

## Why do we want Real-Time Sensing in Soft Robotics?

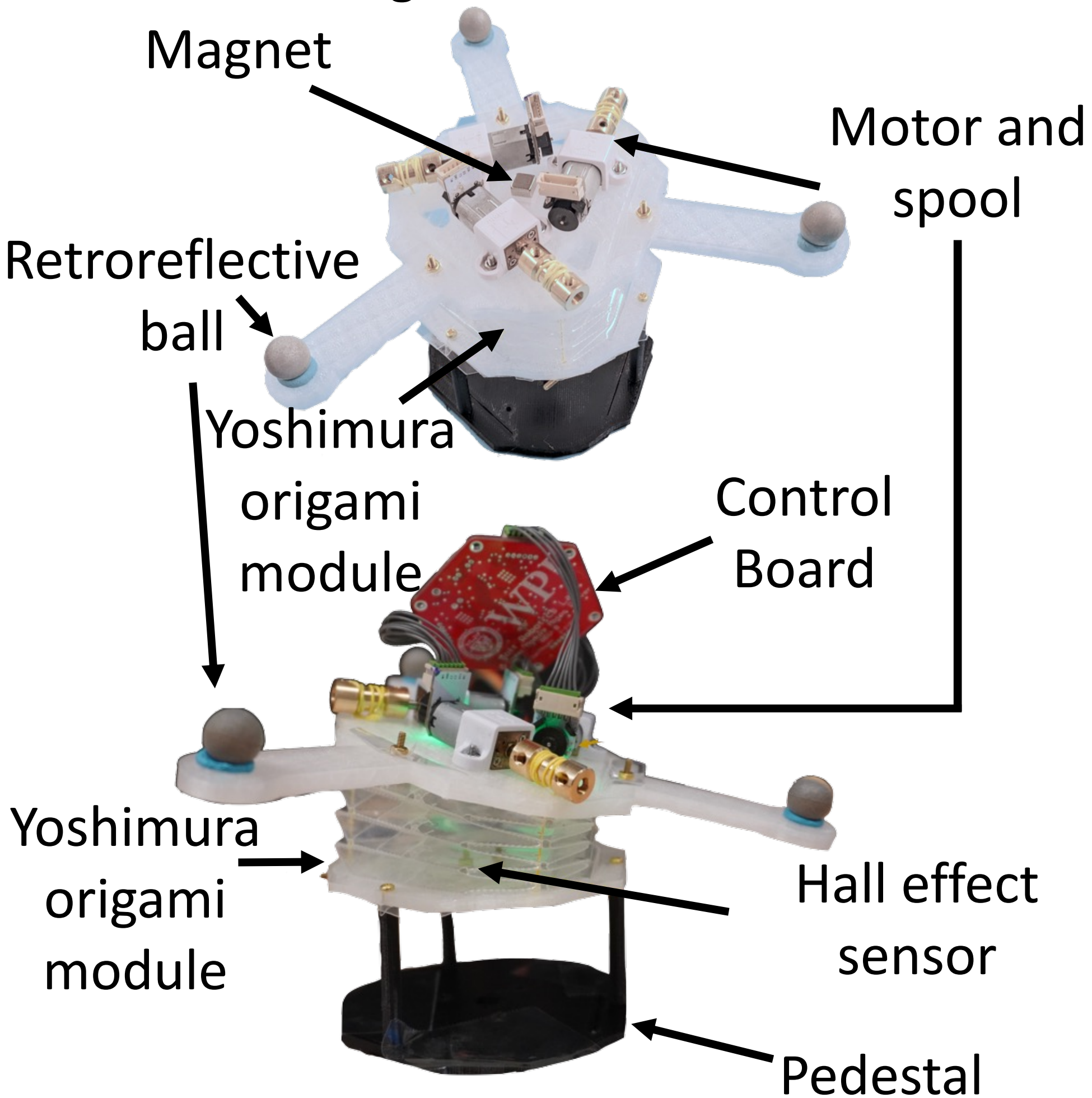
- Soft robotics has major implications in medical robotics, biological mimicry, and dexterous manipulation.
- Classical sensing techniques cannot handle the large DoF cleanly.
- This flexibility allows for more **adaptive** and **manipulatable** structures.

