Multi-Spectral Camera System to Improve Food and Material Identification

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Abstract

Visible cameras have been widely used in many places for food and material identification, such as food sorting and produce labeling. Visible camera sensors, working in the 400nm-700nm range, can identify food with different colors, shapes, or other visible characteristics that are otherwise unidentifiable to visible cameras. Visible image sensors struggle to identify food and material with similar color, as they are limited to the colors ranges human eyes can sense[1]. In this study, a Sony IMX991 sensor was used to capture both visible and infrared images. It was demonstrated that some materials can be distinguished with either visible or infrared narrow band images[2]. Material identification accuracy can be improved by analyzing both visible and infrared images. A machine learning algorithm can be developed by analyzing all images captured under different conditions, accuracy of food and material identification can be significantly improved with continuous image process algorithm development and machine learning training.

1. Introduction

Coming up with an effective way to identify food and material is challenging due to the wide variety of types of food and materials around a kitchen and other places. Putting a wrong ingredient into food could ruin the food's taste, establish grounds for food contamination, and create other health issues in some cases, especially in restaurants. Additionally, food identification and preparation are often labor intensive and subjective to human errors. Workers employed by businesses for food identification and preparation often require careful and sometimes excessive training, thus increasing costs. Food quality is also a critical issue in the agricultural sectors and food contamination remains at a high risk. Kitchen environments can vary widely and have a few challenges which makes food recognition processes difficult.

Fig. 1, shows examples of reflectance spectrum from 400 nm to 2500 nm[3]. Different materials have different reflection factors. For example, water has low reflectance in the visible wavelength range between 400 nm to 700 nm. Its reflection decreases at longer wavelength range and becomes very low beyond a wavelength of 1200 nm. Snow, on the other hand, has very high reflection at visible light range and its reflection decreases at longer wavelength, but with several maxima and minima across the spectrum. Some vegetation , such as green leaves, also have low reflections at visible light range. Their reflections, however, increase significantly beyond 750 nm wavelength. The same idea can be also applied to identifying foods of different materials. Therefore, infrared measurements can easily detect the existence of certain substances in a specific food compound. The concentrations of these substances can be expressed through the various levels of intensities at specific infrared wavelengths.

With technology advancements in recent years, visible cameras have been widely used in many places for food and material identification, such as food sorting. Visible camera sensors, working in the 400nm-700nm range, can identify food with different colors, shapes, or other visible characteristics. However, visible image sensors have challenges in identifying food and material with similar color.

In this study, we plan to capture images with light at different wavelengths for several materials commonly found in the kitchen, such as salt, sugar, baking powder, starch, and sweetener. By combining both visible spectral and NIR spectral could improve food and material identification accuracy.

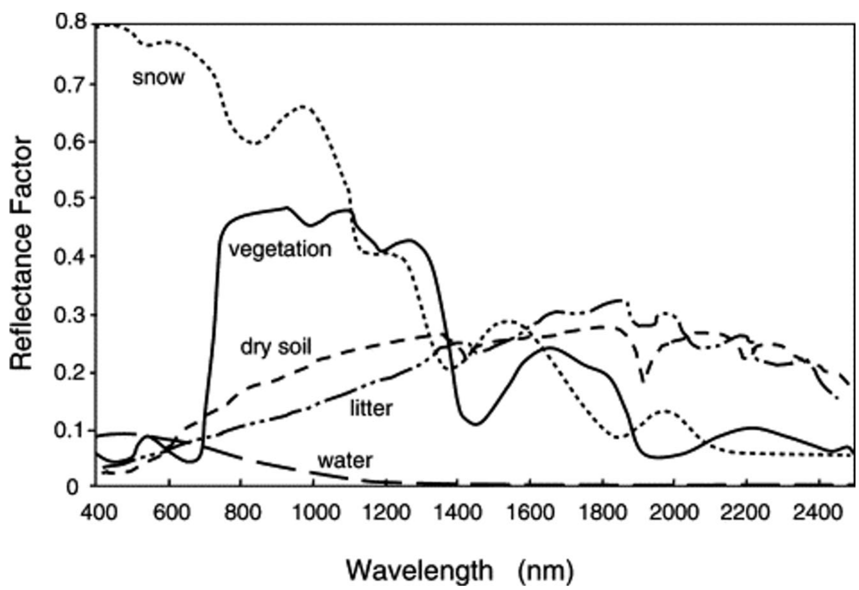

Figure 1: Example of material reflectance from 400 nm to 2500 nm[3]

