Technical Milestone Report

Pressure sensing for chopstick picking using an anthropomorphic robotic hand

Louis Relandeau

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Abstract

This project aims to test the potential of a new tactile sensing technology relying on pressure sensing embedded in a soft skin. This will be achieved by chopstick manipulation tasks, a complex problem yet to be thoroughly explored in the field of robotics. A control framework has been implemented to test the already-made anthropomorphic hand and experiments have shown that tactile data collected contains useful information to make predictions about the relative position of the hand and objects.

1 Introduction

Robots lack the adaptability humans have when asked to perform a diverse tasks; human hands are powerful tools that allow us to accomplish complex tasks such as screw a bottle cap on or manipulate chopsticks. This is achieved thanks to the fine sensing and feedback we get from millions of nerve endings on the surface of out bodies.

This project relies on sensors mimicking human skin by using a silicon-cast skin which contains small air chambers linked to pressure sensors through flexible tubing as shown in Figure 1. The robotic hand also has an inner anthropomorphic skeleton tested in [3] & [4] and previously built by Kieran Gilday along with the skin. This type of robotic hand is highly anthropomorphic; the human-like skeleton theoretically allows it to have a range of motion similar to a human's and the soft silicon skin provides further compliance and increased friction coefficient which is beneficial for precise manipulation or picking tasks.

2 Background

2.1 Robotic Hands

This section describes notable implementations of robotic hands. The first is the robotic hand by Zhe Xu [9]. Very close to the human hand in morphology and functions, it shows the potential but complexity of anthropomorphic approaches with tendon driven motion. Another approach is to use rigid links as shown by the TUAT Hand [1], exhibiting better

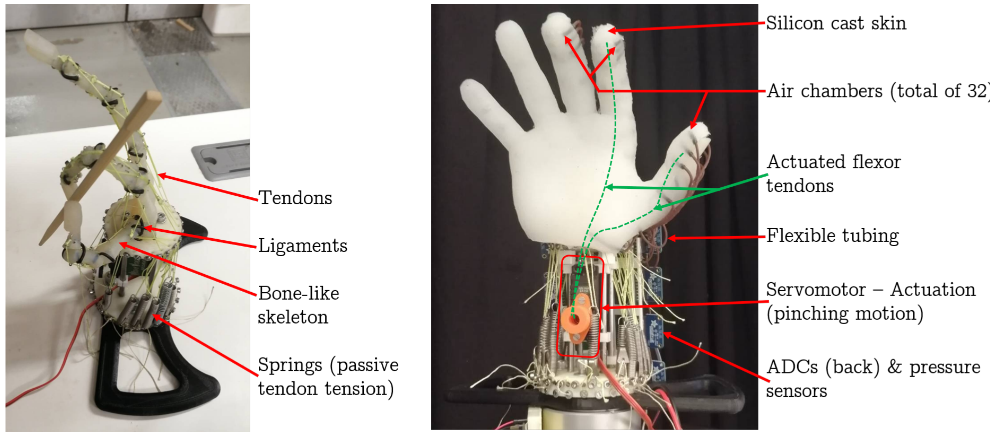

Figure 1: Hand previously built by Kieran Gilday; skeleton (left) and skin on top (right). Actuation mechanism was added during Michaelmas term

controllability but less compliance. The above paper highlights the dexterity required to achieve a range of grasps, illustrating quite well the complexity of chopstick manipulation; only achieved with the use of an auxiliary device. There are other very dexterous hands such as the very recent BCL-26 [10] which is entirely soft and relies on pneumatic chambers to control joint angles. The passive compliance embedded in the design allows for many complex grasps and tasks such as in-hand manipulation and writing.

2.2 Sensing

For a robotic hand, tactile sensing technologies greatly facilitates the control as it provides a direct feedback mechanism to the system. A comprehensible review of existing sensing technologies can be found in [6]. This paper details the most common approaches to tactile sensing and describes applications in robotic hands and haptics, highlighting that there should be a focus on interpreting the sensor data for dexterous solution. A sensing technology unexplored is the use of air pockets embedded in the robot skin and connected to pressure sensors. Our approach includes six individual sensors per fingertip. This reduces the amount of information to process but remains sufficient to manipulate objects the size of chopsticks.

