Al-light: An Alcohol-Sensing Smart Ice Cube

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Inappropriate alcohol drinking may cause health and social problems. Although controlling the intake of alcohol is effective to solve the problem, it is laborious to track consumption manually. A system that automatically records the amount of alcohol consumption has a potential to improve behavior in drinking activities. Existing devices and systems support drinking activity detection and liquid intake estimation, but our target scenario requires the capability of determining the alcohol concentration of a beverage. We present Al-light, a smart ice cube to detect the alcohol concentration level of a beverage using an optical method. Al-light is the size of 31.9 x 38.6 x 52.6 mm and users can simply put it into a beverage for estimation. It embeds near infrared (1450 nm) and visible LEDs, and measures the magnitude of light absorption. Our device design integrates prior technology in a patent which exploits different light absorption properties between water and ethanol to determine alcohol concentration. Through our revisitation studies, we found that light at the wavelength of 1450 nm has strong distinguishability even with different types of commercially-available beverages. Our quantitative examinations on alcohol concentration estimation revealed that Al-light was able to achieve the estimation accuracy of approximately 2 % v/v with 13 commercially-available beverages. Although our current approach needs a regressor to be trained for a particular ambient light condition or the sensor to be calibrated using measurements with water, it does not require beverage-dependent models unlike prior work. We then discuss four applications our current prototype supports and future research directions.

CCS Concepts: • **Human-centered computing → Ubiquitous and mobile devices**; • **Applied computing → Health informatics**;

Additional Key Words and Phrases: Alcohol concentration sensing, smart ice cube, near-infrared spectroscopy

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1 INTRODUCTION

Alcohol consumption may cause health and social problems [1], including liver and heart disease, depression, and harassment. Rapid and chronic intake of alcohol can lead to acute intoxication and addiction, respectively. Governments define alcohol consumption guidelines [25] for avoidance of such disease and symptoms. Controlling the intake of alcohol is thus important to prevent potential fatal diseases and addictions.

Alcohol intake tracking can contribute to healthy drinking activities, and there exist systems and services for this purpose. AlcoDroid Alcohol Tracker [1], for example, is a smartphone app that offers a drinking diary to help its users track drinking. IntelliDrink [2] is another mobile app which estimates users' blood alcohol content based on their annotations. However, systems like these apps require manual logging of the alcohol content and volume of the drink users have taken. Users may also simply forget making these entries after drinking, which potentially results in low compliance and sparse data records or under-estimation of the consumption [19].

[1] https://www.appbrain.com/app/alcodroid-alcohol-tracker/org.M.alcodroid
[2] http://www.intellidrink.com/

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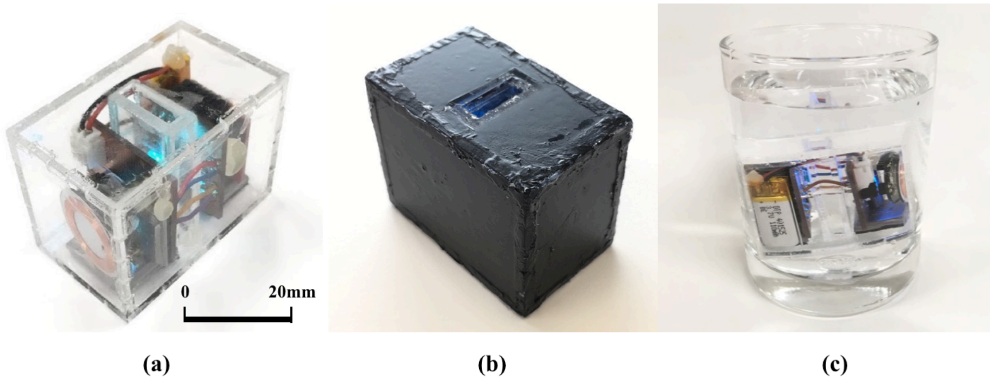


Fig. 1. Al-light is a smart ice cube that can estimate the alcohol concentration level of a beverage using near-infrared and visible light. (a) the transparent version; (b) colored in black to minimize effect by ambient light; and (c) Al-light in use.

A key technology in alcohol intake logging systems is an automated way to measure alcohol concentration of a beverage users are taking. Quantitative methods and devices for alcohol concentration estimation exist [3, 9, 13], but are generally designed for professional analysis or laboratory use. Research in ubiquitous computing therefore needs investigations on technology for liquid alcohol concentration estimation for daily use.

We develop Al-light, a smart ice cube device that is small enough to be put into a glass and can estimate the alcohol concentration of a beverage. It uses off-the-shelf near-infrared (NIR) and visible LEDs and optical sensors for alcohol concentration estimation. The NIR LED has a peak wavelength where the light absorption property of water and ethanol is distinctive. This smart ice cube can infer alcohol concentration by analyzing light intensities observed by the optical sensors. Although prior work by Benes [3] has reported this optical property of ethanol, our primary contributions are an instantiation of this method in the form of a smart ice cube and an evaluation of its estimation performance with a variety of commercially-available beverages. Through our revisitation studies on Benes' approach, we found that light at the wavelength of 1450 nm has strong distinguishability even with different types of commercially-available beverages. Our quantitative examinations with the Al-light prototype revealed that the estimation accuracy was approximately 2 % v/v with 13 commercially-available beverages. The system was able to achieve this performance when a regressor was trained for a particular ambient light condition or the sensor was calibrated using measurements with water before use. Our results thus suggest that Al-light does not require beverage-dependent models.

This work offers the following research contributions to the fields of Human-Computer Interaction and ubiquitous computing:

- **Revisitation study of Benes' results**: We revisit Benes' method [3] with a broader set of commercially-available beverages, confirming that NIR light at the wavelength of 1450 nm has strong estimation power.
- **Implementation of Al-light**: We design a smart ice cube that embeds NIR and visible LEDs as well as photodetectors for alcohol concentration sensing. Users can simply place Al-light into a beverage for alcohol concentration estimation.
- **System evaluations on alcohol content estimation**: Using Support Vector Regression, we found that Al-light was able to achieve the estimation accuracy of approximately 2 % v/v with 13 commercially-available beverages if a regressor was trained for a particular ambient light condition or the sensor was calibrated using measurements with water. Our approach does not require beverage-dependent training, extending the generalizability of Benes' results [3].

In this paper, we first discuss related work on beverage classification and identification, methods for alcohol concentration determination, and smart devices and tracking systems for drinking activities. We then report our experiments to revisit Benes' method using alcohol aqueous solutions and 18 commercially-available beverages. The results of this revisitation studies confirm a potential to estimate alcohol content of commercially-available beverages with 1450 nm NIR light. We then explain the design and prototype implementation of Al-light. This paper also reports our system evaluations on alcohol content estimation with 13 commercially-available beverages. We discuss potential applications enabled by Al-light and conclude the paper with future work.

2 RELATED WORK

2.1 Beverage Classification and Identification Methods

Automatic identification of beverage can help health management because liquid occupies 21% of daily calorie intake [6]. Researchers in the field of food engineering have developed various methods of beverage identification to address the demand for food safety and authenticity. A traditional classification approach is to determine the quality and content of different constituents by using chemical analysis methods and machines. To classify milk tea, for example, a system would measure milk quality, sugar content, and other ingredients like catechin and iron [16]. However, these chemical methods are time-consuming and often require professional equipment. Near-infrared spectroscopy [20] is another identification method for beverage identification. It measures the absorption of NIR light (700 to 2500 nm) in a test liquid. It enables a fast, non-destructive, and non-invasive analysis and offers accurate identification results [4, 16]. Chen et al. [4] achieved identification of 20 kinds of green tea at accuracy of 95% by using near-infrared spectroscopy and a machine learning method. But, these approaches rely on expensive hardware, and can not be easily incorporated in sensors for daily use. Lester et al. [15] designed a rod-like hardware prototype that replaces a spectroradiometer with less expensive electronic components, including eight LEDs and a color sensor. Users can put their prototype in a glass for beverage identification. Their experiment showed that it achieved identification of ten beverages at 60% accuracy.

