Compliant Sensorized Testing Device to Provide a Model Based Estimation of the Cooking Time of Vegetables

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Abstract. Many cooking tasks rely on physically interacting with and sensing soft objects. One assessment widely performed is identifying when a vegetable or soft structure is cooked. Commonly, we may interact with the food item and use tactile feedback to estimate if the food is cooked or not. This is also a task performed at scale in food supply chains. To address this, we have developed a general purpose model for modelling the kinetics and thermal properties of the vegetable cooking. We show that by identifying the size, and stiffness of the vegetable at two points in the cooking process the time for the vegetable to cook can be identified. With this in mind, we have developed a compliant tactile testing device which includes a tactile force sensor which can be used for measuring stiffness, and proprioceptive sensing method which can be used to measure the size. The mechanism is robust and high torque, in addition to being simple and low cost in terms of fabrication. Using this model and device we demonstrate the accuracy in predicting the cooking time for potatoes of various sizes, and benchmark this in comparison to when used a fixed cooking time. We demonstrate that the model based approach significantly improves the estimation and outcome of the cooking process. Whilst we demonstrate this approach on potatoes, the hardware and model to other vegetable cooking processes.

Keywords: robotic kitchen, tactile sensing, flexible grippers, food modelling

1 Introduction

'Sensory analysis' refers to a scientific discipline where the human senses are utilized systematically to evaluate consumer products [1]. This discipline entails complex experimental procedures, and is systematically employed in food industry, to ensure standardization, quality, taste across food products [2]. With the advent of robotic automation, many attempts have been made to achieve the physical and sensory aspects of this work, including robotic taste testing [3, 4]. One such 'sensory analysis' task is detecting when food is perfectly cooked; this is particular challenging as in many cases it relies on tactile feedback of a soft object. For example, we often use a fork or other implement to interact with the soft vegetable, to provide an indication of 'done-ness'. Throughout the food industry there is real need of a experimental, automated approach for identifying and predicting when vegetables should be cooked, which can be tailed for the specific vegetable and its size and shape. Examples of this requirement include the boiling or cooking of beetroot for packaging, or potatoes for making crisps [5].

To address this challenge, the goal of this work is to create a robust and reliable system for accurately estimating the cooking time for vegetables. A quick, simple and non-destructive approach is required which requires minimal testing of the vegetables to accurately estimate the optimal cooking for a given vegetable sample. This should generalize across different root vegetables which have a variety of different shapes and sizes.

One challenge in achieving this goal is the development of a generalized model for predicting the cooking time. This must consider heat diffusion and also the corresponding change in stiffness and physical properties. In addition, every vegetable tested will have a different size and different cooking behaviors, so the model must be able to account for this using sparse test data. In addition, we require a physical tactile testing device. This must be physically adaptive to a wide variety of sizes and shapes of vegetables. There is also a considerable range in stiffness of vegetables during the cooking process, so it must be able to apply large forces to stiff vegetables whilst delicate sense more delicate samples to prevent damage. We require a robust device that can operate on a variety of size of vegetables, with a sensor that can show high accuracy and reliability.

Prior work has examined the use of tactile feedback to asses the ripeness of fruit produce [6], or the degree of readiness of food [7], consumers use a combination of tactile sensing and visual cues. The automation of tactile sensory analysis has recently seen an plethora of advances [8, 9] which have changed the landscape for tactile based inference procedures [10, 11]. For example, work in [12] and [13] have shown how it is possible to achieve robotic ripeness estimation via piezoelectric and capacitive tactile sensing technologies respectively. However, in these past works, however, there has been little focus on the use of the sense of touch for estimation of when an item is cooked. In this work, we focus on the estimation of degree of cooking of potatoes. Although there has been existing work on the textural quality of potatoes across cooking times and methods [14], many of these techniques require extremely costly equipment or are heavily destructive, they are also not generalize across different vegetables.

