Ripeness Detection by Force Control

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Abstract

Food quality control is a repetitive process that traditionally requires a human to carefully inspect individual pieces of fruit. We believe this is a perfect opportunity to integrate a robot arm. Current collaborative robots are equipped with force sensors which can provide a tactile perception of their environment. By making a robot contact a piece of fruit, we can classify the fruit's ripeness by using the tactile perception of the UR5e robot's actuation and sensing.

1 Introduction

Robots are becoming more widely implemented in industry all over the world, used for automated testing and quality checking. In the food industry, it is important to check fruit to identify their ripeness to avoid selling under-ripe or overripe items[1]. Most fruits tend to change their hardness as they ripen, becoming softer through a series of chemical processes[2]. We hypothesize that this chemical process can be leveraged to analyze the ripeness of fruit using the integrated sensors in the Universal Robotics (UR) UR5e robotic arm.

The UR5e robotic arm has a built in force sensor capable of reading reactionary forces on its surface. In this paper, we test the ability of this sensor to detect the hardness of various fruits using a blunt end effector. We then use this information to evaluate the ripeness of a given fruit. The results in this paper are based on the peak response of the force sensor of the robot. We tested various types of fruits to understand the reliability of our method, and we analyze how this form of testing could be used to classify ripe and unripe fruits automatically.

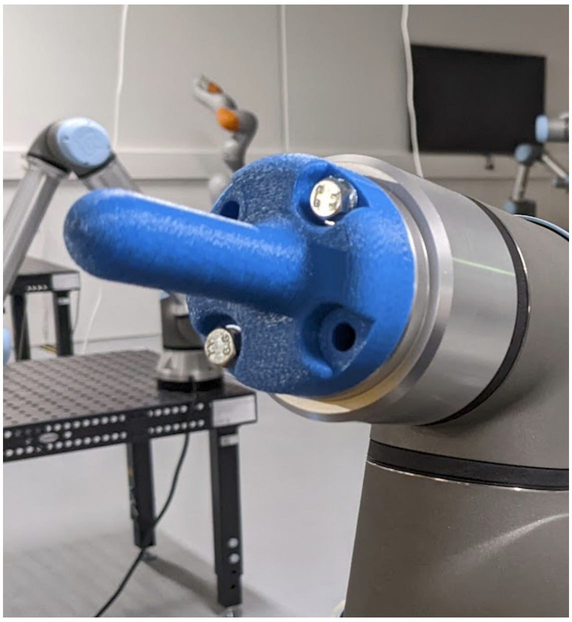

Figure 1: Robot End Effector

2 Framework and Experiment.

In this experiment, we use the embedded force sensor in the UR5e robot to determine the hardness of fruit, which we compare between samples of ripe and overripe fruit. To accomplish this, the robot will perform a linear movement from above the fruit until it contacts its surface, recording the data from the force sensor over time.

We created a custom designed end effector for this process as shown in Figure 1. This end effector uses a blunt tip to interact with the fruit to avoid puncturing the skin[3]. This ensures that the test is non-destructive for repeated testing.

To set up the test, we programmed the robot in force mode to move downward with a constant force and slight damping attenuation until it reaches the fruit. By combining force control with a damping force, we can create a sampling method with a consistent speed and force input. Using this controlled input motion, we can measure the output of the built-in force sensor mounted to the tip of the UR5e robot. As the robot moves, we monitor the resulting input force on the tip sensor. When the robot motion contacts the fruit, it generates a unique signal that can be analyzed.

Once the data is collected, it can be represented in a graph over the time to show the force response as shown in Figure 2. The properties of this signal will change depending on the hardness of the surface such as the peak response, settling time, wave frequency, slope to the pick, etc. In our case, we have chosen to focus on the peak response because this property of the signal shows better behavior to characterise a wider range of hardness in surfaces. [4] This amplitude of the signal is then used to classify the fruit[5]. The fruits selected for this experiment are: bananas, apples, kiwis and mandarins.