## Our Design





Soft sensors come in many forms such as

- Resistive & capacitive flexible circuits
- Fiber-Bragg grating
- Hall effect table lookups

We chose a magnetic solution

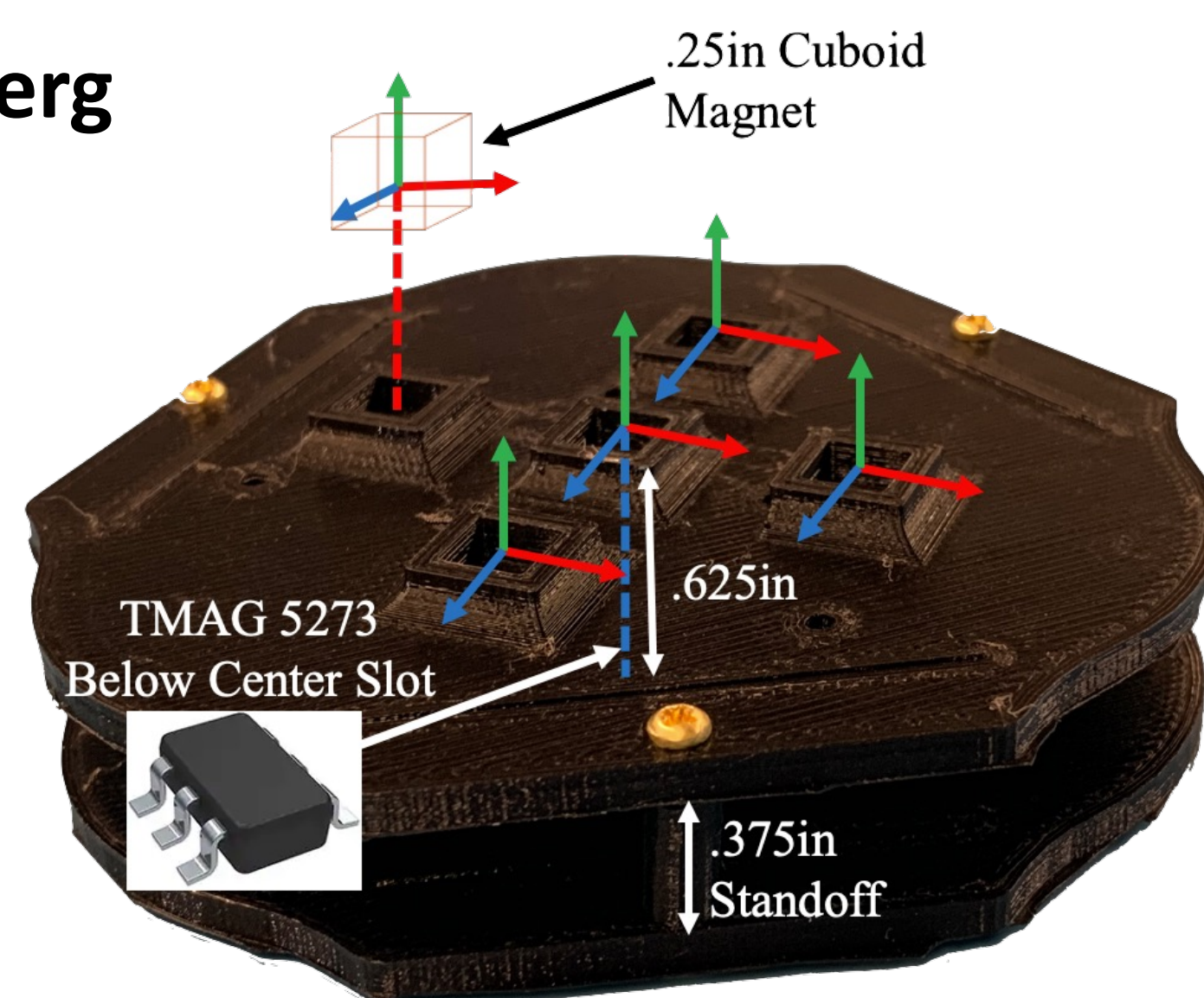


## Design Advantages

-  No contact between components
-  Over 2 kHz speeds with 100 particles
-  High accuracy at <1mm error
-  Low cost & easy to integrate in existing robots

