

Towards accurate non-contact moisture inspection using THz imaging and thickness information

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Abstract. This study proposes an approach for a non-contact moisture inspection in dried food products, which is crucial to maintain optimal quality and shelf-life, using terahertz (THz) signal. To achieve this, a sample-specific calibration curve needs to be determined first. HAITAI crackers were chosen in this work for demonstration purposes. Fifteen stacks of crackers with different heights were prepared and moisturized by covering with a wet tissue paper for different time periods, resulting in moisture levels between 3 and 40% R.H.. Then, each sample was placed on a conveyor belt system between a THz source and THz a detector, and transmitted signal was measured 5 times. After that, moisture percentage of the sample was determined based on a gravimetric method, whose results served as a ground-truth measurement. A thickness of the sample was also measured using a vernier. All signal measurements, together with their corresponding known thicknesses and moisture percentages, were used to calculate necessary coefficients that define a sample-specific calibration curve. Once a calibration curve for the cracker was obtained, it was used to estimate the moisture percentages in samples with different thicknesses. Mean absolute error (MAE) of the moisture percentage is found to be less than 12% when the sample thickness is modelled as part of the calibration curve, which is over 50 times less compared to the case when the sample thickness is not modelled. Therefore, the utilization of an automatic thickness determination would be promising for real-time and accurate non-contact moisture inspection. This approach can be also integrated into a production line to improve quality control in the food industry without interrupting existing processes.

1. Introduction

Terahertz (THz) is an electromagnetic wave whose frequency lies between those from microwave and infrared, thus exhibiting several unique properties [1, 2]. THz wave can penetrate non-polar materials such as papers, woods, clothes, and can be reflected by metallic materials. In addition, THz is strongly sensitive to liquids, such as water, which constitute polar molecules that absorb wave energy. Considering these advantages, it is possible to use THz to scan for concealed items in most of the packages as well as identify their moisture distributions and contaminants.

In food industry, moisture is a crucial factor affecting food quality [3–5]. Moisture in food products can promote spoilage that can lead to serious health impacts in consumers. Therefore, appropriate moisture level needs to be well maintained to allow long shelf life and also ensure

that products are safe to consumers. Since THz wave can penetrate through most packages and is sensitive to moisture, it then has a potential in in-line quality-control (QC) systems, where the transmitted THz wave can be processed to obtain an image of internal moisture distribution as well as a moisture percentage of a given sample. There are already approaches that determine moisture level in food samples, such as ones based on gravimetric and infrared methods. Despite they are reasonably accurate, the gravimetric-based method is slow, and the infrared-based method can only detect moisture around surface region. Such limitations have led several researchers to attempt to utilize THz to detect moisture, which offers both good penetration and rapid scanning time.

Nonetheless, measuring the sample moisture by using THz signal intensity can be challenging. Unless acquiring THz signals in ideal settings [6], calculating moisture by only analyzing the THz signal intensity after passing through the sample does not always work well. This is because the remaining signal intensity is also affected by the sample thickness. There have been attempts to calculate moisture non-destructively by utilizing THz spectrum [7–9], which contains phase shift information and thus can account for sample thickness. However, spectroscopic methods are not cost-effective and productive solutions in industry. Fast and cost-effective THz moisture measurement method is therefore necessary since otherwise it would delay the progress in translating THz in-line QC systems to food industry.

As such, we propose an approach to measure the sample moisture from both THz signal intensity and sample thickness. Our main contribution is to include effects due to sample thickness, which allows more accurate moisture calculation. The sample thickness can be measured easily and quickly by various tools or depth sensors. We also propose a protocol to collect datasets needed for constructing a calibration curve, which describes relationship between the remaining signal intensity in terms of sample moisture and thickness. Later, we will show that the proposed moisture model could yield a significant improvement over a conventional model. This is useful because it allows us to calculate moisture for various sample’s sizes and shapes that are present in realistic situations.

This paper is organized as follows. Section 2 provides understanding about how transmitted signal intensity is affected by sample moisture and thickness, and proposes an absorption model that describes their relationship. Section 3 describes hardware components necessary for data collection, and also procedure to construct a sample-specific calibration curve. Section 4 presents results to confirm our hypothesis, and their discussion and conclusions can be found in section 5.

2. Background

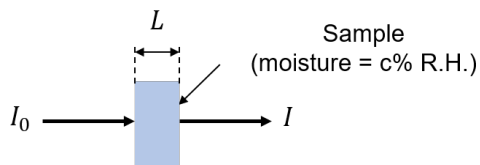


Figure 1. A graphical representation of how transmitted signal is absorbed by sample moisture (c) and thickness (L), resulting in a change of signal intensity from I_0 to I .