2. Experiment Setup

For image sensing applications in the visible light and near IR spectral ranges, up to about 1000 nm, silicon image sensor arrays are generally the technology of choice. Silicon image sensor chips with high resolution (i.e., fine pitch) and high sensitivity are inexpensive and widely available[6][7] . Most camera sensors used in advanced mobile phones are Silicon based CMOS image sensors. At longer wavelengths, however, the absorption reduces significantly due to Si bandgap . In fact, beyond about 1100 nm, thin wafers of silicon are essentially transparent.

Infrared sensors may comprise various sorts of infrared sensitive materials, such as a semiconductor material with II-VI or III-V compounds. For this study, Sony IMX991 special design infrared sensor was chosen. This sensor features 5um pixel size and 656 x 520 array size. Innovative wide-band and high-sensitivity short wave infrared (SWIR) image sensor technology [8] implemented by the combination of compound semiconductor InGaAs photodiodes and Silicon readout circuits through Cu-Cu bonding [4]. The image sensor design has been optimized to achieve a good sensitivity from 400 nm to 1700 nm as shown in Figure 2. The sensors have high quantum efficiency even in visible wavelengths. This enables broad imaging of wavelengths from 0.4 µm to 1.7 µm. A single camera equipped with the sensor can now cover both visible light and the short wave infrared (SWIR) spectrum, which previously required separate cameras. This results in lower system costs. Image processing is also less intensive, which accelerates inspection.[4]