We propose a model of a cooking vegetable which considers the physical and thermal properties. We show how this model requires stiffness evaluations of vegetable to be made when cooking. To allow this data to be gathered we introduce a novel sensorized gripper which utilizes a high torque compliant mechanisms to squeeze the vegetable. The gripper utilizes the compliant mechanism to achieve proprioceptive sensing to allow the size of the vegetable to be estimated. In addition, a robust, sensitive tactile sensor is introduced, which utilizes fluidic sensing for accurate, highly linear monitoring of stiffness.

To demonstrate the application of our model to vegetable cooking, we use our tactile sensing device to predict the cooking time for potatoes of various sizes and shapes. We benchmark the performance of this approach in comparison to when using a constant cooking time, and show the our approach shows a far close match to the ground truth for a cooked potatoe across a wide range of samples of different sizes.

In the remainder of this paper we before presenting out generalized model of vegetable cooking in Section II, followed by the development of our sensorized testing device which allows the necessary data to be gathered. In Section IV, we present a number of results using this device and demonstrate how it can be used to predict the cooking time of a number of vegetables. Finally, we conclude with a results and discussion section.

2 Methods

We propose a model of a cooking approximately spherical vegetable which considers thermal and mechanical properties of the vegetable boiling. This model can be adjusted for a given vegetable by gaining stiffness measurements at different cooking times, after which the optimal cook time can then be predicted for a given vegetable. We pair the model with the development of a sensorized gripper which provides the sensory information required by the model: stiffness and size of the vegetable. In this section, we first introduce the model of cooking potatoes before introducing the mechanical device.

2.1 Vegetable Mechanical Model

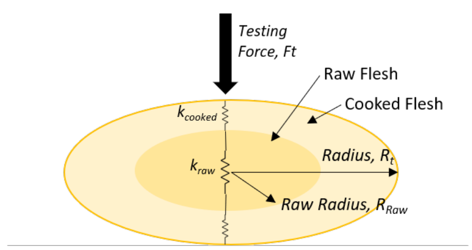

Fig. 1. The mechanical model of a cooking vegetable modelled as an uncooked core inside of a cooked external shell, each region has a different Young's Modulus and hence spring coefficient, k.

The vegetable is modelled as a raw core with a cooked shell around it, with the two having different stiffness, as shown in Figure 1. The potato can be modeled as a spring system, governed by Hooke's Law ($F = k\Delta x$), where the stiffness (k) can be expressed as a function of of the Young's Modulus (E), and cross sectional area (A) to give $k = \frac{EA}{L}$. Applied to out potato model, we can define the stiffness of the raw and cooked regions as:

$$k_{raw} = \frac{E_{raw}A_{raw}}{2R_{raw}}, \quad k_{cooked} = \frac{E_{cooked}A_{cooked}}{2(R_t - R_{raw})} \tag{1}$$

Such that stiffness of the total potato system can be given by the sum of the spring system:

$$k_{total} = \frac{k_{cooked}k_{raw}}{E_{cooked} + k_{raw}} \tag{2}$$

We make the simplifying assumption that $A_{raw} \approx A_{Cooked}$ such that the full spring constant becomes:

$$k_{total} = \frac{A}{2}\frac{E_{cooked}E_{raw}}{E_{cooked}R_{raw} + E_{raw}(R_t - R_{raw})} \tag{3}$$

2.2 Kinematic Model of Vegetable

The physics of potato cooking has been previously explored and has been proven by practical experimentation [15]. In this, the potato was modeled as a homogeneous sphere, which is exposed to a constant external temperature. This induces a "cooking front" which describes the boundary between the cooked and uncooked parts of the potato which varies as a function of cooking time. The "cookedness" of the potato can be described by the ratio between the inner and outer sphere. When this is 1, the potato is raw, and when 0 it is fully cooked. The thermodynamics model specifying this ratio can be given by:

