Poster: SSCense: A Millimeter-Wave Sensing Approach for Estimating Soluble Sugar Content of Fruits

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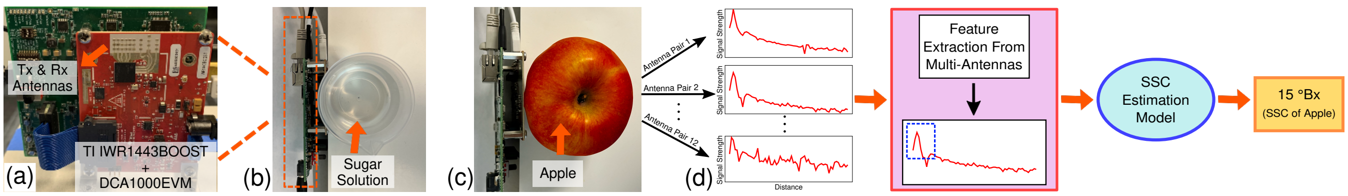

Figure 1: *(a)* SSCense *uses a millimeter-wave (mmWave) transceiver with 3 transmitters and 4 receivers to estimate the Soluble Sugar Content (SSC) of fruits; (b) Top-down view of data collection setup for controlled experiments with sugar solutions inside a container; (c–d) Fruits are positioned in front of the transceiver, and reflected signals from multiple antenna pairs are collected. The extracted features from these signals are fed to an estimation model for predicting SSC on a °Brix scale [1].*

ABSTRACT

Soluble Sugar Content (SSC) of a fruit is indicative of its ripeness and is used in the fruit industry for quality control in the production chain. We present the design and implementation of *SSCense*, a low-cost, non-destructive system to estimate a fruit's SSC using the millimeter-wave wireless technology in 5G-and-beyond devices.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing systems and tools**.

KEYWORDS

Millimeter-Wave; Wireless Sensing; Soluble Sugar Content; Fruit Ripeness; Fruit Quality

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1 INTRODUCTION

Fruit products go through a long production chain that involves farmers, distributors, retailers, and consumers. To preserve the quality at each level, fruits undergo drying, cooling, freezing, etc.; each entails methods to analyze and classify the product quality, such as ripeness. Controlling the ripeness of fruits in this process prevents fruit waste, allow fruit to ripen to the optimal harvesting stage, help distributors manage and schedule shipping and storage times, and aid consumers in purchasing high-quality groceries. *Soluble Sugar Content (SSC) is one of the key characteristics that directly determines the fruit ripeness*. Fruits consist of three major soluble sugars: Glucose, Fructose, and Sucrose. The biochemical changes during ripening cause the degradation of polysaccharides and starch, leading to the accumulation of soluble sugars. So, tracking SSC at each step of the production chain can reveal the product's ripeness.

Traditionally, SSC is determined using either high performance liquid chromatography or gas chromatography-mass spectrometry, or Brix measurement where 1° Brix (Bx) refers to 1 gram of sucrose in 100 grams of aqueous solution [2]. These methods subject fruits to laborious and destructive processing, and the assessment must be done by professional analysts with sophisticated equipment. Recently suggested approaches, such as NIR and UV-Visible spectroscopy, are non-destructive but require specialized, expensive hardware and a professional to calibrate and work with these devices.

We propose SSCense, a low-cost, non-destructive means for estimating the SSC in fruits using the millimeter-wave (mmWave) wireless technology in 5G-and-beyond smart devices. SSCense relies on a fundamental idea that the strength of the signals reflected off objects depends on the intrinsic characteristics of their material, and varying levels of the SSC change these intrinsic characteristics and affect the reflected signals [3]. *SSCense* employs a multi-antenna mmWave transceiver that touches the fruit (Fig. 1[c]), transmits and receives mmWave signals bounced off of the fruit, processes the reflected signals from all the antennas to extract features, and feeds them to a machine learning model to predict the SSC in the fruit.

We build the SSC estimation model using reflection data from three sugar solutions, glucose, fructose, and sucrose and evaluate it on apples, oranges, and kiwis. Our preliminary experiments show that *SSCense* can estimate the SSC with an average error of less than

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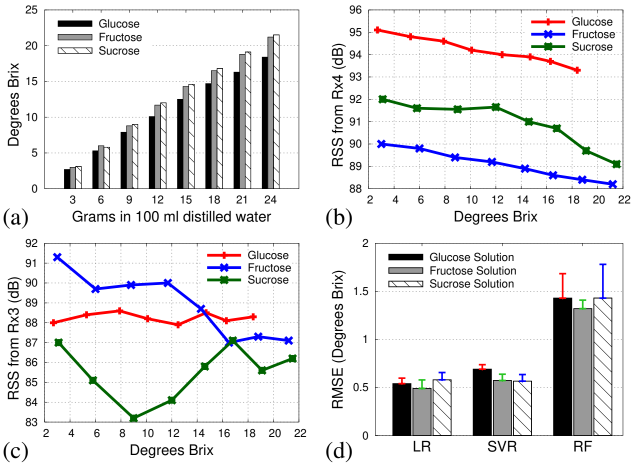