The interaction between THz wave and water molecules results in molecular vibrations and signal energy loss. Figure 1 demonstrates how the THz intensity is changed as it passes through the moist sample. In the figure,

- I_0 denotes THz signal intensity before passing through the sample (treated as constant)
- I denotes THz signal intensity after passing through the sample
- L denotes sample thickness

- c denotes sample relative moisture percentage

According to Beer-Lambert law of absorption, the remaining THz signal intensity can be modelled as equation (1):

$$I = I_0 \exp^{-\alpha c} \quad (1)$$

where α is a coefficient of absorption due to moisture c , which is constant and specific to the sample type. According to this model, it implies that the remaining THz signal intensity decreases exponentially as the sample moisture increases. By simply rearranging equation (1), one can calculate the moisture percentage from the known remaining THz signal intensity as shown in equation (2):

$$c = \frac{1}{\alpha} \ln \left(\frac{I_0}{I} \right) \quad (2)$$

Unfortunately, the model in equation (1) assumes constant sample thickness, so it does not account for effects due to sample thickness that also affect the remaining intensity. It turns out that the remaining THz signal intensity is also related to the sample thickness according to Beer-Lambert law, that is, the signal intensity decreases exponentially as thickness increases. Therefore, one could combine both moisture percentage and thickness into a single absorption model as equation (3):

$$I = I_0 \exp^{-\beta c L} \quad (3)$$

where β is a coefficient of combined absorption due to moisture c and thickness L , which is constant and specific to the sample type. As opposed to equation (1), this modified model includes the term L , which implies that the remaining THz signal intensity is dependent on both sample moisture and thickness. Also, note that β is modified from α in equation (1) in order to account for absorption due to both sample moisture and thickness. From this model, one can derive the moisture percentage from the known remaining THz signal intensity and sample thickness as:

$$c = \frac{1}{\beta L} \ln \left(\frac{I_0}{I} \right) \quad (4)$$

Note that, in order to calculate moisture percentage from equation (2) or (4), constants I_0 , as well as α or β , must be determined. Since these constants are specific to sample type, they can be estimated from the set of samples with known thickness, moisture, and remaining THz signal intensity. Details about estimating these constants will be outlined in section 3.2.

3. Materials and methods

3.1. Imaging components

Figure 2 (a) shows a developed THz in-line imaging system that imitates production lines in food industry. Components related to imaging are displayed in figure 2 (b), which consist of 1) a lens-coupled THz source that generates continuous signal at frequency of 0.1 THz with maximum power up to 180 mW 2) a THz detector, placed under a moving belt, that possesses 1 x 256 pixels for receiving THz signals in 0.05 – 0.7 THz frequency range and generating THz images 3) an RGB-D camera that takes color (visible) and depth images. Image processing and registration algorithms developed in-house allow this in-line system to generate visible, THz, and overlay images in real-time, as demonstrated in figure 2 (c) by images of moist wafer. While it can be seen that the THz image can reveal internal moisture distribution, signals constituting