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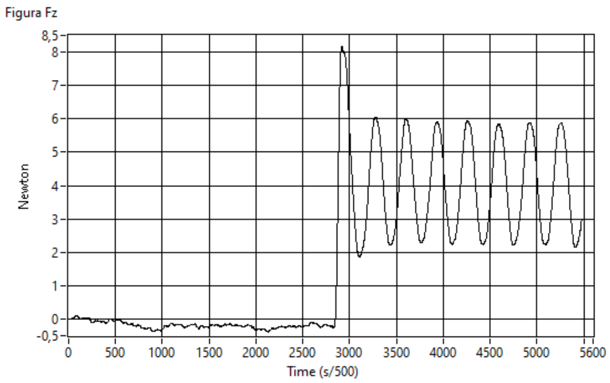

Figure 2: Force Sensor Signal Response

For testing we took sixty hardness samples of each type of fruit. The experiment was performed twice: once immediately after acquiring the fruit while ripe, and again one week after.

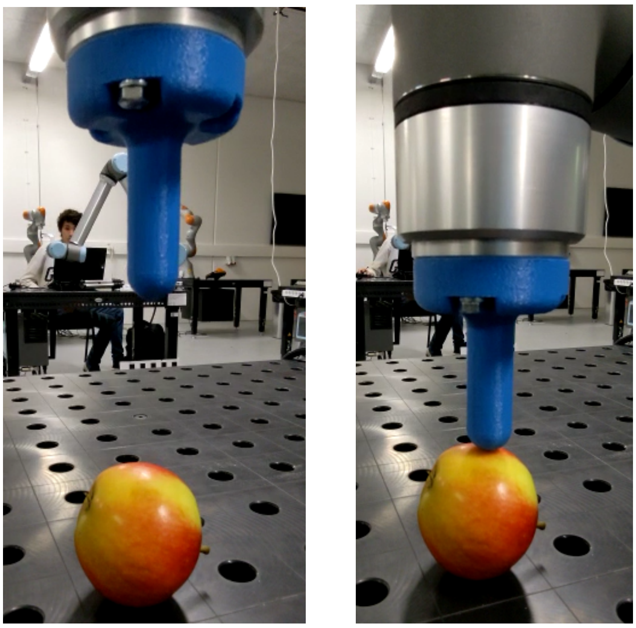

Figure 3: Movement of the robot to test the hardness of the fruit.

3 Results

Our final data in Figure 4 shows the distribution of the peak response measurements from our experiments. The distributions show that some fruit, such as mandarin and kiwi, have distinct measurements between ripe and overripe fruit, while other fruit is has more overlap between the populations.

To analyze these data sets, we first tested the distributions of each fruit, before and after ripening. We used a set of QQ-Plots to visually determine their normality as seen in Figure 5. Using this method, we found that the data for apples and mandarins were normally distributed, while bananas and kiwis had skewed distributions in their overripe data.

Using this data, we performed a series of tests to determine if the two populations are statistically distinct. For apples and mandarins, which were normally distributed samples, we used an independent t-test to test for a difference in mean. For the bananas and kiwis, which were not normally distributed, we used a Mann-Whitney test.

Through these tests, we found that bananas, mandarins, and kiwis have a statistically significant difference in mean between when they are ripe and overripe, while apples were unable to be distinguished, as shown in Table 1. Using this information, we could calculate the 95% confidence interval for their difference in mean as shown in Table 2. The confidence intervals could only be calculated for the fruits with a normally distributed data set.

Table 1: Test Result for Difference in Mean
H_0: No Difference Between Population Means

Fruit	Test	Result
Banana	Mann-Whitney	Reject
Apple	Independent T-Test	Fail to Reject
Mandarin	Independent T-Test	Reject
Kiwi	Mann-Whitney	Reject

Table 2: Confidence Intervals for Difference in mean

Fruit	95% Confidence Interval (N)
Banana	Inconclusive
Apple	[-0.25, 0.31]
Mandarin	[1.59, 1.96]
Kiwi	Inconclusive

4 Discussion

The data shows us that our hypothesis was correct under some conditions. In our experiments, the force sensor of a UR5e is sensitive enough to test the peak response. As we can see in Figure 4 there is a clear difference between the first and second measurement for all the fruits except for apples. This was confirmed by our statistical tests, which showed a significant difference in means between the two populations of each fruit besides apples. This shows us that this type of test is a reliable way to check for fruit ripeness for some fruits. However, our results were not conclusive when applied to apples. This indicates that some fruits are more easily classified than others. A limitation of this approach is its reliance on physical contact with the fruit. It is possible for this test to damage the item, especially after repeated tests. To account for this, in a chain food processing context, this process could be applied to a smaller sample of food in a larger population.