Unlike the work above, the main focus of our work is alcohol concentration estimation using an optical method. Our work complements the prior work by adding the capability of alcohol concentration sensing. For instance, a future device may determine the type of a beverage as well as its alcohol content through integration of Lester et al.'s method [15].

2.2 Beverage Alcohol Content Estimation Methods

The most traditional method for alcohol concentration determination is to use a physical property (e.g., measuring relative density by a hydrometer [13]). But, it requires distillation and temperature adjustment, and does not fit to smart devices in a small form factor. Near-infrared spectroscopy is another method effective for alcohol concentration determination which can be suitable for smart devices. Gallignani et al. [9] examined a method using the first derivative of the near-infrared absorption spectrum to estimate alcohol concentration of 21 alcoholic beverages including beer, wine, whiskey, and ram. Their method measures the derivative absorption values to detect a peak and valley at 1680 nm and 1703 nm, respectively. This contributes to elimination of the interference on the spectral baseline caused by constituents other than water and ethanol. However, measuring derivative absorption values require expensive equipment that can perform high-resolution spectrum sensing, such as a spectroradiometer.

Benes [3] patented his invention on an inexpensive handheld device and method to determine the alcohol content of liquids. The device consists of an NIR detector, a cell into which a test liquid can flow, and three LEDs whose peak wavelengths are at 1200, 1300, and 1450 nm. The device used one of the three wavelengths to compensate for light scattering in liquids and the other two to determine alcohol content and the other substances (e.g., sugar). Benes reported that with his device, he was able to develop a model to estimate alcohol content of 24 kinds of wine (with 9.0 – 13.3 % v/v alcohol) at 0.28 % v/v standard error of cross validation (SECV), and another model to estimate alcohol content of 28 kinds of beer (with 0 – 9.6 % v/v alcohol) with 0.06 % v/v SECV along with density and color measurement. Although his method achieved great accuracy on alcohol concentration estimation, it requires a model to be trained individually for each kind of beverages.

Rahman et al. [23] explored another method for alcohol concentration prediction. Their system, Nutrilyzer, detects adulterants in liquid using photoacoustic effect. Nutrilyzer consists of an array of 16 LEDs which have various peak wavelengths ranging from ultraviolet (385 nm) to NIR (940 nm). Although Nutrilyzer showed successful results for milk nutrient prediction, its performance in alcohol concentration prediction was limited. One possible reason for this limited performance was that the system did not include NIR light in longer wavelengths.

Our work extends Benes' findings by uncovering its performance of alcohol concentration sensing with a broader set of beverages and instantiating the technology as a smart device. It thus demonstrates the feasibility of creating an alcohol-aware smart ice cube.

2.3 Smart Devices for Liquid Intake Activities

Research and industry have made various smart devices to track and support drinking activities (not limited to alcohol consumption). H2OPal Smart Bottle Hydration Tracker [3] is a commercially-available smart water bottle that connects to a smartphone. It estimates users' hydration levels through data obtained from the built-in weight measuring sensor and accelerometer. The device provides notifications when they should get hydrated. Lessel et al. presented WaterCoaster [14], a coaster which measures the weight of the liquid in a container. Their system also offers a gamification application to motivate people to drink water frequently and regularly. Fan et al. [7] developed capacitive sensors which can be easily attached to the outside of containers to track the level of the liquid inside. Their sensor was able to determine a liquid level with correlation coefficients higher than 0.98. IllumiMug [22] is an intelligent cup which can sense and visualize the level and temperature of a liquid inside. It enables interactive applications, such as supporting cocktail making and notifying users when the liquid gets cooled down.

A cube form factor is also common for smart devices to support drinking activities. A concept smart cube developed at MARTINI® automatically places a refill order when a glass becomes empty[4]. Dand created Cheers [5], a smart ice cube which infers how drunken a user is by counting the number of sips and elapsed drinking time using a built-in accelerometer. When the user is considered to be severely drunk, a red LED inside the cube illuminates for a warning, and the user's friends receive an emergency text message.

The work above has demonstrated sensing capabilities of liquid levels, temperature, and intake counts. Our device can co-exist with these technologies, and would enable additional applications. For example, a future system may be able to sense the amount of consumed alcoholic beverages their concentration levels. It could thus estimate the total amount of alcohol consumption, enabling novel tracking applications.

2.4 Alcohol Intake Tracking

Alcohol intake tracking is another technology recently explored around drinking activities. It aims to obtain detailed information to encourage healthy drinking. For example, alcohol addiction is a strong symptom and may lead to fatal disease, and external support is necessary for recovery. According to McKay et al., 50% of alcohol-addicted patients they surveyed suffered a recurrence of addiction within 2 years after their treatment [17]. Research therefore has developed systems to support prevention and treatment of alcohol addiction. Existing systems incorporate various methods for alcohol intake tracking: self-reporting [19]; biological sensing

[3] https://www.h2opal.com/

[4] https://www.bacardilimited.com/new-martini-smart-cube-technology-makes-waiting-bar-thing-past/

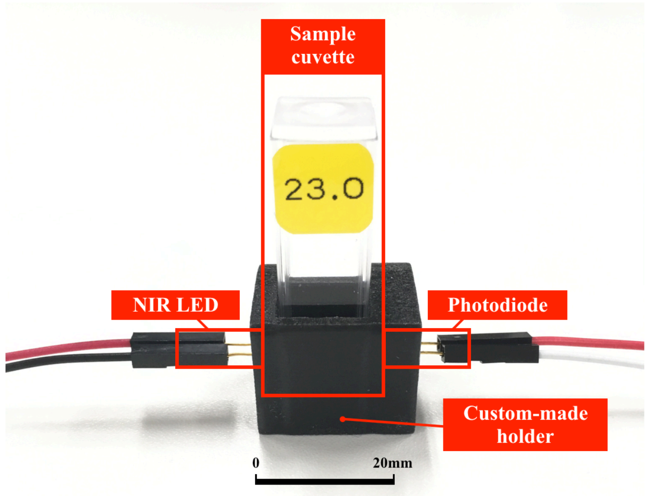


Fig. 2. The apparatus for our revisitation studies. The sample cuvette in this figure contains 23.0 % v/v alcohol aqueous solution.

using a breathalyzer [26]; transdermal alcohol monitors [18, 24]; and behavioral patterns monitoring using wearable sensors [10] and smartphones [2, 8]. BACTrack [5] is a commercially-available breathalyzer that can connect to a smartphone for recording users' blood alcohol content. Hsu et al. created a system to help patients record their drinking activities for professional treatment [11]. Their interviews with clinicians revealed that understanding moments when patients experience their impulse for drinking was valuable in addition to their alcohol consumption. They also developed another smartphone-based system for a person not to commit to drunk driving again [12].

These systems and applications clearly demonstrate the importance of tracking alcohol drinking. Al-light measures liquid alcohol concentration levels, and would offer additional information about users' drinking activities. Our work offers a novel sensing capability of beverage alcohol concentration, potentially enhancing the applications above.