$$\ln\left(\frac{\lambda_1(\frac{r_{raw}}{r_{total}})}{sin(\lambda_1(\frac{r_{raw}}{r_{total}}))}\right) = -{\lambda_1}^2\frac{\alpha}{{r_{total}}^2}t + \ln\left(\frac{A_1}{\Theta_f}\right) \tag{4}$$

where Θ_f is the temperature of the cooking front which is assumed to be constant, and α is a thermal diffusivity of the potato, which is another constant. Therefore, the model is dependent only on three parameters: size of potato - r_{total} and A_1 and λ_1 which are coefficients symbolizing a approximate solution of one dimensional heat transfer equation. The latter two are a function of Biot number only, which is given by $Bi = h * r_{total}/k$ where h is convection heat transfer coefficient, and k is thermal conductivity of the potato, both constants. The Biot number is also proportional potato size, however, for the range of sizes of likely potatoes to be tested there is very little change in A_1 and λ_1 value (less than 3% change) [16]. Thus, we make the assumption that any potato can modeled as an infinitely large potato, such that $A_1 = 2$ and $\lambda_1 = 3.14$. Therefore, we can put (4), the cooking function, $f_c(t)$ into the form of a straight line which is a function of time. The optimal cooking time can be found when the ratio of r_{raw}/r_{total}, and hence the $f(t)$ is equal to 0:

$$f_c(t) = \ln\left(\frac{\lambda_1(\frac{r_{raw}}{r_{total}})}{sin(\lambda_1(\frac{r_{raw}}{r_{total}}))}\right) = \frac{A}{{r_{total}}^2}t + B \tag{5}$$

where A and B and constants that must be found through stiffness experiments for potatoes cooked for different amounts of time to provide $\frac{r_{raw}}{r_{total}}$ for a known radius of potato.

2.3 Fitting the Model

The thermodynamic model thus describes the ratio of the cooked to total radius of the potato as described by the mechanical model. This ratio must be measured through stiffness measurements of the vegetable. Starting from the stiffness model given in (3) by evaluating k_{raw} and k_{cooked} experimentally we can obtain E_{raw} and E_{cooked} from which the ratio between the Young's modulus of cooked and raw potato can be identified, such that the stiffness equation can be given as:

$$k_{total} = const.\frac{1}{R_t - aR_{raw}} \tag{6}$$

where a is a value between 0 and 1, which is a function of Young Modulus for cooked and uncooked vegetable and is a constant for a specific vegetable. To find the values of A and B in (5) two stiffness measurements must be made for different amount of cooking (i.e. for different R_{raw}). From these measurements R_{raw} can be evaluated for both stiffness tests, from which two values of R_{raw}/R_t for different amounts of cooking time can be used to evaluate A and B in (5). From this model the optimal time to cook a potato of a given radius can be given as:

$$t_{cook} = \frac{-Br_{total}^2}{A} \tag{7}$$

To validate that this model works in a controlled scenario five potatoes were shaped into cuboids of the same size and each cooked for 0, 10, 20, 30 and 35 minutes. Using a FT-150 force-torque sensor mounted on a UR5 robot arm, the stiffness was determined by measuring the force to 'stab' the potatoes by a given amount. Using the stiffness values identified a model of the cooking potato has been created, with the results shown in Figure 2 left. To test the robustness of the model to noise, ±10% and ±20% error was introduced into the sensor readings; as shown by Figure the model shows variation in predicted cooking time, but still provides a meaningful prediction and holds despite variation in the input.

To test the model developed in the experiments, a model was formed for a potato with a 1.3 times the radii as the previous. The model developed previously was also adapted for this change in radii to show predictions for this increase in size. In 2 right we show the predicted model and that found experimentally shows a close similarity showing that the model holds for changes in size of the vegetable.