This data can be further applied to create a classifier for the ripeness of new samples. This could be applied to both factory automation and to the use in smaller local food distributors.

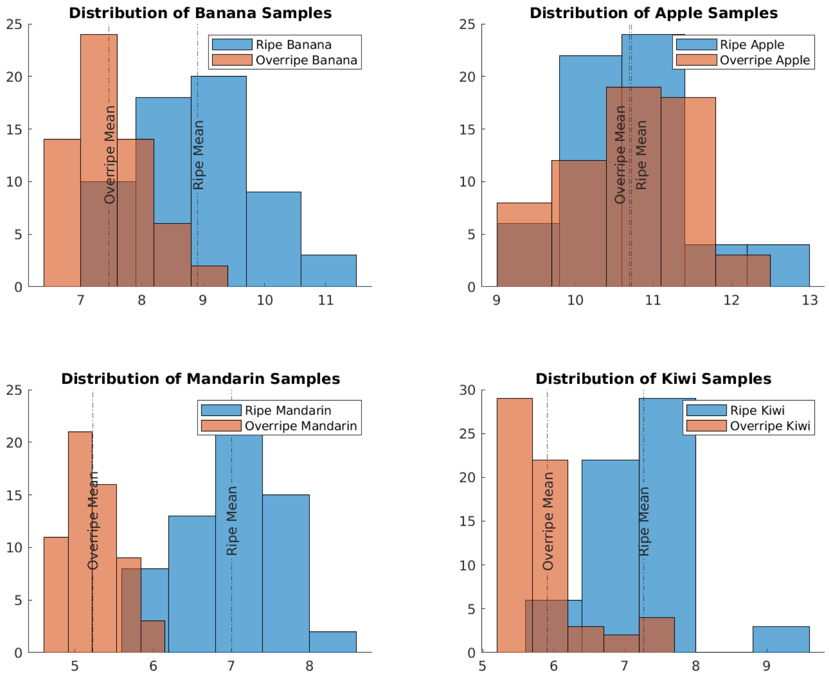

Figure 4: Distribution of Peak Response from Force Sensor for Each Fruit

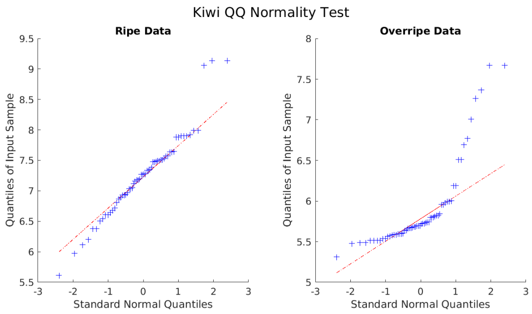

Figure 5: QQ Plot of Kiwi data samples

5 Future Work

One key aspect of future work to investigate is the effects of the testing environment of the fruit. In our tests, the fruit were placed on a tabletop with no support structure, which allowed them to deform. We believe this could impact the readings and reliability of the testing procedure. Future work could develop a more automated system for transporting and holding fruits during the procedure. Another parameter that may inspire future work is the impact of the end effector that was used. Our experiments used a simple rounded cylinder, but more options could be explored. For example, a pinching gripper could be used to apply a symmetric force to the fruit to determine its elasticity. Future work could also investigate the effects of fruit undergoing different processes besides ripening. This could include culinary-type processes such as cooking or freezing. By applying the same test to before and after, it will be possible to understand how a process affects the material properties of the material. This would allow the process to be generalized and implemented in other areas of automation. In a food processing context this setup can have high potential due to the versatility of the test and the low impact it would have on the object.

6 Conclusions

This paper shows a new way to introduce robots in quality control systems of the agricultural and consumer shopping industries [1]. Our process could be expanded to predict many aspects of food quality assurance in various applications, opening a new use case for robotic arms in industries not limited to manufacturing and assembly.[6] The versatility of this setup can be introduced in a low educated environment, creating a cooperation context without a complicated introduction to it.

References

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