## Magnetic Field Equations & Correction

We used **Levenberg Marquadt** optimization to solve the differences between our jig readings & magnetic simulation



## Magnetic Field Equations

For 2kHz 100 particle custom magnetic simulation

$$B_x(x, y, z) = \frac{\mu_0 M}{4\pi} \ln \left( \frac{F_2(-x, y, z) F_2(x, y, z)}{F_2(x, y, z) F_2(-x, y, z)} \right) \quad B_z(x, y, z) = -\frac{\mu_0 M}{4\pi} \left[ F_1(-x, y, z) + F_1(-x, y, -z) + F_1(-x, -y, z) + F_1(-x, -y, -z) + F_1(x, y, z) + F_1(x, y, -z) + F_1(x, -y, z) + F_1(x, -y, -z) \right] \quad (1)$$

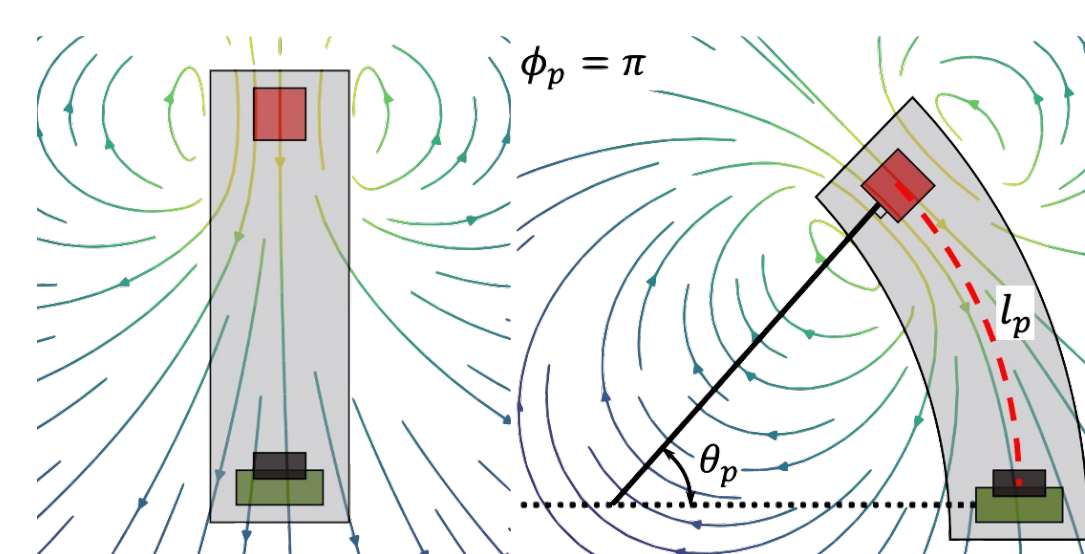
$$B_y(x, y, z) = \frac{\mu_0 M}{4\pi} \ln \left( \frac{F_2(-y, x, -z) F_2(y, x, z)}{F_2(y, x, -z) F_2(-y, x, z)} \right) \quad (2)$$

With

$$F_1(x, y, z) = \arctan \left( \frac{(x+a)(y+b)}{(z+c)\sqrt{(x+a)^2 + (y+b)^2 + (z+c)^2}} \right) \quad F_2(x, y, z) = \frac{\sqrt{(x+a)^2 + (y-b)^2 + (z+c)^2} + b - y}{\sqrt{(x+a)^2 + (y+b)^2 + (z+c)^2} - b - y}$$

## Particle Filtering Approach

By simulating the readings of 100 particles and comparing with the XYZ reading from the physical sensor, we can approximate the pose of the magnet.