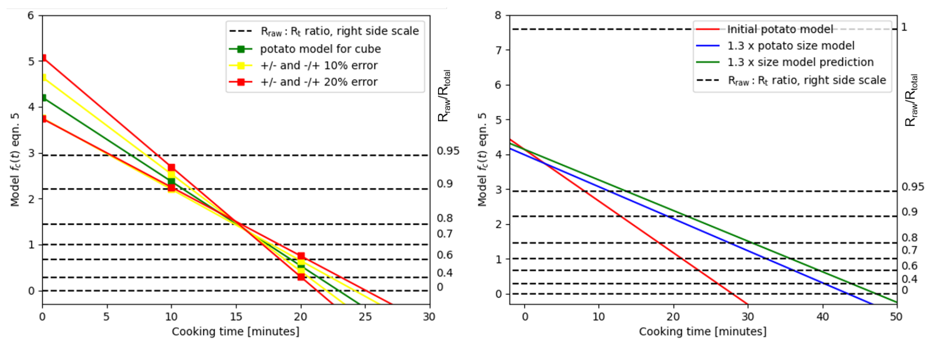

Fig. 2. Left) The model developed for a tested potato cube, with the predicted cooking time shown when the Model, $f_c(t) = 0$. The variation in the model to noise is also shown Right) A predicted model (green) for 1.3x times potato, and that formed from experimental results (blue).

3 Hardware Development

To make measurements of the vegetable stiffness we require a gripper which has the strength and capability to manipulate and 'squeeze' potatoes of a variety of sizes and stiffness. It also requires a sensing technology which is robust and provides sufficient sensitivity. We combine a novel gripping mechanism with a tactile sensor which is robust and sensitive to provide a means of quantifying the stiffness of potatoes.

3.1 Gripper Technology

The novel gripper utilizes four 3D printed flexure based fingers through which a tendon is routed through the tips of the fingers. The gripper is shown in Figure 3. A small DC-motor mounted on one of the fingers and is connected to the tendon such that by pulling the tendon the finger tips can be contracted, forcing the compliant fingers to bend around the object, deforming to their shape yet forming a high force closure. This provides a mechanism that is highly compliant to the objects shape, whilst also providing a high gripping force. This allows for manipulation of objects of a many different forms and weights, due to the compliance, whist the high force enables manipulation and also provides the force to enable stiffness to be assessed using the device. The assembled gripper has been tested on a variety of different vegetables and and shows a high grasping success; this is illustrated with examples in Figure 4.

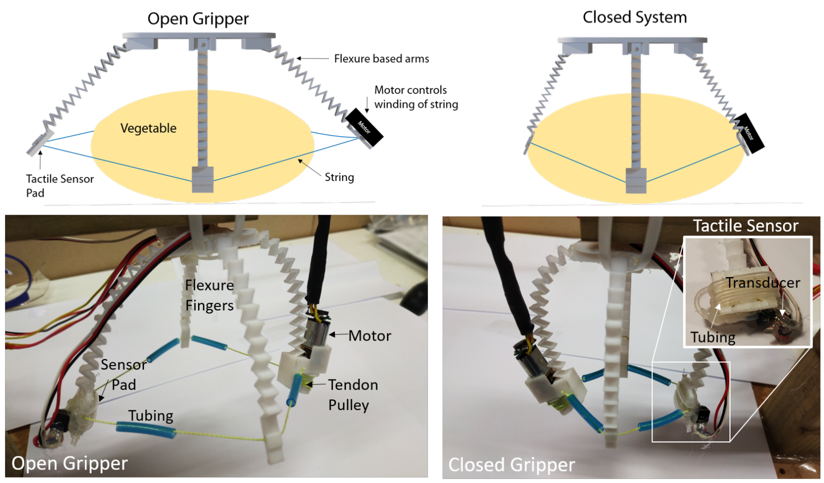

Fig. 3. Image of closed (left) and opened(right) gripper with important elements captioned.

