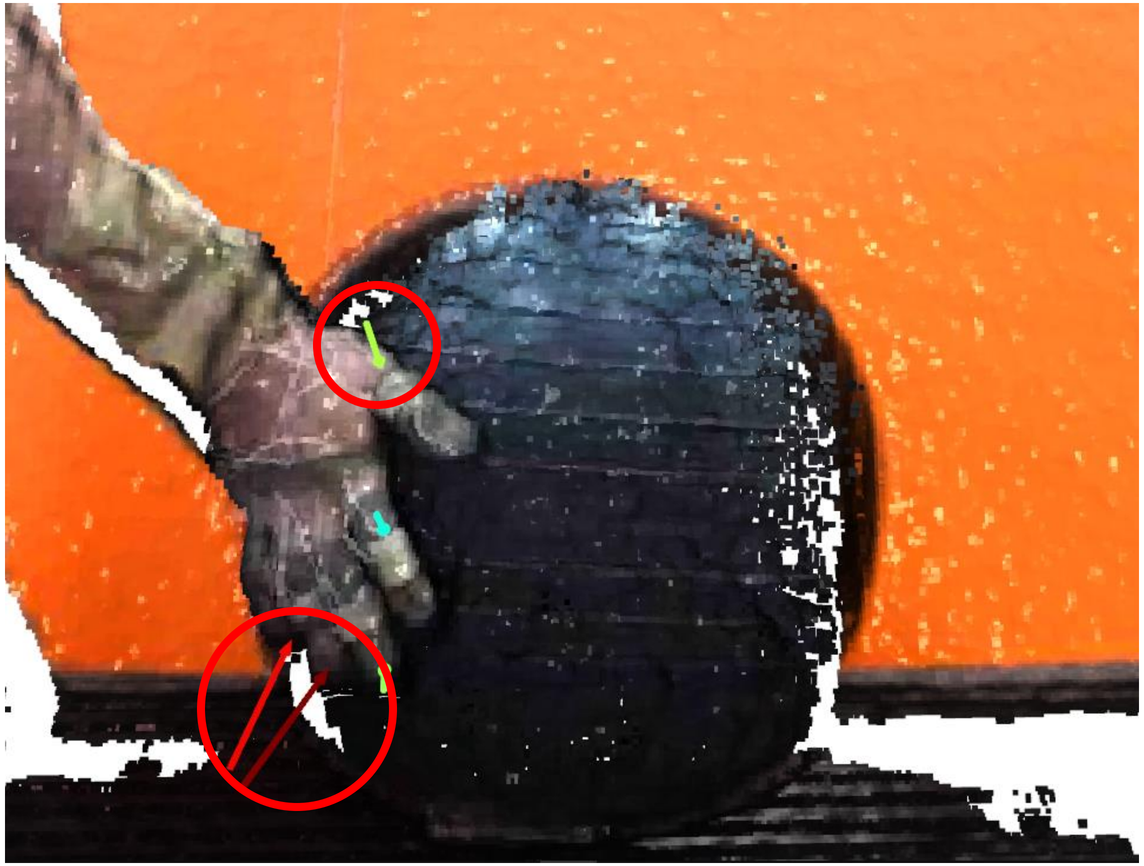
Example with average error

model output

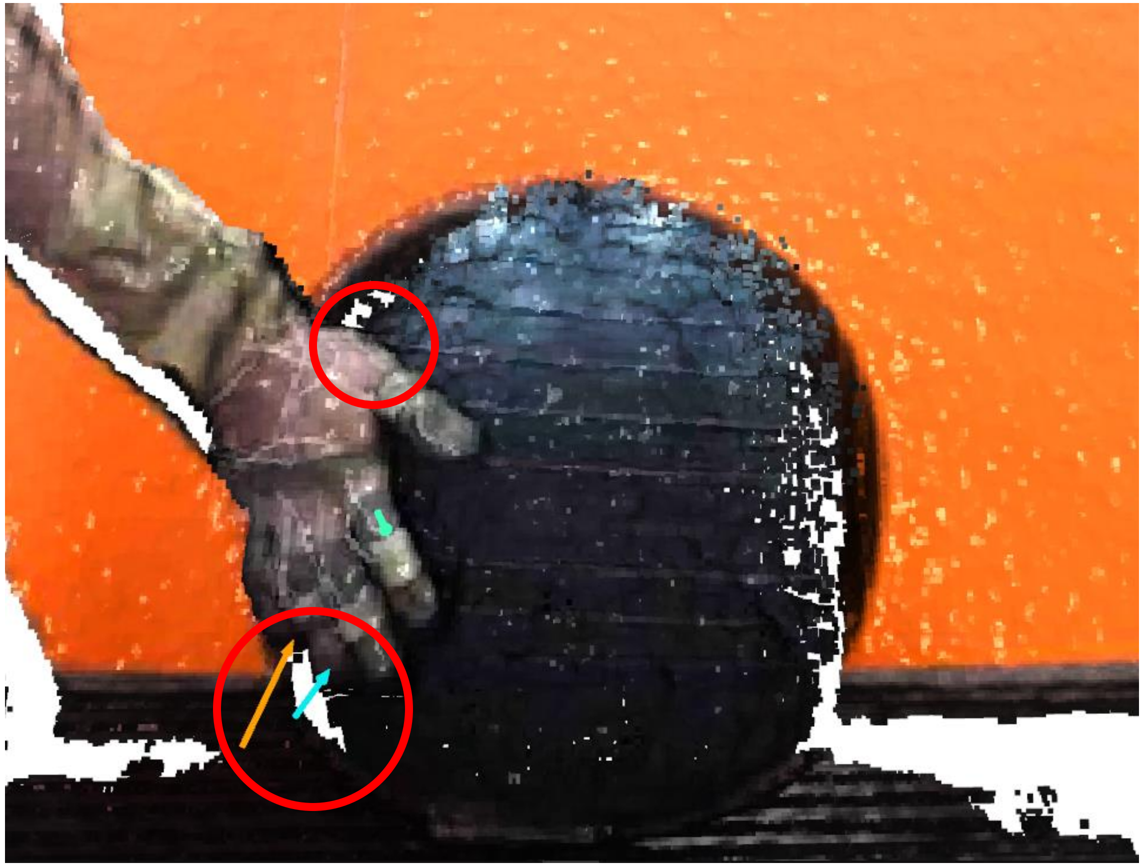
ground truth

[Balance Ball] Visual comparison of model output and ground truth

Example with large error



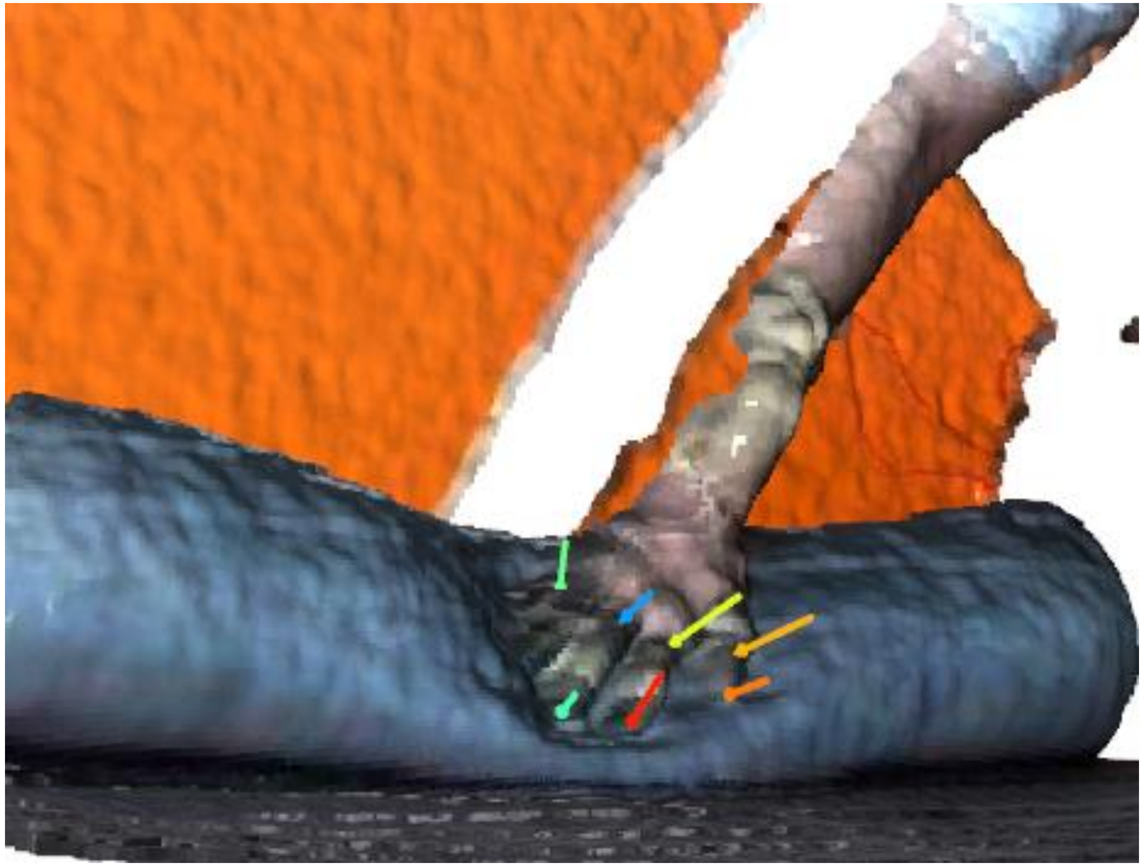
model output



ground truth

[Cushion] Visual comparison of model output and ground truth