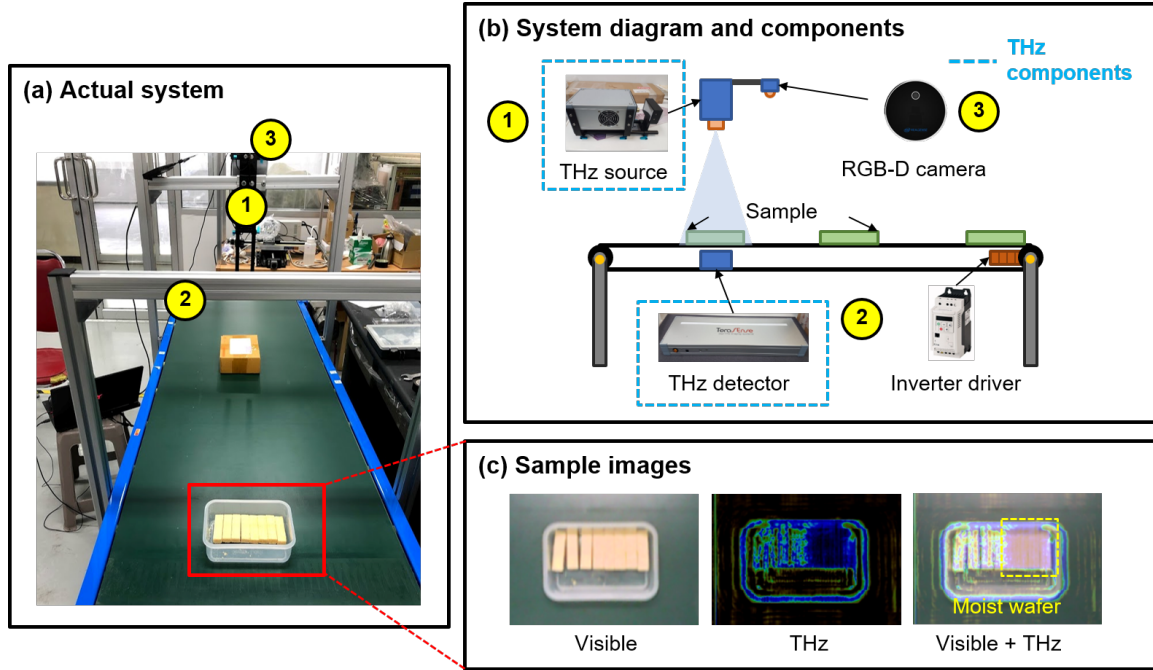


Figure 2. (a) A prototype THz in-line imaging system, whose components are diagrammed in (b). (c) Example of visible, THz, and overlay images of moist wafer.

THz image can also be used to analyze moisture percentage quantitatively. Section 3.2 will describe how this can be accomplished.

3.2. Obtaining calibration curves

For a given sample, calculation of its moisture percentage is possible if absorption model for that sample type, given as either equation (1) or (3), is known. This requires approximation of constants I_0 and α , or β according to procedure below.

- (i) Prepare N samples with different thicknesses and moisture levels. Note that samples can be moisturized by slowly steaming them to maximize uniformity in moisture distribution.
- (ii) For each sample, record remaining THz signals for m times, each at different poses.
- (iii) After recording signals, measure sample moisture level using a gravimetric-based moisture analyzer, and sample thickness using a vernier.
- (iv) After collecting all $N \times m$ datapoints of signal intensity, moisture level, and thickness, then apply a least-square method to estimate the constants I_0 , and α or β in equation (1) or (3), respectively. Note that sample thickness is required only when estimating β .

The procedure above was used for collecting HAITAI cracker dataset, whose results and calibration curve are presented in section 4. Figure 3 shows an experimental setup used for collecting data necessary for constructing calibration curves. The resulting constants can describe the absorption model that serves as a calibration curve for a specific type of sample, and one can use it to calculate the sample moisture from the remaining THz signal intensity.

4. Results

Figure 4 (a) shows distribution of all datapoints consisting signal intensity, moisture level, and thickness. Datapoints were collected from 15 samples of stacked HAITAI crackers ($N = 15$) and

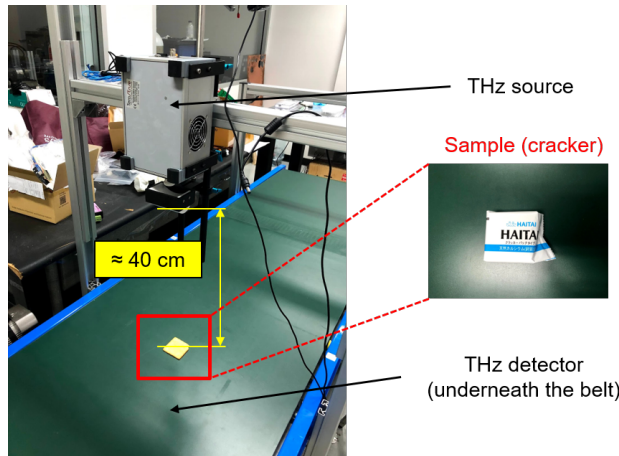


Figure 3. Experimental setup used for measuring THz signal intensity after passing through a given sample, i.e., remaining THz signal intensity.

signal measurement was repeated 5 times ($m = 5$) for each sample. Thickness of sample was varied from 1 to 7 pieces of cracker, where one piece corresponded to the thickness of 4.3 mm, and moisture of sample was varied between 3 and 40% R.H.. Observe that the remaining THz signal intensity, represented as normalized amplitude, tends to decrease as sample moisture or thickness increases. Therefore, this confirms validity of the collected datapoints. Figure 4 (b) shows the resulting calibration curve that is estimated from all 75 datapoints, which can be used for predicting sample moisture percentage. Note that a calibration curve corresponding to equation (1) was also obtained by the same approach for later performance comparison, except the sample thickness was not used.