3 REVISITATION STUDY ON BENES' METHOD

We conducted two quantitative experiments to examine the feasibility of Benes' alcohol content determination method [3]. Although Benes' method is seemingly promising for our purpose, his investigation did not include different kinds of commercially-available alcoholic beverages (e.g., liquor and whiskey). In addition, his findings are based on beverage-dependent models which would limit practicality of the device to be developed. Thus, our objectives of this revisitation are:

- Understanding the performance of Benes' method using various kinds of alcoholic beverages, and
- Uncovering a potential of building beverage-independent models for alcohol concentration estimation.

3.1 Experimental Setup

We created an apparatus with which we can re-experiment Benes' method in a controlled setting (Figure 2). The custom-made black holder (H: 20.0 mm x W: 16.7 mm x D: 23.1 mm) can accommodate an LED, a photodiode, and

[5] https://www.bactrack.com/

a transparent cuvette which contains a test liquid. The LED and photodetector are placed face-to-face across the cuvette for light intensity measurements. We used the three following NIR LEDs: MTE0012-015-IR, MTE0013-015-IR, and MTE5014-015-IR (all from Marktech Optoelectronics). Their peak wavelengths are 1200 nm, 1300 nm, and 1450 nm, respectively, corresponding to Benes' experiment. As our apparatus can hold only one LED at a time, we manually switched them during measurements. We chose SD039-151-011 (from Luna Optoelectronics) as the photodetector because of its wide spectral coverage in the NIR region (from 800 nm to 1700 nm). The cuvette is the size of H: 45 mm x W: 12.5 mm x D: 12.5 mm. Its inside is a square of 10 mm, and can contain up to 4.5 ml of a given test liquid. We performed this experiment under a fixed light condition (in a laboratory with normal ceiling light but without sunlight).

The LED and photodetector were connected to a circuit board for measurements. It includes a transimpedance amplifier circuit to convert the current output of the photodetector to a voltage. The ADC converter in an Arduino Uno on the circuit board receives the converted voltage, and discretizes it as a 10-bit value. We used LMC6484 (an op-amp from National Semiconductor) for the transimpedance circuit.

3.2 Experiment Using Alcohol Aqueous Solutions

We first experimented Benes' approach using alcohol aqueous solutions. As alcohol aqueous solutions are transparent and do not contain impurities, this experiment was intended to uncover the measurement performance in ideal light and liquid conditions.

3.2.1 Procedure. We prepared alcohol aqueous solutions with 32 different concentration levels: 0.0 – 1.5 % v/v at intervals of 0.5 % v/v (percent volume/volume); 2.0 – 23.0 % v/v at intervals of 1.0 % v/v; 23.0 % v/v; and 25.0 – 50.0 % v/v at intervals of 5.0 % v/v. We deliberately set finer granularity for low concentration levels (0.0 – 1.5 % v/v) to examine distinguishability power.

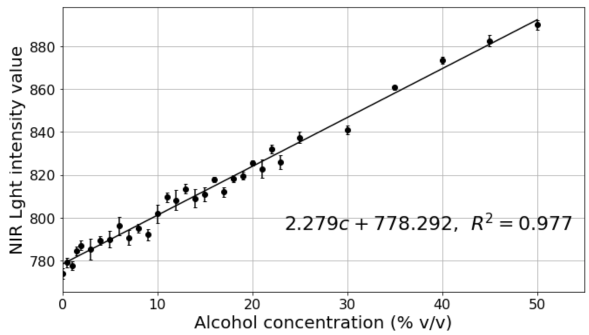
During each measurement, we recorded 1,000 samples of light intensity values with the sampling rate of 200 Hz, and adopted its median as their representation. We measured five times for each liquid sample and LED.

3.2.2 Results. Figure 3 shows the observed light intensity values with the three LEDs. A dot and its error bar represent the average value and standard deviation of five measurements for each concentration level, respectively. The measurements with all the three LEDs exhibited clear linear relationships against concentration levels. This is in line with Benes' report [3]. Our linear regression analysis found high coefficients of determination ($R^2 > 0.97$ for all LEDs). The resulted linear functions for 1200 nm, 1300 nm, and 1450 nm are as follows:

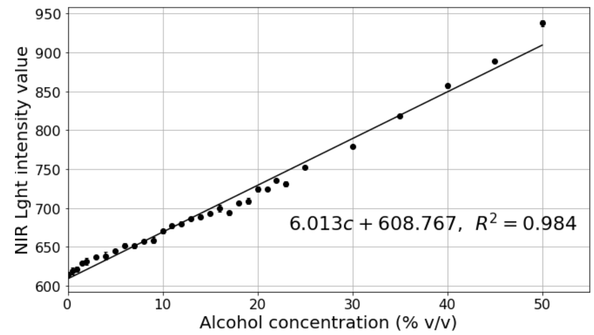
$$\begin{aligned}
1200\,\mathrm{nm}:&\quad \hat{I}_{1200} = 2.279c + 778.292 \quad \text{with } R^2 = 0.977\\
1300\,\mathrm{nm}:&\quad \hat{I}_{1300} = 6.013c + 608.767 \quad \text{with } R^2 = 0.983\\
1450\,\mathrm{nm}:&\quad \hat{I}_{1450} = 1.046c + 45.251 \quad\ \ \text{with } R^2 = 0.979
\end{aligned}$$

In these equations, c represents alcohol concentration (% v/v). $\hat{I}_\lambda$ represents a light intensity value prediction with the λ nm LED.

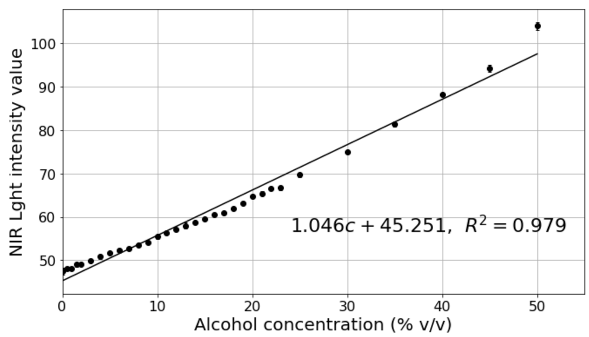
Although all LEDs demonstrated clear relationships with alcohol concentration levels, we also observed several performance differences. The 1200 nm LED tended to exhibit large standard deviations at the alcohol concentration levels of 0.0 % v/v – 23.0 % v/v as shown in Figure 3. Because many alcoholic beverages are below 15.0 % v/v, this is not desirable. Ethanol and water have similar absorbance with light at a wavelength 1200 nm, but the difference becomes larger at 1300 nm and 1450 nm [3]. Thus, 1200 nm may rather serve to calibrate light intensity measurements. Our results thus confirm that 1300 nm and 1450 nm have strong distinguishability power for alcohol concentration.



(a) 1200 nm



(b) 1300 nm



(c) 1450 nm

Fig. 3. Observed light intensity values against concentration levels of alcohol aqueous solutions with the three NIR LEDs. Each dot represents the average value of five measurements for each concentration level. The error bars represent the standard deviation. The measurements with all the three LEDs exhibited linear relationships against concentration levels. The linear regression analysis found high coefficients of determination ($R^2 > 0.98$ for all the NIR LEDs).

3.3 Experiment with Commercially-Available Alcoholic Beverages

We next experimented with commercially-available alcoholic beverages. The goal of this part of the experiments was to confirm how well Benes' method performs with real beverages.

3.3.1 Procedure. Table 1 shows 18 commercially-available beverages tested in this experiment. Our set of beverages included wines, beers, sake, spirits (distilled alcoholic drinks), and liquor-based drinks (e.g., cocktails and sours). We deliberately chose beverages with different colors, content, additives, and concentration levels. The range of stated alcohol concentration levels was 3 – 40 % v/v. Thirteen of the beverages included sugar (i.e., natural sugars or added sucrose). Eight of them were carbonated, and only one contained probiotic drinks. We used the same apparatus and data collection procedure as the previous experiment.

