First Bite/Chew: distinguish typical allergic food by two IMUs

Juling Li*
lijuling@mail.ustc.edu.cn
Keio University
Japan

Xiongqi Wang*
aidan108wang@gmail.com
Keio University
Japan

Junyu Chen*
924342513@qq.com
The University of Tokyo
Japan

Thad Starner
thadstarner@gmail.com
Georgia Institute of Technology
United States

George Chernyshov
send.letters.for.me.here@gmail.com
Keio University
Japan

Jing Huang
hkoukenj@gmail.com
Keio University
Japan

Yifei Huang
hyf015@gmail.com
The University of Tokyo
Japan

Kai Kunze
kai@kmd.keio.ac.jp
Keio University
Japan

Qing Zhang
qzkiyoshi@gmail.com
Keio University
Japan

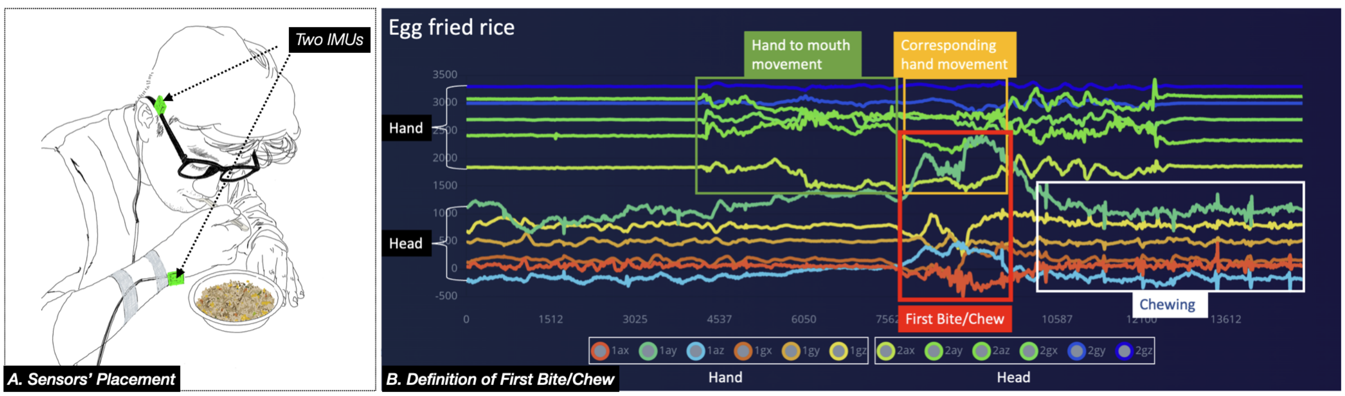

Figure 1: First bite/chew are like the red, and yellow rectangles indicate; they are significantly different from the following bites/chews, which are relatively the same among different food types.

ABSTRACT

Eating or overtaking allergic foods may cause fatal symptoms or even death for people with food allergies. Most current food intake tracking methods are camera-based, on-body sensor-based, microphone based, and self-reported. However, challenges that remain are allergic food detection, social acceptance, lightweight, easy to use, and inexpensive.

Our approach leverages the first bite/chew and the corresponding hand movement as an indicator to distinguish typical types of the allergic food. Our initial feasibility study shows that our approach can distinguish six types of food at an accuracy of 89.7% over all four participants' mixed data. Particularly, our method successfully detected and distinguished typical allergic foods such as burgers (wheat), instant noodles (wheat), peanuts, egg fried rice, and edamame, which can be expected to contribute to not only personal use but also medical usage.

*Three authors contributed equally to this research.

CCS CONCEPTS

• **Human-centered computing** → **Interaction devices**; **User interface toolkits**; • **Hardware**;

KEYWORDS

smart eyewear, food intake, diet monitoring

AHs '23, March 12–14, 2023, Glasgow, United Kingdom

ACM ISBN 978-1-4503-9984-5/23/03.
https://doi.org/10.1145/3582700.3583708

ACM Reference Format:
Juling Li, Xiongqi Wang, Junyu Chen, Thad Starner, George Chernyshov, Jing Huang, Yifei Huang, Kai Kunze, and Qing Zhang. 2023. First Bite/Chew: distinguish typical allergic food by two IMUs. In *Augmented Humans Conference (AHs '23), March 12–14, 2023, Glasgow, United Kingdom.* ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/3582700.3583708

1 INTRODUCTION

Food intake monitoring is intensively explored, in which manual food intake estimation methods contribute to poor accuracy [6, 15]. Manual methods also require significant time and effort and are prone to be forgotten or abandoned [11]. Smartphone methods are also inconvenient as the user must stop eating to interact with the phone. Such wearable agents [17] can significantly reduce the amount of time between a user's first intention to do a task and their first action to do it [16], which greatly increases the likelihood that the interface will be used [18]. Another constraint for many users is that they do not want to wear devices that call unnecessary attention to themselves or might cause onlookers to believe the user has a disability [12].