All elements of the gripper (the fingers and the base structure) are 3D printed using PLA and interlocking allowing for rapid and low cost fabrication. One finger supports the motor enabling actuation of the device, while the opposing finger has a larger finger pad upon which a fluidic tactile pressure sensor has been placed. The motor used is a Polulu micro-metal DC motor with a 298:1 gearbox. A pulley forms the interface and winding mechanisms for the tendon on the motor shaft. The gripper is controlled using an Arduino MEGA and a motor driver. A magnetic encoder is attached to the motor to enable tracking of the position and hence the length of the tendon which controls the gripper. The encoders are read via interrupts, and with the setup developed provides 34 interrupts per mm of the tendon. The use of the encoders allow for both position control and provides some proprioceptive sensing capabilities.

3.2 Sensing Technologies

The gripper has both proprioceptive sensing capabilities through the motor encoder and also tactile sensing for determining stiffness. Starting with a known length of the tendon, by measuring the change in encoder position when the gripper is then closed around the object, the circumference of the object can be estimated. This capabilities arises from the placement of the tendon in the gripper mechanisms, and provides a high accuracy mechanisms for detecting the size of the potato which is critical for the potato model. To demonstrate the accuracy of the proprioceptive sensing using this approach Figure 5a shows the ground truth of the circumference vs. that measured using the gripper.

The tactile sensor consists of a MP3V5010G pressure transducer connected to a silicon tubing which is wrapped around the sensor's fingertip. The tube is hermetically closed, such that when an external force is applied to the tube in

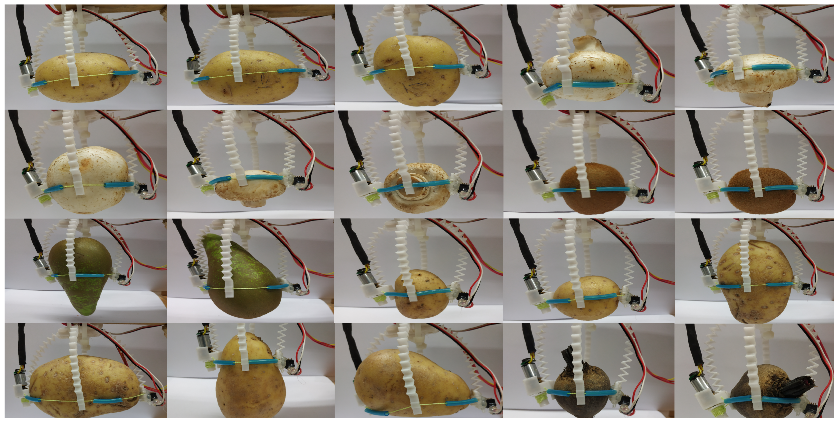

Fig. 4. Gallery of pictures showing a variety of vegetables of varying sizes and shapes, grasped at different positions.

a adiabatic process, the internal pressure increases; this is similar to the sensing approach introduced in [17]. This change in pressure is then measured by the pressure transducer, which provides an analogue output. This output is converted to a digital reading by using a 12 bit ADC and oversampling to increase the robustness and accuracy. To demonstrate the capabilities of the sensor, various forces were repeatedly applied to the sensor and the change in pressure measured. The average response for a given normal force is shown in Figure 5. This shows the response is highly linear below 20N and provides a sensitivity which is appropriate for measuring the difference in stiffness of vegetables.

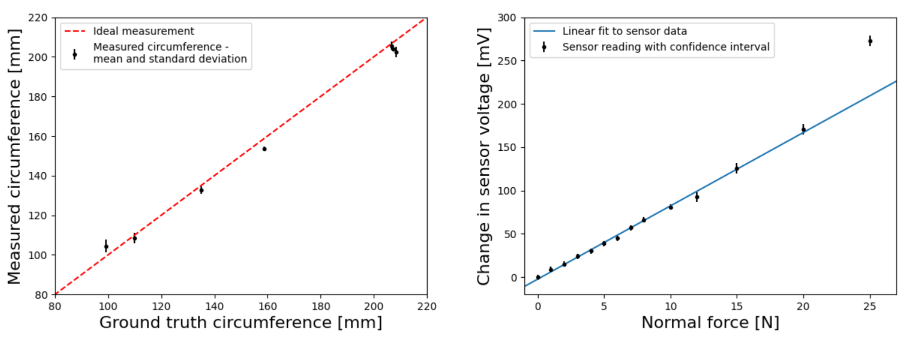

Fig. 5. Plots showing the performance of the proprioceptive measurement of radius of grasped object using the encoder (left) and response of the tactile sensing showing the variation in sensor response with normal force applied (right.)