2.3 Data Interpretation and Control

Modelling and simulating the behaviour of a robot is an efficient tool but a soft robot's kinematics often do not have analytical solutions and sim-to-real transferability is often an issue. There exist systems which self-model [7] by recording many action-sensation pairs, but this requires additional state sensors. Another approach consists in bypassing modelling by mapping directly sensor inputs to in-hand manipulation tasks [5], creating a robust closed loop feedback controller. The use of neural networks is a solution many seem to use for data interpretation and control. In [2], the author trains a LSTM network to map the strain sensor information to robot state. Methods known from image processing [8] can also be used for tactile servoing and picking tasks.

3 Progress Summary

3.1 Framework

The existing hand and software were modified (from [4]) to create a framework that can be used to perform a range of manipulation experiments. A servomotor was added to actuate the index and thumb to produce a suitable motion for pinching tasks. The motor and sensors are both connected to the controller as shown in Figure 2. The software architecture for the open-loop experiments is described in the flowchart (Figure 2, left).

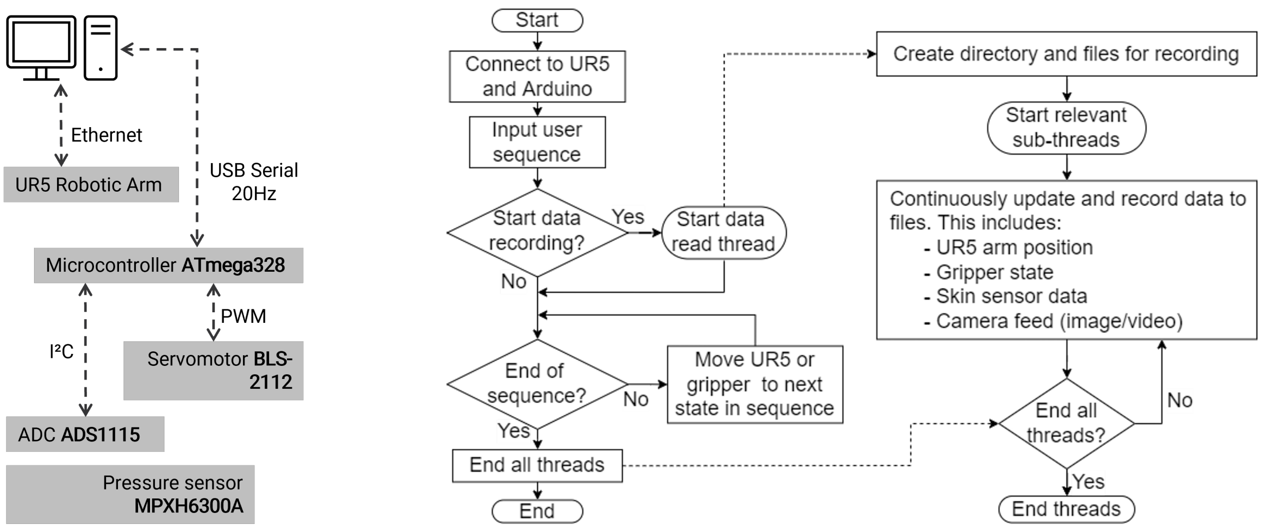

Figure 2: Hardware system (left) and software architecture for open-loop controller (right)

3.2 Experiments and Results

3.2.1 Finger coming in contact with a flat surface

In this first experiment, the hand was left unactuated and the arm was simply lowered 4 times by the same amount for the index fingertip to come in contact with the table. Additionally, the orientation of the hand was changed during the last iteration. The results are shown in Figure 3. The right-hand side plot clearly shows very repeatable pressure readings for some of the sensors as they come in contact with the surface over the first 3 iterations (from 2s to 11s) so the system is controllable. The last impact (11s onwards) shows that varying the angle of the hand does vary the sensor response as the fingertip is in contact with the table. So the next step was to quantify how much useful information is contained in the sensor data by attempting to predict a position simply from sensor data.