3.3.2 Results. Figure 4 shows our measurement results with the 1450 nm LED. The results again clearly demonstrate a linear trend in this case. Contrary to our expectations, the liquid colors did not affect much in this experiment. We had similar results with the other LEDs though linearity was the most clear in 1450 nm.

As the results still revealed relatively strong linear relationships, we next examine alcohol concentration level prediction performance using machine learning methods. We used the following machine learning methods:

Table 1. Eighteen beverages used in our revisitation study. A blank field in the Color column represents that the beverage is non- or thin-colored.

Beverage	Stated alcohol content (% v/v)	Carbonated	Color	Opaque
White wine 1	11			
Red wine 1	11		wine red	
White sparkling wine 1	13	✓		
Red wine 2	13.5		wine red	
Beer 1	5	✓	pale gold	
Beer 2	5	✓	dark brown	✓
Sake 1	14			
Sake 2	15.5			
Distilled liquor 1	12			
Distilled liquor 2	20			
Distilled liquor 3	25			
Vodka 1	40			
Whiskey 1	40		brown	
Mixed drink 1 (Vodka, soda, and plum juice)	3	✓		
Mixed drink 2 (Vodka, soda, and probiotic drinks)	3	✓	white	✓
Mixed drink 3 (Vodka, soda, and pineapple juice)	5	✓		
Mixed drink 4 (Whiskey and carbonated water)	7	✓	amber	
Mixed drink 5 (Vodka, soda, and grapefruit juice)	9	✓		

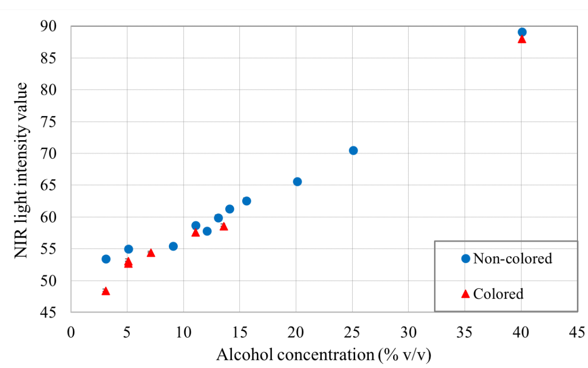


Fig. 4. The 1450 nm LED light intensity plot for the 18 alcoholic beverages shown in Table 1.

- Linear Regression (LR),
- Gaussian Process Regression (GPR),
- Decision Tree (DT), and
- Support Vector Regression (SVR) with the linear kernel.

Table 2. The mean absolute estimation errors for commercially-available beverages in our revisitation study. The value in the parenthesis represents the standard deviation. The bold font represents the best performance among the combinations of the light sources for each machine learning method.

Feature	LR	GPR	DT	SVR
1200	5.05 (4.38)	4.29 (3.34)	2.75 (2.19)	2.98 (3.84)
1300	1.56 (1.14)	2.92 (3.10)	**1.87 (1.53)**	1.12 (0.87)
1450	**1.32 (1.09)**	**2.78 (2.65)**	1.93 (1.57)	1.13 (0.90)
1200 + 1300	1.53 (0.79)	3.15 (3.29)	2.08 (1.59)	1.66 (0.88)
1300 + 1450	1.42 (1.19)	14.5 (10.8)	1.97 (1.52)	**1.11 (0.83)**
1200 + 1450	1.43 (1.16)	13.8 (11.3)	2.06 (1.59)	1.32 (0.86)
1200 + 1300 + 1450	1.51 (1.01)	3.15 (3.32)	2.15 (1.47)	1.64 (2.04)

We performed cross-validation for our estimation accuracy evaluation. We left the data for one beverage out for testing, and used the rest for training (Leave-one-beverage-out, or LOBO). The feature values were normalized before training and testing. We replaced negative estimated values with zero.

Table 2 summarizes the mean absolute errors across the four machine learning methods and the combination of light sources. All the methods except GPR generally performed well. In particular, DT and SVR showed stable performance. The regulation in the country we conducted an experiment allows labeling of alcohol concentration levels to have tolerance of 1 % v/v. In addition, an exception of 2 % v/v tolerance is allowed for beverages which are made through fermentation and do not involve distillation (e.g., beer and sake). Thus, the overall estimation errors in this experiment were reasonable.

The combinations of light sources that achieved the best performance were different across the machine learning methods: 1450 nm for LR and GPR; 1300 nm for DT; and 1300 nm and 1450 nm for SVR. A closer look into the result found that the performance using 1450 nm was close to the best for DT and SVR. We thus decided to further examine the estimation performance for SVR with 1450 nm as the feature.

Table 3 shows the mean estimation errors using SVR with 1450 nm as the feature. Most of the estimations were accurate, confirming the distinguishability power of 1450 nm. The performance with the mixed drinks, on the other hand, was not well. There are possible factors that can negatively impact on estimation. Carbon dioxide gas in sparkling drinks may cause estimation errors because bubbles disturb NIR light absorption. Thus, carbonated liquid absorbs less NIR light than a mixture of water and ethanol. For the sparkling mixed drink with probiotic drinks (Mixed drink 2), the light diffusion by the precipitate may have further lowered observed intensity. As a result, estimations might have become less accurate for such beverages.

In summary, our revisitation studies uncovered that measurements with the 1450 nm LED were the most promising for alcohol content estimation. As our smart device needs to be downsized, integration of an 1450 nm LED may be sufficient for our purpose. Our revisitation studies also suggest that we need compensations for additives and carbonated drinks. We therefore took this into consideration for our device and hardware design of Al-light.

4 AL-LIGHT PROTOTYPE

4.1 Device Form Factor Exploration

Our revisitation studies on Benes' method confirm its potential of alcohol concentration sensing. In particular, an 1450 nm LED is the key light source for determining alcohol concentration. These findings lead us to developing a prototype device based on this approach.

Table 3. The estimation results using SVR and the 1450 nm LED data as the feature in our revisitation study.

Beverage	Stated	Estimated	Beverage	Stated	Estimated
Mixed drink 1	3	6.23 (0.19)	Distilled liquor 1	12	10.1 (0.08)
Mixed drink 2	3	1.17 (0.19)	Sparkling wine 1	13	12.6 (0.27)
Beer 1	5	5.93 (0.15)	Red wine 2	13.5	11.0 (0.31)
Beer 2	5	5.55 (0.17)	Sake 1	14	14.4 (0.09)
Mixed drink 3	5	7.56 (0.23)	Sake 2	15.5	16.0 (0.19)
Mixed drink 4	7	6.80 (0.09)	Distilled liquor 2	20	19.2 (0.17)
Mixed drink 5	9	7.80 (0.13)	Distilled liquor 3	25	26.3 (0.09)
White wine 1	11	11.3 (0.19)	Vodka 1	40	40.4 (0.08)
Red wine 1	11	10.1 (0.31)	Whiskey 1	40	39.6 (0.16)