Figure 2: *(a) Measured °Bx of glucose, fructose, and sucrose solutions; (b) The RSS from Rx4 decreases as SSC increases; (c) But no relation found between RSS from Rx3 and SSC; (d) Regression models developed using data samples from three sugar solutions.*

0.58 °Bx for controlled sugar solutions and less than 1.43 °Bx for real fruits. Moreover, we show that a prior approach using a single antenna for estimating the SSC [1] performs poorly in a practical environment, and our multi-antenna mmWave transceiver based design promises hand-held estimation of SSC in fruits.

2 SSCENSE SYSTEM DESIGN

We briefly describe the Friis Transmission model that demonstrates the relationship between mmWave Received Signal Strength (RSS) and materials' physical properties, and then show that SSC changes the properties of materials and thus affects the RSS. *SSCense* capitalizes the relationship between SSC and RSS to estimate SSC.

Reflected Signal and Material Properties: The Friis Transmission model can be used to determine the signal power at a receiving antenna for a signal transmission [3]: $A_r/A_t = G_r G_t \cdot \lambda/(4\pi(2d)) \cdot r$, where A_r and A_t denote the amplitude of the receiving and transmitting signals, respectively, $2d$ is the round-trip propagation distance, G_t and G_r are the Tx and Rx gains, λ is the carrier wavelength, and r is the reflection coefficient of the target material, which is related to its permittivity [3]. If A_t, G_t, G_r, d, and λ remain constant, then the received power, A_r, relies only on the reflection coefficient or permittivity of the target material.

Estimating SSC Using mmWave Reflection: When SSC increases in an aqueous solution, the number of free water molecules drops, and the permittivity of the solution decreases [1]; so, the RSS of the reflection from that solution should also decrease. To observe the relationship between RSS and permittivity, we conduct controlled experiments by varying the sugar content inside a container with water, placing it in front of the mmWave device (Fig. 1[b]), capturing the mmWave signal reflection, and measuring the true SSC using a digital refractometer. Figs. 2(a–b) show the change in °Bx levels for different amount of sugars, and change in RSS for different °Bx levels observed from one pair of transmit and receive antennas: This result conforms with the theoretical model. However, not all antenna pairs show consistent decrease in RSS: For the same Tx antenna, the relation between RSS from a different Rx antenna and °Bx level does not match the theoretical model (Fig. 2[c]). This is due to the spacing between the antennas and the curved shape of the objects, the reflected signals captured from different antennas could be distinct and vary in strength. So, relying on a single antenna pair, as in a previous study [1], is not suitable for SSC estimation.

To this end, *SSCense* proposes to use multiple Tx and Rx pairs to estimate SSC. The key idea is intuitive: Instead of selecting any one of the antenna pair, which may not conform with the theoretical model, we train a machine learning model with hundreds of data samples to learn the pattern between reflected signals and °Bx levels. Then, at run-time, it can predict the true °Bx levels from the reflected signals. We use a 77-81 GHz mmWave device (TI IWR1443BOOST) (Fig. 1[a]) to capture the multi-antenna reflections off the sugar solutions, extract features from the data to focus on the peak zone of the reflected signals that correspond to where the solution is placed, and use this pruned data to build a learning model that can predict the SSC. The mmWave transceiver consists of 3 Tx and 4 Rx that can measure the reflections simultaneously from 12 (3×4) virtual channels. For ground truth °Bx data collection, we use an industry-standard digital refractometer, Atago PAL-Patissier Refractometer.

3 PRELIMINARY RESULTS

We test three machine learning models: Linear Regression (LR), Random Forest Regression (RF), and Support Vector Regression (SVR) with a linear kernel to build our SSC estimating model, and use RMSE between ground truth and prediction to evaluate them. Fig. 2(d) shows that our system achieves the best result using LR, which can be attributed to the linear relationship between the features (RSS) and target variables (SSC), and the model automatically selects antenna pairs with the best linear relationship. Our LR model can predict the SSC with an average error of 0.54 °Bx, 0.49 °Bx, and 0.58 °Bx for glucose, fructose, and sucrose solutions, respectively. Finally, we evaluate the model on apples, kiwis, and oranges, with true °Bx levels ranging from 10 to 15.8, and observe that *SSCense* estimates SSC in these fruits with an average error of 1.43 °Bx.

4 FUTURE WORKS AND CONCLUSION

We designed *SSCense*, a low-cost, non-destructive system for predicting SSC in fruits. *SSCense* achieves an acceptable error for predicting SSC using a multi-antenna mmWave transceiver. Next, we plan to customize the machine learning model, fine-tune and evaluate it on more fruits with different shapes and textures, and build a real-time, hand-held SSC estimator on 5G mmWave smartphones.

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