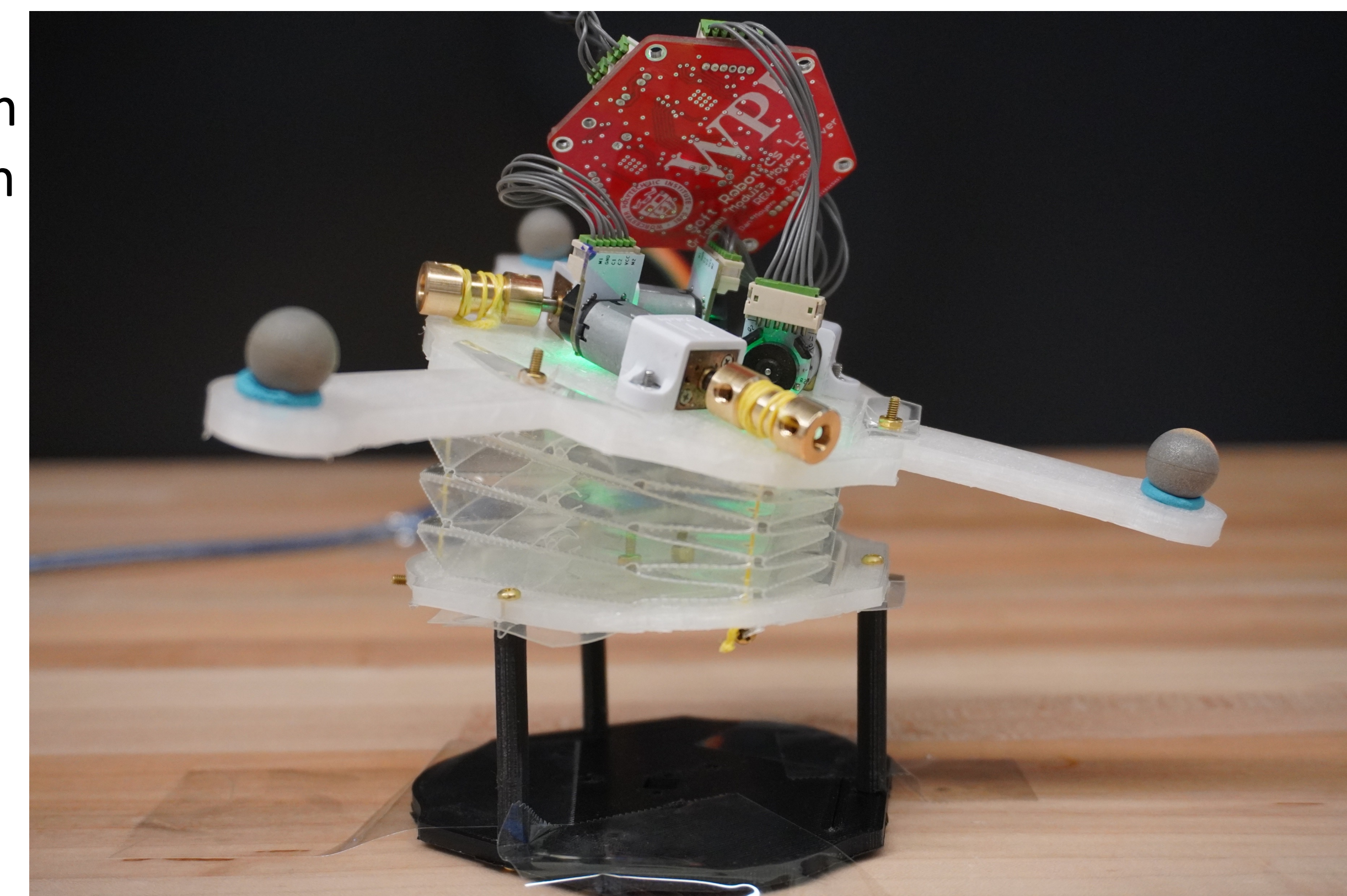


The four main steps of our particle filter:

- Weighting
 
$$\mathcal{L}(\vec{x}_p | \vec{y}) = \frac{\mathcal{L}(\vec{x}_p | \vec{y})}{\sum_{n \in N} \mathcal{L}(\vec{x}_n | \vec{y})}$$
- Predicting
 
$$\hat{\theta} = \frac{\sum_{s \in S} \theta_s}{|S|} \quad \& \quad \hat{l} = \frac{\sum_{s \in S} l_s}{|S|}$$
- Resampling
  - Random sampling with replacement
- Updating
  - Particle update with rejection sampling