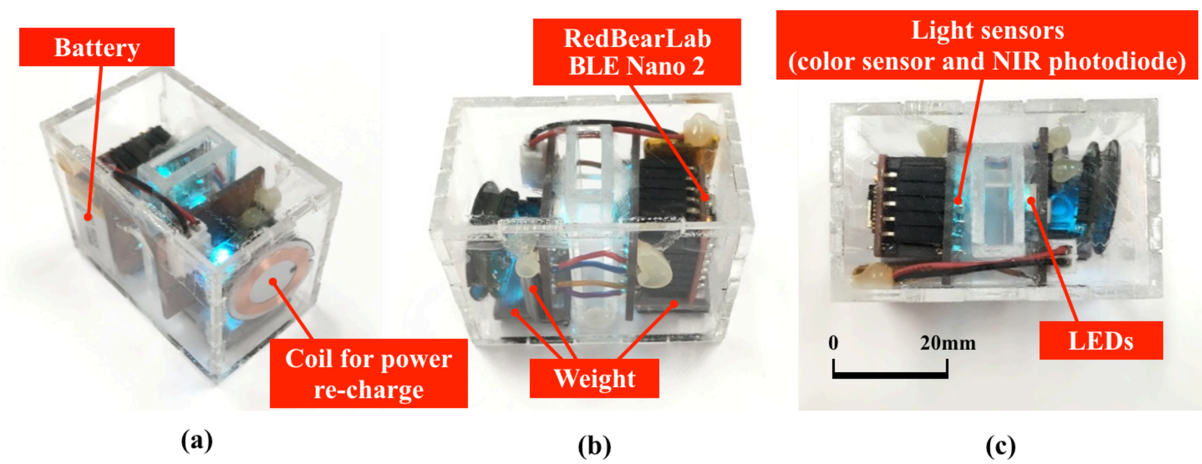


Fig. 5. The Al-light prototype. It is the size of 31.9 x 38.6 x 52.6 mm. The circuit inside includes an NIR and RGB LED, an NIR photodetector, a color sensor, RedBearLab BLE Nano 2, a receiver coil for wireless powering, and a battery. The device also contains small weights so that the direction of the hollow would be orthogonal to the bottom of a glass.

There are several potential form factors for alcohol-sensitive smart devices. For instance, integration into a straw or swizzle stick can be a candidate design. Direct integration into a glass or cup could be another direction. To determine the device form factor, the most critical consideration is that the device needs to have a certain gap between the light source and receiver for accurate estimation. If an LED and photodetector are placed too close, light absorption would decrease in general. Thus, measurements would become less reliable. With a straw-like device, ensuring a sufficient gap would be challenging. The form factor of a swizzle stick would suffer from the same problem. We thus determined an ice cube shape for our prototype to accommodate hollow space necessary for liquids to flow for alcohol concentration measurement. Although Dand [5] demonstrated the idea of a smart ice cube, they did not include alcohol sensing capabilities. Compared to glass or cup-shaped devices, ice cube-shaped devices have an advantage for usability with different glasses, containers, and beverages. We thus decided to use the form factor of an ice cube for our prototype. It can accommodate additional sensors in the future (e.g., an accelerometer for counting gulps and a barometer for estimating the amount of a beverage) to extend possible applications though this is not the primary scope of this work.

Note that the optical alcohol sensing method used in this work is not limited to the ice cube form factor. Future work should investigate its integration to a variety of devices. One main contribution of this work is our demonstration of an optical alcohol sensing method in a plausible device for daily use.

4.2 Hardware

Figure 5 is our current Al-light prototype. It is the size of 31.9 x 38.6 x 52.6 mm and can be placed in a glass. The exterior is made of transparent plastic and sealed with silicone sealant to be waterproof. We color the exterior in black to eliminate the ambient light (see Figure 1b). It embeds two small printed circuit boards (PCBs) that are connected with each other by wires.

One PCB embeds a 1450 nm and RGB LED (MTSM5014-843-IR from Marktech Optoelectronics and OST-BABS4C2B from OptoSupply, respectively) as light sources. The RGB LED serves for performing additional measurements in the visible light spectrum for removing effect by color and impurities in beverages [9]. This circuit board is also connected to a wireless power receiver coil (TSWIRX-5V2-EVM from Semtech Corporation). It charges the lithium ion polymer (Li-ion) battery placed in the other side of the cube when a power transmitter is sufficiently close. Otherwise, the device automatically gets activated and performs measurements. The other PCB includes an NIR photodetector and digital color sensor (SD012-151-001 from Luna Optoelectronics and S9706 from Hamamatsu Photonics, respectively). It also connects with RedBearLab BLE Nano 2[6] for controlling the LEDs and measuring the light intensity observed in the photodiode and color sensor. The NIR photodiode is connected to a two-stage amplifier circuit before an AD converter I/O pin in RedBearLab BLE Nano 2. The color sensor is directly connected to the pins. The AD converter generates a 12-bit value of the given voltage.

In addition to these circuits, the device also includes four weights (30 g in total) at its bottom. These weights make the cube sink and stay in a way that the hollow is orthogonal to the bottom of a glass. Light intensity measurements can be stable in this manner. In addition, bubbles in carbonated beverages can escape from the hollow easily. We expect this design to minimize the negative effect caused by such bubbles.

The number of the I/O pins in RedBearLab BLE Nano 2 is only nine besides TX/RX for Bluetooth communication. The LEDs, the color sensor, and the photodetector need 4, 4, and 1 I/O pins, respectively. We decided not to include additional sensors which could enhance the use of our device (e.g., an accelerometer). This would not defeat the main objective of our work though a future prototype is encouraged to accommodate such sensors.

As RedBearLab BLE Nano 2 contains a Bluetooth Low Energy (BLE) module, it wirelessly transmits measurement data to a computing device (e.g., a smartphone). The computing device then performs alcohol concentration estimation using machine learning approaches (explained in the next section).

5 ALCOHOL CONCENTRATION ESTIMATION STUDY

We conducted quantitative evaluations with our Al-light prototype to examine its performance on alcohol concentration estimation.

5.1 Experimental Setup

5.1.1 Light conditions. To investigate the performance of Al-light in realistic light settings where drinking activities occur, we set the following three conditions.

- *Bright*: At the window in a room in the afternoon. The average light intensity was 1898 lx (*SD*=143). This condition represents a case where people drink in a restaurant during daytime.

[6] https://redbear.cc/product/ble-nano-2.html

Table 4. Thirteen beverages used in our evaluation with Al-light. A blank field in the Color column represents that the beverage is non- or thin-colored.

Beverage	Stated alcohol content (vol %)	Carbonated	Color	Opaque
Bottled water	0			
Alcohol-free beer	0	✓	pale gold	
Cider	3	✓		
Beer 1	5	✓	pale gold	
Beer 2	5	✓	dark brown	✓
Mixed drink 6 (Vodka, soda, and lemon juice)	5	✓		
Mixed drink 7 (Vodka, soda, and orange juice)	5	✓	orange	✓
White wine 2	10			
Red wine 3	11		wine red	
Sake 3	13.5			
Sake 4	19			
Whiskey 2	37		brown	
Vodka 2	37.5			

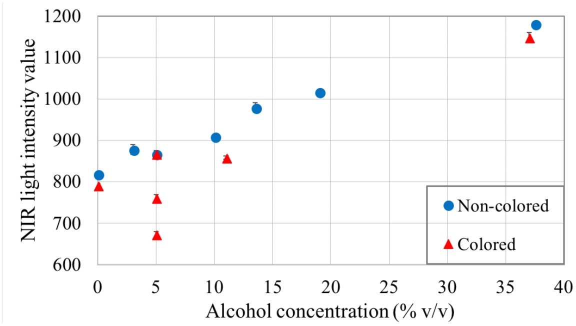
- *Normal*: Inside a room in the afternoon with lighting but apart from the window. The average light intensity was 692 lx (*SD*=247). This condition represents a case where people drink at restaurants or home.
- *Dark*: Inside a dark room with indirect lighting. The average light intensity was 39 lx (*SD*=8). This condition represents a case where people drink at bars.