Example with average error



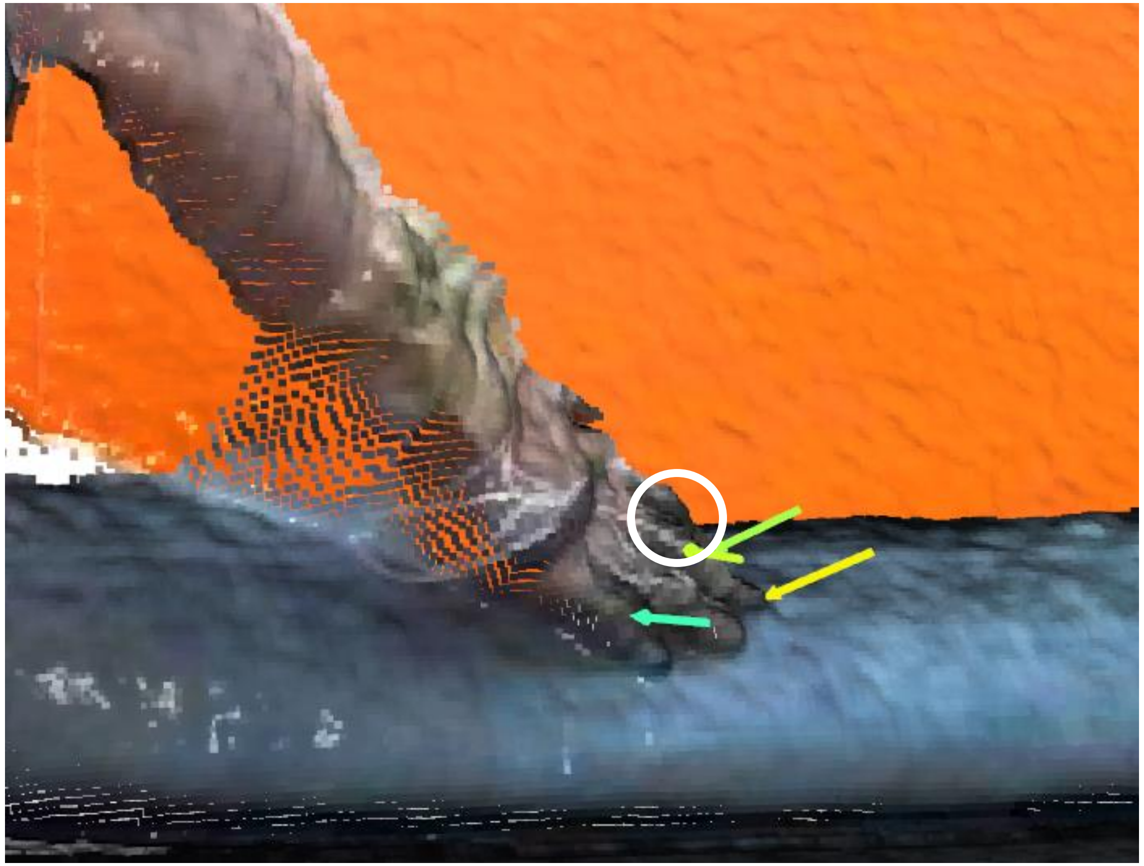
model output

ground truth

[Cushion] Visual comparison of model output and ground truth

Example with large error

model output



ground truth

Discussion of error factors

Image processing noise

- Noise on the contours of shapes