3.2.2 Angle of contact prediction using fingertip sensors

To assess the usefulness of the sensor data before implementing a closed-loop controller, an experiment was run where the index fingertip was in constant contact with a flat surface

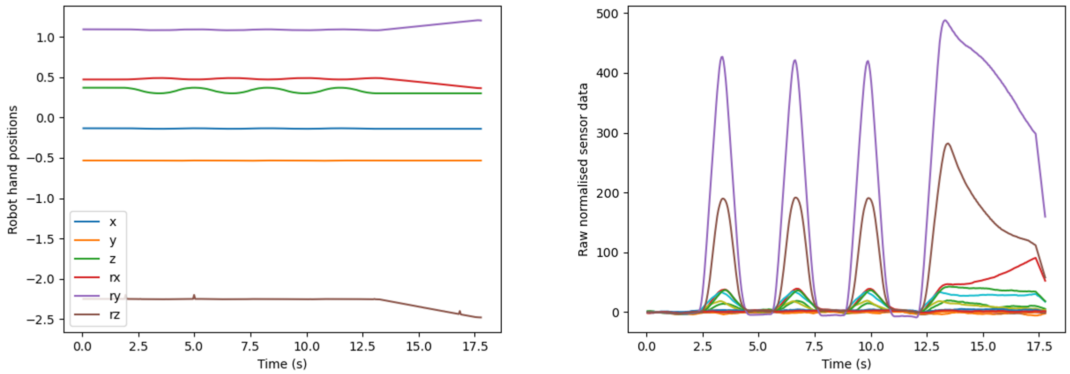

Figure 3: Hand coordinates (left) and normalised and filtered sensor data (right)

and the hand angle was randomly changed while recording sensor data and robot position (Figure 4, left). From this data, a regression artificial neural network was trained to obtain robot positions (3 degrees of freedoms: 3 rotations) as an output from inputting sensor data. The results of the training and testing are shown in Figure 4 (centre). Figure 4 also shows 2 typical comparisons between the output of the neural network (in red) and the real rotations (in blue). The 3 rotations are represented as a scaled 2D vector. The regression relied on a mean squared error loss function and the optimization algorithm used for stochastic gradient descent was Adam. These results were obtained using a 3-layer neural network; 16 nodes on the first layer for the 16 sensor inputs, 6 on the intermediate and 3 for the output layer corresponding to the 3 hand rotations.

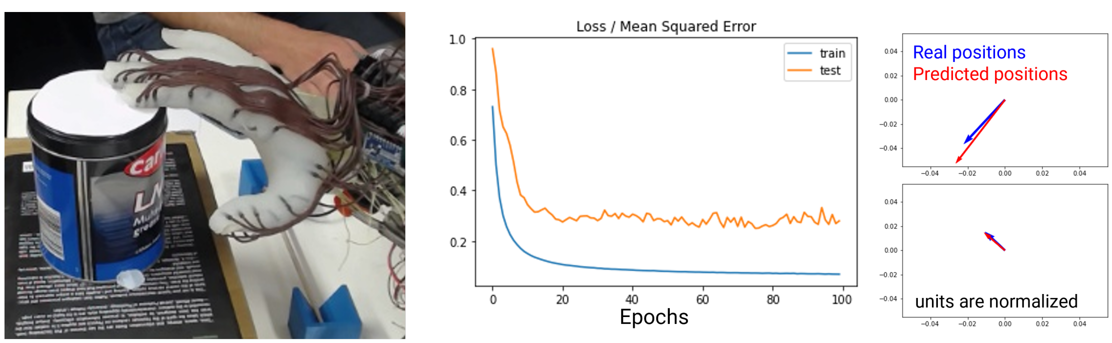

Figure 4: Experimental setup (left), neural network training results (centre), examples of predictions (right) for hand orientation

3.2.3 Chopstick manipulation in ball joint with pinching grasp

An experiment similar to the previous section was performed with the hand grasping a single chopstick between it's index and thumb with one end stuck in a ball joint attached to the table (Figure 5). The hand then moved in random directions (horizontal x-y plane) around the ball joint while recording the hand positions and sensor data. The same neural network was used as in the previous section. This time the number of data points, was increased from 8200 to 69303 with similar results (Figure 5, centre) but less over fitting.