5.1.2 Beverages. We chose 2 non-alcoholic beverages and 11 commercially-available alcoholic beverages (3 – 37.5 % v/v) that had various colors and alcohol contents. Table 4 shows all the beverages we tested. There were six kinds of carbonated beverages. Six of the 13 beverages were colored, and two of them were opaque. We deliberately chose different beverages that were not used in our revisitation study. Alcohol aqueous solutions showed clear linear relationships in our revisitation study because they are colorless and contain no impurities. We removed transparent, non-colored distilled liquors for the same reason. We also included a different mixed drink that is also opaque (Mixed drink 7) as well as alcohol-free beer for comparison against beer.

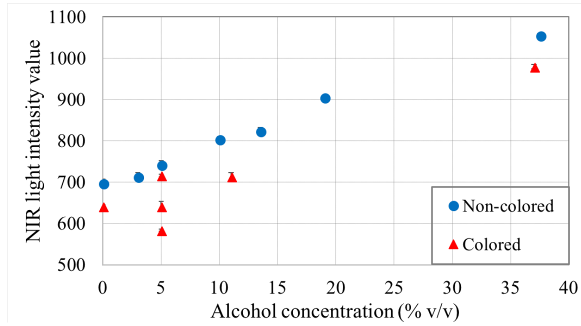
5.2 Data Collection

At each measurement trial, we first collected the intensity values when all the LEDs were off, and then turned them on in sequence. The measurement with the NIR LED takes 200 msec. We changed exposure durations for the digital color sensor when the RGB LED was on (8, 40, 20 msec for R, G, and B, respectively) and off (200 msec for all). The color sensor returns the accumulated observed values over the duration. When the RGB LED was off, the returned value with a short duration would thus be very small (i.e., under-exposure). Similarly, the color sensor would be easily over-exposed with a long sensing duration. The duration values were experimentally determined to avoid both under- and over-exposure in both states of the RGB LED. As the NIR photodiode outputs an analog value as voltage, we did not change measurement durations in NIR measurements. The current prototype thus took roughly 1 sec for obtaining the whole series of measurements and sending it to a computing device.

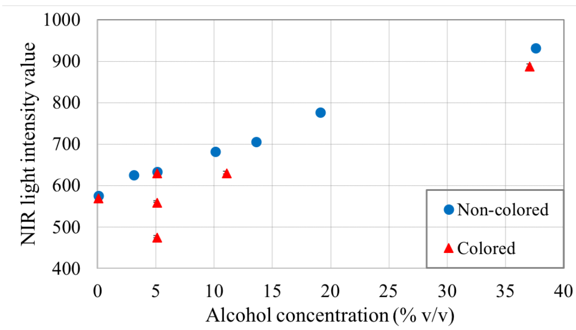
We collected four data samples for each beverage and light condition. For each data sample, we rotated the prototype along the axis perpendicular to the hollow by 90 deg before starting measurements. After placing the



(a) *Bright*



(b) *Normal*



(c) *Dark*

Fig. 6. The mean observed NIR intensity values under the three light conditions. The error bar represents the standard deviation. Note that most of the standard deviations were very small. Blue circles and red triangles represent non-colored and colored beverages, respectively.

device, we randomly started measurements for one second. During measurements, the prototype stayed still at the bottom of a glass. The direction of the hollow was orthogonal to the plane of the glass bottom.

After measurements, we subtracted intensity values collected when the NIR LED was off from measurements with the NIR LED on to eliminate the ambient light effect. We denote the resulted value as NIR_{Δ}. For RGB measurements, we first calculated the measured light intensity value per msec for the two LED states, and subtracted to obtain similar metrics to NIR (denoted as R_{Δ}, G_{Δ}, and B_{Δ}). During the data collection, the prototype was connected with a computer over Bluetooth.

5.3 Light Intensity Measurement Results

Figure 6 shows our NIR light intensity measurement results under the three light conditions. Similar to our revisitation studies, we found clear linear relationships on many of the tested beverages. Carbonated beverages in thin colors (e.g., cider) also exhibited similar tendencies to those that are still and non-colored. However, beverages in dark colors demonstrated lower light intensity measurements (i.e., high absorption). We also observed that the measurements were shifted across the light conditions, but the trends were the same. We re-plotted the data by subtracting NIR light intensity measurements from that of water under each condition (denoted as $\overline{NIR_{\Delta}}$, Figure 7). All three conditions are closely overlapped. This plot suggests that NIR light intensity measurements can become stable if we have baseline data (e.g., measurements with water).

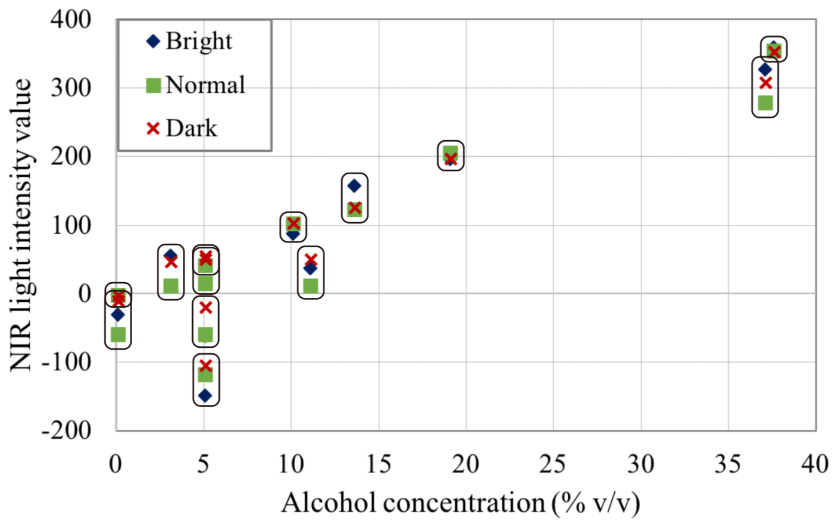


Fig. 7. The mean NIR intensity plot with standardization of water for each light condition. The dots representing the same beverage are grouped.

Table 5. The mean RGB values normalized with the measurements of water under the *Bright* condition. Note that the RGB values for each beverage were stable across the light conditions. All the standard deviations were less than 0.01.

		Bright			*Normal*			*Dark*		
	Beverage	Red	Green	Blue	Red	Green	Blue	Red	Green	Blue
	Bottled water	1	1	1	1.00	1.00	1.00	1.00	1.00	1.00
Non-colored	Cider	1.01	1.01	0.97	1.00	0.99	0.97	1.00	0.99	0.97
	Mixed drink 6	1.00	1.01	1.01	1.01	1.01	1.01	1.01	1.01	1.01
	White wine 2	1.00	0.99	0.96	1.01	0.99	0.96	1.01	0.99	0.96
	Sake 3	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
	Sake 4	1.01	1.01	1.00	1.01	1.01	1.01	1.01	1.01	1.01
	Vodka 2	1.02	1.02	1.02	1.02	1.02	1.02	1.02	1.02	1.02
Colored	Alcohol-free beer	0.98	0.92	0.82	0.98	0.92	0.82	0.98	0.92	0.82
	Beer 1	0.97	0.93	0.82	0.97	0.92	0.82	0.97	0.92	0.82
	Beer 2	0.43	0.10	0.01	0.43	0.10	0.01	0.43	0.10	0.01
	Mixed drink 7	0.79	0.74	0.46	0.79	0.74	0.46	0.79	0.74	0.46
	Red wine 3	0.58	0.03	0.04	0.58	0.03	0.04	0.58	0.03	0.04
	Whiskey 2	0.97	0.91	0.77	0.97	0.91	0.77	0.98	0.91	0.77

We next look into the effect of liquid colors. Table 5 illustrates the measured RGB values of the tested beverages normalized with that of water under the *Bright* condition. Unlike the NIR measurements, the RGB values for all the beverages were very similar regardless of the light conditions. This implies that additional calibration for ambient light may not be necessary for the RGB LED. In addition, beverages in dark colors exhibited distinguishably low values (e.g., Beer 2). These beverages also exhibited lower light intensity observations with the NIR light than non-colored drinks. Therefore, this result suggests a potential to compensate NIR measurements with RGB light.