## Continuum Robot Use Cases

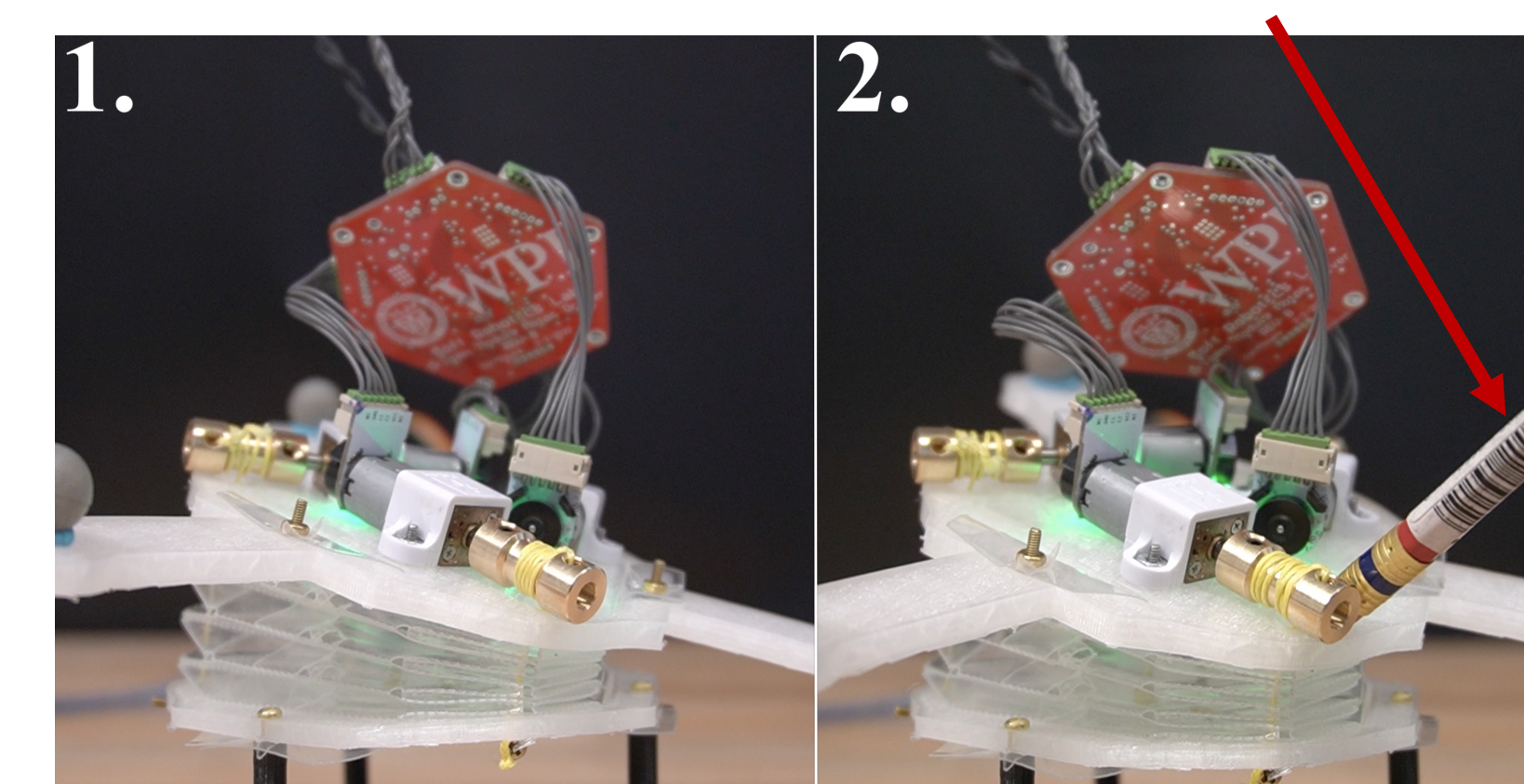
- Our proprioceptive origami module can
- Sense bending in any direction at any angle at <1mm accuracy
  - Predict position under external force loads
  - Enable complex control systems on mobile soft robots