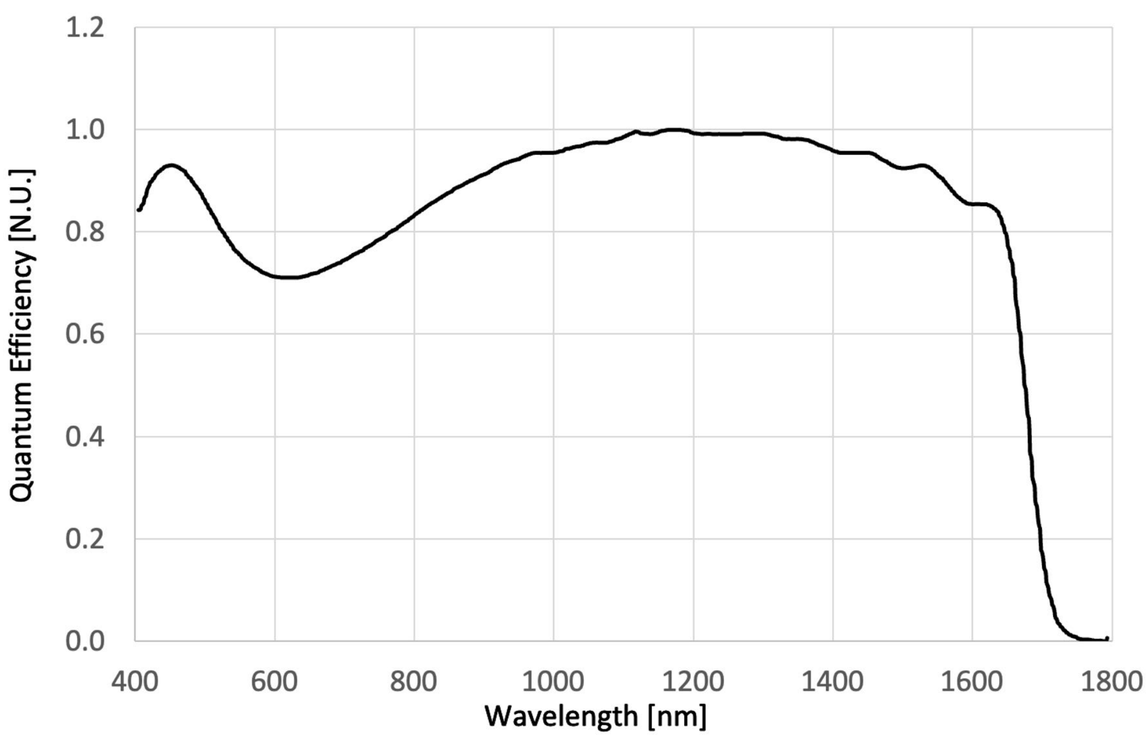

Figure 2: Relative Quantum Efficiency of Sony IMX991 sensors

Figure 3 shows the setup for image capture. The sensor was mounted on the board with a C-mount lens in front. The focus position and lens aperture can be manually adjusted to obtain best images. The capture system was connected to a PC computer through USB 3 cable. Dedicated software from Sony was used to control image sensor, image capture, imaging viewing, and image storage to the computer or a USB drive. This image sensor supports 12-bit digital image output.