5.4 Alcohol Concentration Estimation Methods

We next examined how well the Al-light system can infer the alcohol concentration level using supervised machine learning approaches. We used SVR with linear kernel as it demonstrated the overall best performance in our revisitation studies.

We also examined estimation performance through two different training procedures (explained below). All the feature values were normalized before training and testing. We replaced negative estimated values with zero. We calculated the absolute difference between the label (stated in the beverage container) and predicted alcohol concentration as our error metric.

5.4.1 Light-condition-dependent Training (LCDT). In this procedure, we trained and tested a regressor using the data under the same light condition. We left the data for one beverage out for testing, and used the rest for training (i.e., LOBO). We used $R_\triangle$, $G_\triangle$, $B_\triangle$, and $NIR_\triangle$ as the features.

5.4.2 Light-condition-independent Training (LCIT). In this procedure, we trained a regressor using the data under the two of the light conditions. We then tested it with the data under the other light condition. We also employed LOBO in our cross validation. For example, in order to test estimation for whiskey under the *Bright* condition, we trained a regressor with the data of the other beverages under *Normal* and *Dark*. We used $\overline{R_\triangle}$, $\overline{G_\triangle}$, $\overline{B_\triangle}$, and $\overline{NIR_\triangle}$ as the features. $\overline{R_\triangle}$, $\overline{G_\triangle}$, and $\overline{B_\triangle}$ are the RGB intensity values after we subtracted from that of water under each condition. As shown in Table 5, these values were the same across the conditions, including the water measurements. Thus, the values of $\overline{R_\triangle}$, $\overline{G_\triangle}$, and $\overline{B_\triangle}$ were the same regardless of which of the three water measurement data we used.

5.5 Alcohol Concentration Estimation Results

Table 6 shows the estimation performance results under the LCDT and LCIT procedure using SVR. The inclusion of the RGB channels contributed to improvements on estimation. However, their combinations did not necessarily lead to better performance. Even only one of RGB offered comparable improvements to the cases of using two or all channels. In addition, we did not see clear differences among the RGB channels. We thus chose the combination of NIR and blue light for further analysis.

Table 7 presents estimated alcohol concentration for the beverages excluding water using SVR and the NIR and blue light as features. The estimation was generally accurate, but colored beverages tended to result in large errors. In particular, Mixed drink 7 (Vodka, soda, and orange juice) led to clear under-estimation due to low observed light intensity.

We observed similar performance results with the LCIT procedure, presented in the rightmost column in Table 6. SVR with the features of NIR, green, and blue showed a comparable result of 2.11 (SD=2.02). Table 7 shows the estimation results for each beverage. Again, the colored beverages tended to exhibit large errors. However, the estimation was generally accurate in this case as well. Using more visible LEDs did not lead to noticeable improvements in estimation accuracy of colored beverages.

6 DISCUSSION

6.1 Findings

The experiment showed promising results for alcohol concentration estimation with Al-light. In the LCDT setting, Al-light was able to achieve 1.72 – 2.47 absolute errors from the stated alcohol concentration levels under the best combination of the features and machine learning methods. We observe similar performance results in

Table 6. The mean absolute estimation errors with the light-condition-dependent training (LCDT) and the light-condition-independent training (LCIT) procedure using SVR. The value in the parenthesis represents the standard deviation.

Feature	LCDT			LCIT
	Bright	*Normal*	*Dark*	
NIR	3.41 (2.33)	4.10 (3.45)	2.86 (2.42)	2.90 (2.18)
NIR+R	**2.07 (1.82)**	3.11 (2.87)	1.79 (1.98)	2.15 (1.85)
NIR+G	2.89 (1.97)	3.66 (3.24)	2.06 (2.05)	2.42 (2.37)
NIR+B	2.41 (1.73)	**2.71 (2.55)**	1.80 (1.80)	2.12 (2.07)
NIR+RG	2.70 (1.83)	3.44 (3.16)	2.40 (2.64)	2.53 (2.47)
NIR+RB	2.82 (2.15)	3.21 (3.08)	2.10 (1.87)	2.31 (2.21)
NIR+GB	2.10 (1.76)	2.98 (2.34)	**1.72 (1.22)**	**2.11 (2.02)**
NIR+RGB	2.41 (1.60)	3.10 (3.17)	2.87 (2.50)	2.12 (2.21)

Table 7. Estimated alcohol concentration for the thirteen beverages in Table 4. The LCDT procedure used NIR and blue light as features. Using all visible light channels did not lead to noticeable improvement under LCIT.

Beverage	Stated	Color	Estimated (LCDT)			Estimated (LCIT)	
			Bright	*Normal*	*Dark*	NIR+B	NIR+RGB
Bottled water	0		0.00 (0.00)	1.04 (0.98)	0.00 (0.00)	0.42 (0.41)	0.26 (0.37)
Alcohol-free beer	0	pale gold	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.62 (0.73)	1.34 (1.99)
Cider 1	3		5.65 (0.45)	2.55 (1.31)	4.80 (0.25)	4.96 (2.36)	4.82 (2.43)
Beer 1	5	pale gold	7.39 (0.73)	5.49 (0.31)	6.43 (0.33)	6.76 (2.12)	7.65 (2.22)
Beer 2	5	dark brown	2.13 (1.12)	1.52 (0.33)	4.31 (0.32)	3.84 (2.92)	8.13 (3.98)
Mixed drink 6	5		4.80 (0.71)	4.93 (1.20)	5.51 (0.49)	5.28 (0.99)	5.14 (0.89)
Mixed drink 7	5	orange	0.00 (0.00)	3.17 (1.65)	0.00 (0.00)	0.08 (0.29)	0.24 (0.61)
White wine 2	10		9.31 (0.13)	12.4 (0.62)	10.9 (0.18)	11.0 (0.68)	11.02 (0.70)
Red wine 3	11	wine red	15.4 (0.53)	18.1 (1.37)	12.5 (0.52)	16.9 (3.41)	13.67 (5.24)
Sake 3	13.5		16.4 (1.51)	13.8 (1.09)	12.9 (0.32)	13.4 (1.63)	14.68 (2.17)
Sake 4	19		20.7 (0.26)	21.8 (0.33)	21.0 (0.29)	18.5 (1.37)	19.42 (1.16)
Whiskey 2	37	brown	32.5 (0.61)	29.2 (0.69)	31.4 (0.28)	35.0 (3.05)	35.62 (2.67)
Vodka 2	37.5		34.0 (0.42)	32.2 (0.39)	34.2 (0.59)	37.1 (0.81)	36.85 (1.04)

the LCIT setting. These results suggest that a system using Al-light does not need to build beverage-dependent models for alcohol content estimation. We would like to note again that the regulation in the country we conducted an experiment allows labeling of alcohol concentration levels to have tolerance of 1 or 2 % v/v. Thus, our results confirm reasonable accuracy performance and the generalizability of the estimation approach.

Our results revealed that not all the RGB light would be necessary. This tendency appeared regardless of the light conditions. We included RGB light for acquiring information about the chroma and brightness of a beverage. All RGB channels may still be necessary if a future device attempts to identify a type of a beverage as well as its alcohol concentration level [15]. However, our examination suggests that one of the RGB light may be sufficient for alcohol concentration estimation, and it is a positive result for device downsizing.