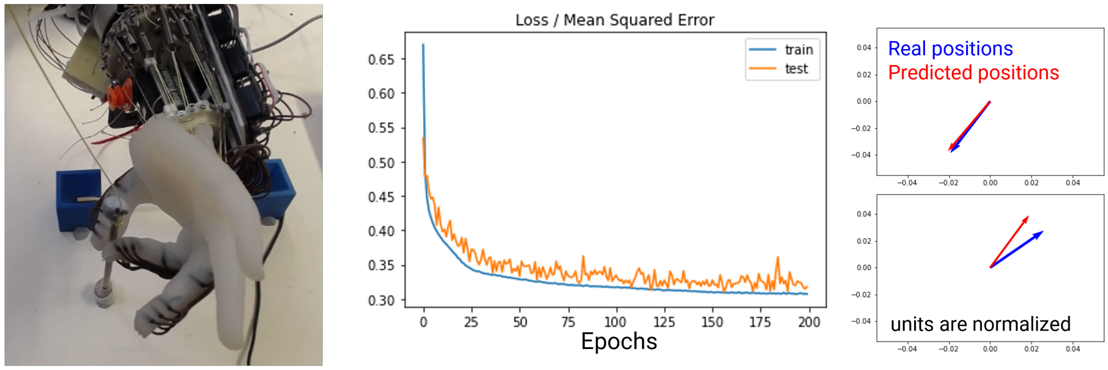

Figure 5: Experimental setup (left), neural network training results (centre), examples of predictions (right) for ball joint positioning

3.2.4 Chopstick picking

This experiment was done to see the type of data obtained when doing simple chopstick picking. The experimental setup was to have a chopstick positioned on two v-shaped holders. The hand then lifts it, drops it and repeats this a large number of times. The v-shaped holders ensured that the chopstick always fell exactly back in it's original positions to have repeatable initial conditions throughout the experiment. The setup is shown in Figure 6 along with a comparison of the same experiment when there is no chopstick. We can see that there is a clear difference between the two cases, this is promising if we want to reach a specific state, for example achieving stable picking through a closed-loop controller.

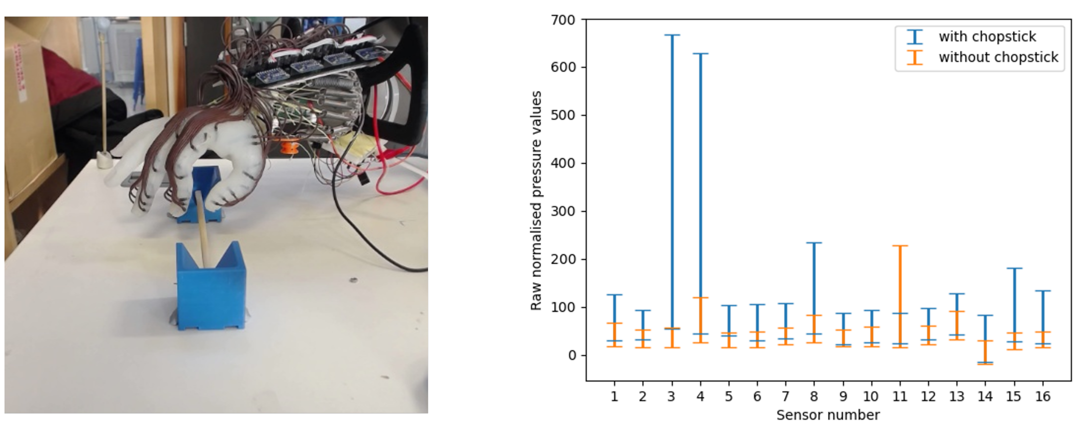

Figure 6: Experimental setup (left) and comparison between sensor data pinching with and without chopstick in between index and thumb (right)

4 Forthcoming Work

The next steps include improving the predictions done in the previous results by optimising the architecture of the neural networks and experimenting using an LSTM network. Having a soft skin means that there is always a noticeable time response in the deformation of the skin and therefore the air chambers. An LSTM network would take into account this time response and avoid any slight over-fitting as observed in Figure 4 (centre).

To demonstrate the potential of air pressure sensors, more complex experiments will be performed. This includes accurate sensor characterisation (eg. sensitivity). A chopstick could then be used to make force predictions in a similar fashion as section 3.2.3 but by placing the ball joint on a force-torque sensor. Finally, a demonstration of picking a chopstick and using it to explore and map the environment could showcase all previous work.

An additional goal of this project is to develop a closed-loop controller that would rely on the sensor data to perform a task (e.g. chopstick picking with random noise). The success rate can then be compared to an open loop controller's. Using an ideal pick's image of the sensor values (Figure 6), the controller will adjust the hand position to find this same position, thereby reducing the risk of dropping the chopstick.

5 Conclusion

Relative to other robotic hands and with the aim of chopsticks picking our hand is less controllable, but considering the time constraint of the project it is be preferable to start with a functional prototype that has successfully performed different tasks. As we have seen from section 3, we are able to make predictions with a mean squared error falling below 0.35. The accuracy and reliability of the sensor data is promising for the next step of designing closed loop controllers which rely on this skin's tactile sensing.

References

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