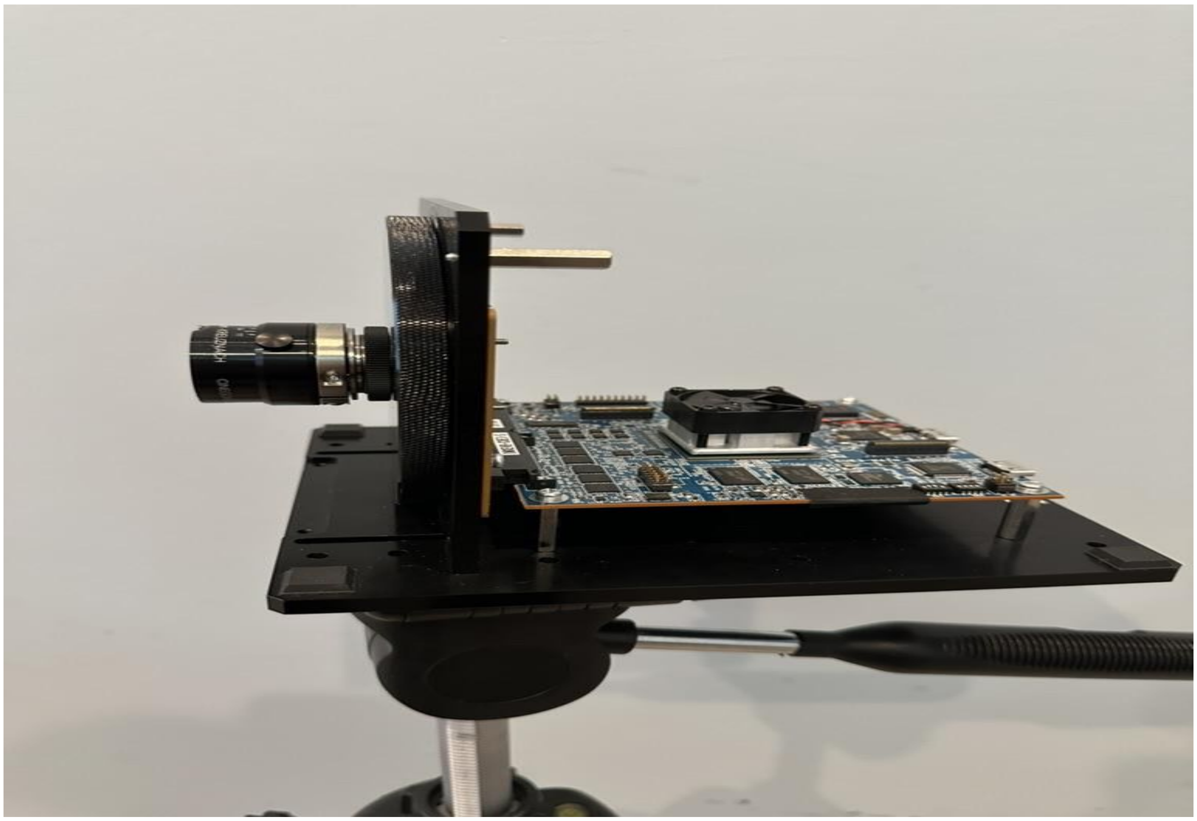

Figure 3: Sony IMX991 sensor image capture setup

Experiment ResultsIn order to look at images in different light conditions, several materials were chosen for this experiment, including salt, sugar, starch, sweetener, and baking soda. All of them are commonly available in a kitchen. A bright halogen lamp was used to provide wide spectrum light to illuminate the scene.

Figure 4 shows a visible image captured by an iPhone RGB camera. Material with different colors can be easily recognized due to color differences. From the image, it can be seen that all 5 materials look very similar and it is very difficult to differentiate them with standard visible cameras.

Figure 4: visible image capture captured by iPhone camera

With the same setup, now let’s look at images captured with the IMX991 camera. Figure 5, shows the images with 400nm-650nm visible bandpass filter, similar to the iPhone images, all 5 materials look very similar brightness. It is difficult to distinguish any of them by looking at the images. Now we change visible bandpass filter to different narrow band filters, Figure 6 shows the image with narrow band blue filter centered at 450nm, it is quite interesting to see both sweetener and sugar are darker than the rest of 3, which indicates the reflection on sweetener and sugar are lower around 450nm wavelength compared to other 3.

Now the reference made to Figure 7, the narrow band color filter was changed to green with 530nm peak, both sweetener and sugar images are still slightly darker than other 3, but brightness difference is slightly less compared to blue narrow filter as shown in Figure 6.

Figure 5: Bandpass filter (400nm to 650nm)	Figure 6: Narrow band blue filter (450nm)	Figure 7: Narrow band green filter (530nm)

Figure 8: Narrow band red filter (630nm)	Figure 9: Narrow band filter (700nm)	Figure 10: Narrow band 900nm near infrared filter

Figure 11: Narrow band 1350nm infrared filter	Figure 12: Narrow band 1550nm infrared filter	

Figure 8-10 showed images with 630nm, 700nm and 900nm narrow band filters, respectively. The brightness is quite close for all 5 materials with subtle differences. Figure 11 shows the image with 1350nm narrow band filter, the brightness of both sweetener and sugar becomes darker. With narrow band filters moving to 1550nm as shown in Figure 12, brightness of sweetener and sugar are significantly lower than other 3. The sweetener is the darkest among all of them, starch becomes slightly brighter, and salt is the brightest due to high reflection at this infrared wavelength. These substances can be easily distinguished using all images captured here.

3. Summary and Next Steps

In this study, it was demonstrated that some materials can be distinguished with either visible or infrared narrow band images. Material identification accuracy can be improved by analyzing both visible and infrared images.

A machine learning algorithm can be developed by analyzing all images captured under different conditions, including visible wideband filter, RGB narrow band filter, near infrared narrow band, short wave infrared narrow band, etc. A depth camera can also be valuable to provide extra information to improve food identification. Image preprocessing and segmentation are applied on all combined images, then combined images are processed through a machine learning algorithm with the cloud processing and calibration database as extra inputs. Based on all these inputs, machine learning algorithms can provide food identification information and output such information to a user interface. The image data or portions of the image data are presented to a human user to confirm material type. Inputs from the human user are then fed back to machine learning based algorithms to expand the material database and improve the accuracy for future food and material identification. With a continuous tuning, accuracy of food and material identification can be significantly improved.

The database as well as the algorithm can then be expanded to different types of materials. With allergies and cross contamination still being a prevalent issue, even with preventative measures, this technology can be incredibly helpful in being able to identify different foods. If there are peanuts in a dish, and it’s hard to distinguish visibly, users can use the algorithm to help detect them.

It is widely believed that one in fifty patients in the US suffer from some degree of an anaphylactic reaction[5]. This algorithm can be applied to a larger scale and have the potential to save lives in the future.

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