The results confirmed that the system can eliminate effect by the ambient light if it has measurements with water. This can be plausible in some use scenarios (e.g., lightly rinsing Al-light in water before putting into a beverage). Otherwise, additional calibrations would be necessary as our results in the LCDT procedure showed differences in estimation.

Examinations on estimation errors for each beverage led to reasonable accuracy except colored beverages. We did not observe clear negative effect by carbonated gas. This suggests that our device design to make the hollow perpendicular to the glass bottom was successful. On the other hand, accurate alcohol content estimation for colored beverages is still challenging. One possible explanation was that we only had six kinds of colored beverages, and thus a regressor might not have enough training data. Future work should investigate estimation performance with a broader set of drinks.

6.2 Limitations

We note that there are several limitations on our prototype device and experiments. The current prototype has not been tested in actual drinking activities due to hygiene issues. Some materials (e.g., glues) used in the current Al-light prototype are not safe for use in drinking scenarios. Future work should investigate the user experience of Al-light and its applications in a realistic setting. Such studies may need additional considerations because they involve alcohol consumption.

The experiment for alcohol concentration estimation included 3 light conditions and 13 different beverages. A future study needs to investigate the performance of Al-light under a broader set of light conditions and drinks. In particular, colored beverages tended to result in large estimation errors. Our beverage set was all manufactured drinks, and we did not test our device with cocktails (mixed manually by people). Because the regulation in the country allows labeling of alcohol concentration levels to have tolerance up to 2 % v/v, our results may need to be revisited with reliable alcohol sensing methods, such as spectroscopic analysis.

We did not measure the power consumption and running time of the current Al-light prototype as it is not the main focus of our work. It is a reasonable assumption that the alcohol concentration of a beverage would not change drastically except for the scenario of creating a cocktail or mixed drink. Thus, sampling on Al-light would not need to be very frequent. A future study should also study the power consumption of Al-light and an efficient power management approach.

Although the current Al-light prototype is not very small yet (31.9 x 38.6 x 52.6 mm), we note that further size reduction of Al-light is possible. We used the off-the-shelf micro controller (RedBearLab BLE Nano 2), but a future design would directly place the chip on a custom-made circuit board. A future device may include a heavier battery and remove weights. We set the gap in the cube to 5 mm, and a future study should examine what the minimum distance is for reliable alcohol concentration estimation.

6.3 Applications

Al-light enables different applications around alcoholic beverage drinking in addition to simple tracking. Our current system supports the following applications to demonstrate the versatility of Al-light. The accompanying video includes the demonstrations of the following applications (Figure 8). Due to the limited number of I/O pins in RedBearLab BLE Nano 2, we are not able to include additional LEDs for user feedback. We thus use a transparent version of Al-light for the demonstration purpose, and the current Al-light devices uses the same RGB LED for both visual feedback and measurements. Future prototypes should include additional light sources for feedback to users.

Individual users may use Al-light for the following applications when they consume alcoholic beverages at home. Restaurants and bars may also want to use Al-light to encourage customers to drink appropriately. The smart cube developed by MARTINI®is also intended to be used in similar settings though the supported scenario is different (i.e., automatic refill ordering). The applications presented in this section are examples that the current Al-light prototype supports in common drinking scenarios.

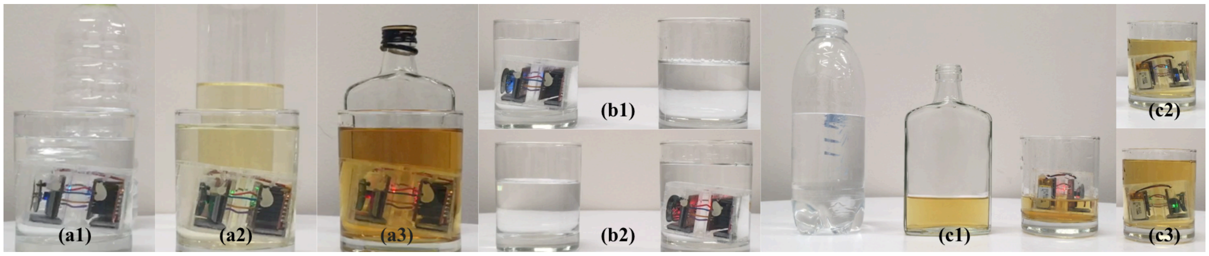


Fig. 8. Al-light application examples. (a) Visualizing alcohol concentration: it blinks in blue, green, and red for (a1) water, (a2) wine, and (a3) whiskey, respectively. (b) Warning to people who cannot drink: it flashes in red to notify them that the beverage of interest contains alcohol (b2). Otherwise, it blinks in blue, indicating that the beverage is safe to drink (b1). (c) Supporting cocktail making: when users reach to the target alcohol concentration level, Al-light blinks in green (c3). Otherwise, it blinks in blue and red if the current alcohol content level is (c2) below or (c1) above the target, respectively.

Visualizing alcohol concentration

Al-light can visualize how strong an alcoholic beverage is. When a user puts Al-light in a beverage, it blinks in various colors to indicate the alcohol content level, ranging from blue (0 % v/v), green (10 % v/v) to red (37 % v/v). In addition, there are people who cannot take any alcohol (e.g., people in pregnancy or people with allergies) and it is difficult to distinguish whether a beverage contains alcohol by its visual appearance. Al-light has a mode dedicated to such user populations. It flashes in red to warn them that the beverage of interest contains alcohol. Otherwise, it blinks in blue, to indicate that the beverage is safe to drink.

Supporting cocktail making

Another application of Al-light is to support users' cocktail making. After choosing a cocktail they desire to create on a smartphone, Al-light is set to detect the target alcohol concentration level. Users then place it into a glass and pour liqueur. When users reach to the target alcohol concentration level, Al-light blinks in green. Otherwise, it blinks in blue and red if the current alcohol content level is below or above the target, respectively. The intensity of the light indicates how far the target concentration level is. In this manner, users can create a cocktail at a desired level of alcohol concentration.

Encouraging slow drinking

Drinking too quickly may cause acute alcohol intoxication, a serious symptom which might lead to death. Al-light can inform users of their drinking pace by changing its blinking speed. The system loosely estimates their drinking pace from a pre-defined number of consecutive 0 % v/v estimations (i.e., time for not drinking or non-alcoholic beverage intaking). If the pace is faster than a threshold, Al-light rapidly flashes in red and blue alternatively to inform them that they should slow down their pace.

7 CONCLUSION AND FUTURE WORK

Alcoholic beverages may harm health when their consumption is too large or rapid. Automatic tracking can help people regulate alcohol consumption, but existing work has under-explored an approach to directly measure beverage alcohol concentration designed for general user populations. We present Al-light, a smart ice cube device which can sense the alcohol concentration level of a beverage. Al-light utilizes the NIR spectrometry principle for alcohol concentration estimation. Our evaluations found that Al-light was able to achieve the estimation accuracy of approximately 2 % v/v with 13 commercially-available beverages if a regressor was trained for a particular ambient light condition or measurements were calibrated with water. Our results also suggest that the system does not require beverage-dependent models. This work demonstrates the feasibility of sensing beverage alcohol concentration in a device form factor suitable to daily use. It thus encourages researchers to further investigate integration of the Al-light technology into existing dietary sensing as well as improvements on estimation accuracy.

Our future work will cover examinations on the user experience of Al-light in drinking contexts. Such studies may include different stakeholders, ranging from consumers to restaurants and bar owners. We also plan to develop mobile apps with Al-light to examine how the technology can encourage people who suffer from drinking problems to change their behaviors. Methanol intoxication is another common problem related to alcohol consumption. Detection of methanol mixing can expand use scenarios supported by Al-light [21]. We will investigate such enhancement as well as its performance in the future.

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