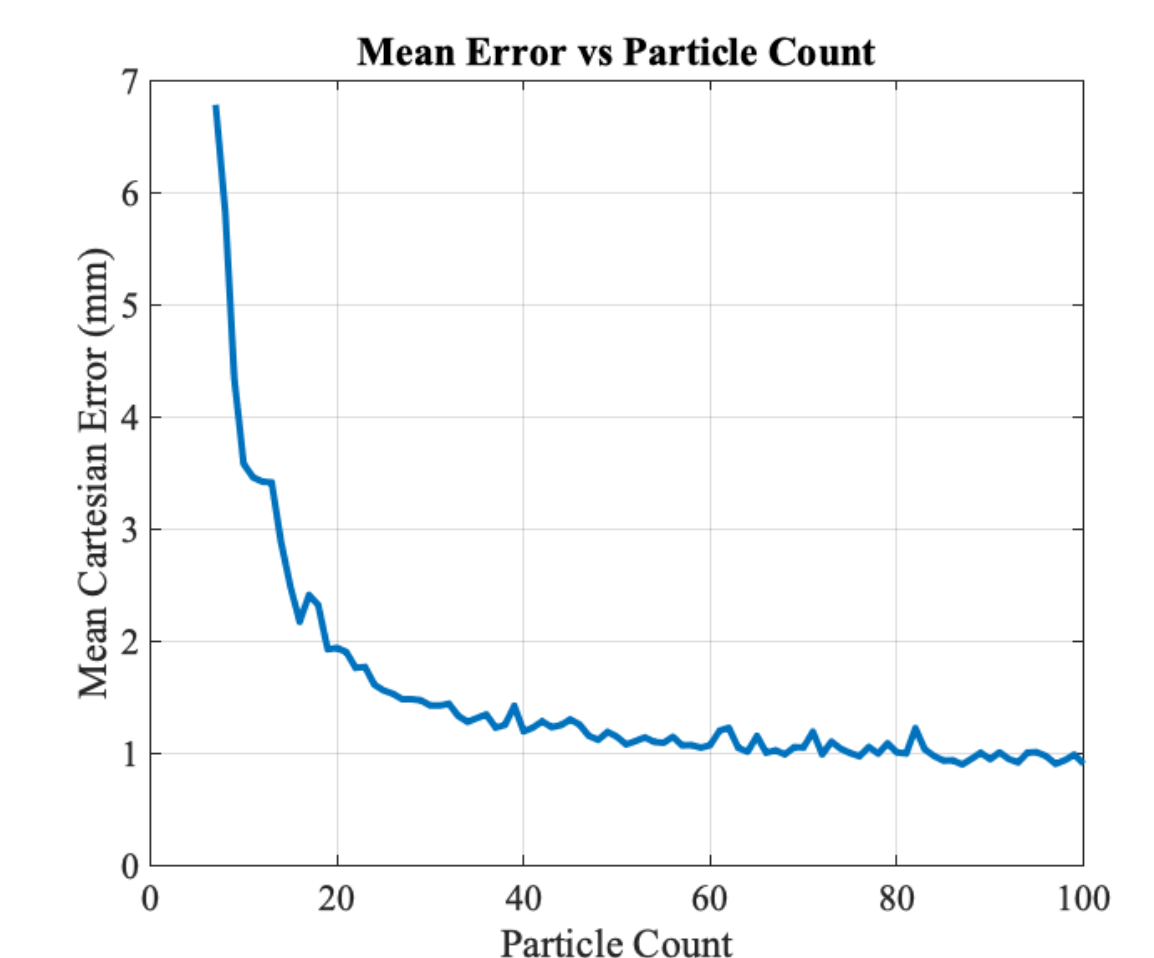
## Model Verification & Testing

### Experimental Setup

No external force      External force



### Diminishing reduction in error with more particles



### Sensor validation results using Motion Capture ground truth