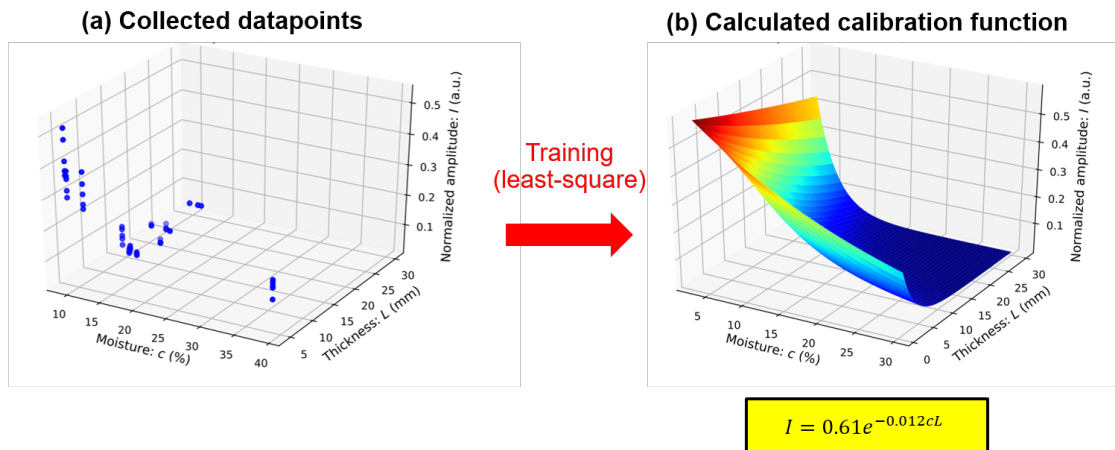


Figure 4. (a) Distribution of all collected datapoints. (b) Corresponding calibration curve, estimated by training the collected datapoints using least-square method to determine the required constants.

Table 1 shows the accuracy and fluctuation of the prediction results, calculated from two different calibration curves. In this comparison, datapoints were collected from 5 additional samples of stacked HAITAI crackers ($N = 5$) and signal measurement was repeated 5 times ($m = 5$) for each sample. This results in 25 test datapoints in total. Thickness of sample was varied from 2 to 7 pieces of cracker, and moisture of sample was varied between 3 and 40% R.H.. In calculation of moisture percentages, it is found that using the calibration curve that accounts

Table 1. Mean absolute error (MAE) of moisture prediction and standard deviation of absolute prediction errors, obtained as results of using different calibration curves.

Type of calibration curve	Mean absolute error (MAE) of prediction	Standard deviation of absolute prediction errors
With thickness information	11.5% R.H.	2.20% R.H.
Without thickness information	667% R.H.	350% R.H.

for the sample thickness leads to the mean absolute error (MAE) of prediction of 11.5% R.H.. This is significantly less than 667% R.H., obtained when using the calibration curve that does not account for the sample thickness. In addition, using the proposed calibration curve results in less fluctuation in the absolute prediction errors, as observed in the standard deviation of absolute prediction errors that is reduced from from 350% R.H. to 2.20% R.H..

5. Discussion and conclusions

This paper has demonstrated that THz technology shows promise in detecting moisture in crackers and potentially other food products. Furthermore, moisture calculation could be greatly improved by taking into account the sample thickness. It is important to note that even though the proposed calibration curve greatly improves the accuracy, the mean absolute error of 11.5 %R.H. is still too high to be used practical applications. Sources of error could be attributed to poor signal-to-noise ratio, vibrations, temperature fluctuations, or non-uniform moisture distribution in the sample. Nonetheless, this improvement is promising because, despite great challenge in THz moisture imaging, there are still lots of room for improvements, and this work has brought it one-step closer to practical applications.

In the future, it is suggested that the experiment should be conducted in well-controlled environments. Samples should be prepared in a closed chamber to ensure uniformity of the moisture distribution. The in-line imaging system could be refined to minimize vibrations. The THz source and detector locations could be optimized to maximize the signal-to-noise ratio. Most importantly, the proposed absorption model used in this work assumes linear absorption coefficients and independent effects of moisture and sample thickness. This might not be valid for all sample types. Therefore, to achieve more accurate moisture calculation, one could attempt to model more realistic relationship between intensity, moisture, and sample thickness.

References

- [1] Dhillon S S *et al* 2017 *J. Phys. D Appl. Phys.* **50** 043001
- [2] Mittleman D M 2017 *Opt. Express* **26** 9417–31
- [3] Nielsen S S 2017 *Food Analysis* (New York: Springer)
- [4] Hailu G and Derbew B 2015 *J. Biol. Agric. Healthc.* **5** 49–64
- [5] Mathlouthi M 2001 *Food Control* **12** 409–17
- [6] Oyama Y, Zhen L, Tanabe T and Kagaya M 2009 *NDT E Int.* **42**(1) 28–33
- [7] Federici J F 2012 *J. Infrared Millim. Terahertz Waves* **33** 97–126
- [8] Parasoglou P, Parrott E P J, Zeitler J A, Rasburn J, Powell H, Gladden L F and Johns M L 2010 *Terahertz Sci. Technol.* **3**(4) 172–82
- [9] Banerjee D, von Spiegel W, Thomson M D, Schabel S and Roskos H G 2008 *Opt. Express* **16**(12) 9060–6