3.3 Stiffness Estimation

The gripper must return stiffness measurements of the tested vegetable. This can be found using both the proprioeptive and force sensing tactile sensor in the gripper. The spring constant is determined by closing the gripper around the vegetable for a given time period or until the maximum torque is achieved. Using the strain (change in length of tendon) against sensor reading data, we identify the linear region corresponding to the squeezing action and use linear regression to determine the slope, the spring constant. This procedure is the repeated 5 times for each sample in order to get average value. Averaging is crucial as the reading may be noisy, mainly due to varying sensor placement. The circumference of vegetable can also be estimated by detecting the length of tendon corresponding on the onset of the increase in tactile sensor readings.

4 Results

To demonstrate the effectivness of the model and gripper, we first demonstrate the stiffness measurements that can be made using the gripper. We then show how the data from the gripper can be combined with the cooking model to accurately predict potato cooking times.

4.1 Stiffness measurement

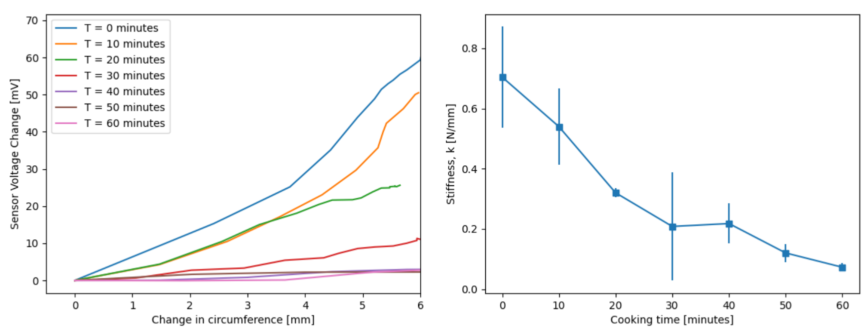

Fig. 6. The plot shows an example raw tactile sensor reading versus the changing circumference of the gripper for potatoes cooked for various times. The slope of these curves is an effective spring constant of the vegetable.

To demonstrate how the stiffness can be captured during squeezing, the tactile sensor response is shown for the squeezing of potatoes which have been cooked for different amounts. As shown in Figure 6 we see a significant difference in the gradient of these lines depending on the cooking time. Whilst there is the most significant difference between a cooking time of 0 and 30 minutes, after this the reduction is stiffness is far less as the potatoes are cooked, or very close to cooked. This shows how the gripper can be used to determine stiffness, and it is good indication of how cooked a potato is.

4.2 Model Computing

Using the gripper, we next test the gripper to develop a model of the potatoes being tested. For these test we choose to test larger 'baking potatoes'. By performing stiffness measurements during testing we developed a model of the potato as shown in Figure 7 left. The model can be adjusted for different sizes of potato as its slope is inversely proportional to the radius of cooked vegetable. The point the line crosses x-axis is a predicted cooking time (Eq. 5).

To gather a ground truth to allow assessment of the independent performance of this approach, similar sized potatoes were cooked for between 0 and 60 minutes. Each potato was then tested, to determine the 'cutting' force on a given sized potato cube from the centre of the potato, and also a human assessment (Table 1). This approach is destructive, and complex making it unsuitable for large scale tests. From these results we see that we can establish a ground truth for the cutting force of a cooked potato as 2N. Thus, to test the model developed we can perform this cutting test on 'cooked' potatoes to test the performance relative to this benchmark which represents when a potato is correctly cooked.