Loss of information due to the nature of depth cameras

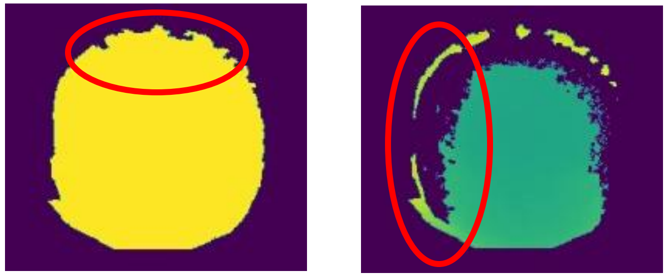
- The nature of depth cameras causes defects

Occlusion issues

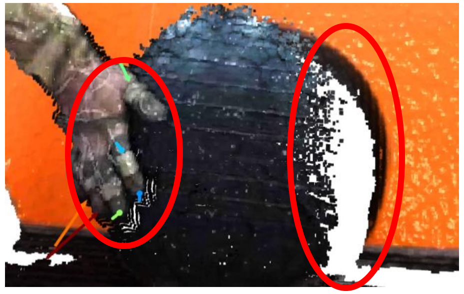
- Occlusion issues occurs behind hands and objects

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 shape deformation information

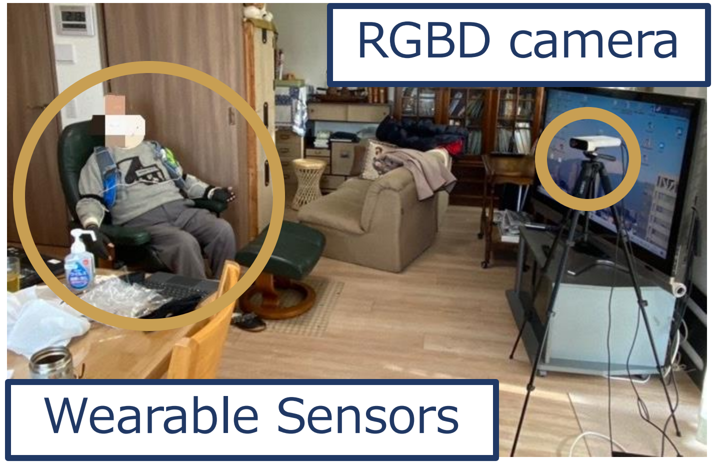
Experiments with an integrated system for measuring and estimating shape change information

- 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 the position 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

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

Turning a bed into a sensor by observing its deformation