Cooking time (mins)	0	10	20	30	40	50	60
Cutting Force (N)	33	24	23	10	4	2.8	2
Human Assessment	Raw	Raw	Raw	Not Ready	Not Ready	Al Dente	Cooked

Table 1. Identification of ground truth for when potatoes are cooked. A potato is cooked for various time and the cutting force measured, so identify the cutting force which corresponds to a cooked potato.

4.3 Model Predictions

To demonstrate how this approach can be used to achieve optimal cooking for a potato of a given size, the cooking time was estimated using a model. The potato was cooked for this time, and a ground truth measure of the performances determined by measuring the hardness of the potato, and comparing this to the optimal hardness as identified in Table 1. To demonstrate the effectivness of this approach in comparison to cooking for a fixed amount of time, potatoes of various sizes have also been cooked for a fixed time interval, in this case 30 minutes. The results are shown in Figure 7 for 3 repeats of each experiment. When using the model based approach we see that the error in the cooking of the potatoes is far reduced in comparison to using a fixed time. In particular, the model holds for significant changes in size of the potato, down to 0.2 of the tested potato which only a small deviation from the stiffness ground truth.

5 Discussion & Conclusions

In this work we introduce a versatile model for representing the cooking of vegetables that considers both the mechanical and thermal properties. This model

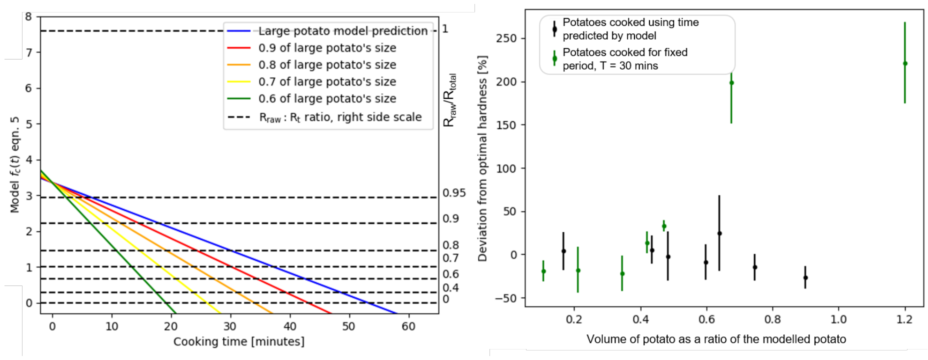

Fig. 7. Left) The model developed using the gripper, and the adapted model for different sizes of potato. Right) The deviation from the optimal cutting force (2N) of the model based approach for different sizes of potato in comparison to those cooked for a fixed amount of time. Each experiment was repeated three times.

requires measurement of stiffness of a number of test specimens, and also their size. Thus, we introduce a novel compliant sensorized gripper which has both the physical capabilities to perform stiffness tests, whilst can also measure both the size of the vegetable, and the force during these stiffness tests. This provides a way of automating the testing rapidly and a low costs. Using the model and testing device we should how the cooking time can be accurately predicted for potatoes which significant variation in size.

The model could be further refined to reduce error in the estimations, in particular by considering a non-spherical object, and modelling the inner structure (e.g. the skin) more accurately. Although the model appears to work well without this, this would potentially allow the model to work across a wider variety of sizes and shapes of vegetables. In addition, the sensor readings could be improved the accuracy of the model; increasing the sensitivity of the tactile sensor could be increased by introducing a larger area tactile tip.

The model developed in this work is widely applicable in the food industry. In addition, the sensorized gripper with combined sensing functionality could be deployed widely to allow for more bespoke optimization of cooking time of vegetable of smaller batches opposed for fixed cooking times independent of variety or size of vegetable. In addition, the capabilities of the gripper are potentially more widely applicable for robotic kitchen application as it shows a high force, yet compliant nature with dual sensing functionality.

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