This work's key contribution is the concept of First Bite/Chew-based allergic food detection system. Our approach has several benefits: (1) computational simplicity: our system only contains two IMUs (one is built-in the following MCU) and an inexpensive machine-learning capable MCU[1] as the main parts, (2) easy-to-use: to monitoring the different types of food intake, our approach does not require extra manual practice and heavy load of learning, (3) replicable: our approach can be easily replicated concerning cost and design, (4) socially acceptable appearance: as our method does not require camera nor bulky computational heavy design, but maintained an ordinary glasses-like appearance.

2 RELATED WORKS

Current food intake monitoring methods can be roughly categorized as IMU-based, IMU combined with other sensors, image process-based, sound-based, and wearable on-body sensor based. **IMU sensor-based.** Kim et al. [8] provided a smartwatch-based method to address different eating patterns and food types and only handled rice and noodle in their tests. **Sound based.** Sound-based food intake detection has two main methods. The most studied one is using microphones from hearing aids, earphones, or headsets to capture users' chewing noise and use it as an indicator of food intake action[11]. **Image-based.** Regarding image-analysis-based methods, processes like image segmentation, food recognition, and portion size estimation are required to complete food intake estimation [6]. **Glasses-based chewing detection.** Mertes et al. [9, 10] developed a glasses-based method that detects the chewing motion of elderly people. Chung et al. [4] designed a pair of smart glasses that can classify food intake motions from physical activities.

However, to our knowledge, none of those existing smart glasses-based studies could distinguish different types of food, especially those allergic to food that could be fatal threats.

3 OUR APPROACH: FIRST BITE/CHEW BASED FOODS INTAKE MONITORING

Our approach leverages the first bite/chew and the corresponding hand movement as an indicator to distinguish the typical allergic types of food. As Figure 2 shows, the concept of first bite/chew contains two parts of signals. The first part (red rectangle) is the data generated by biting/chewing as well as the head and muscles' activities responding to the food during the first biting or chewing. The other part (orange rectangle) is the movement data of the hand that grabs and moves the food during the first biting/chewing period.

Hardware Design. To design the device that can obtain the first biting and/or chewing vibration via skull and muscles, we attached an IMU[2] on the inner side (near the head) of the glasses' right leg – close to the area of superior auricular muscle and temporalis muscle referring [5]. See Figure 3. To also obtain the corresponding movements of the hand during the biting/chewing, we leveraged an IMU[3]-embedded MCU[4] and designed a wristband connected to the IMU on the glasses' leg with four wires via IIC-Bus. The device connects to a MacBook pro laptop (i7 16gb) with a type-c cable.

4 INITIAL FEASIBILITY STUDY

To evaluate the concept of first bite/chew, we conducted an initial feasibility study having four participants (two male and two female), aged from 23 to 32, MEAN = 26.5, SD = 3.4. They were compensated by gift cards for their time. Their eating activities data were recorded during their self-reported general meal time. In total, we recorded five meals for each participant in three days. Participants were required to confirm and sign a consent form and allergic food checking form, and they were also asked *food and drink prohibitions* to make sure no one takes inappropriate foods.

Foods Selection. To examine the feasibility of our approach while distinguishing allergic food from daily non-allergic food, we selected five types of the common allergic food. They are peanuts, edamame, burger, instant noodle, and egg (fried rice), among which burgers and noodles both stand for the allergen of gluten. We also selected one type of commonly non-allergic food, which is apple. The food selection was based on Hefle et al. [7] and other related works on food allergy [1–3, 13, 14, 14].

4.1 Result & ML Model Structure

For the food category recognition, a single-layer Neural Network with 20 fully connected neurons was adopted. We trained and tested the classifier over four participants' mixed data by using 80% as training data and the remaining 20% as testing data. As the figure 5 shows, the classifier achieves an overall accuracy of 89.7%. In detail, 82.4% accuracy for distinguishing Burgers, 84.8% for Edamame, 96.6% for Egg fried rice, 87.7% for Noodles, 92.9% for Peanuts, and 94.7% for Unknown food (apple).

5 DISCUSSION & LIMITATION

Currently, the system is at risk of distinguishing allergic food mixed in other materials, for the food texture can be somewhat different from the original. Distinguishing foods with similar textures and eating manners is also challenging. To minimize the contact between allergic food and actual patients, as well as in terms of real-life usage, advanced machine learning designs such as Few-shot learning could contribute to building ready-to-use by using the data generated from people who experience no or few food allergies.

[1]Micro Controller Unit

[2]MPU6050 based IMU modular module.

[3]LSM6DS3

[4]Seeeduino Xiao BLE sense. https://www.seeedstudio.com/Seeed-XIAO-BLE-Sense-nRF52840-p-5253.html

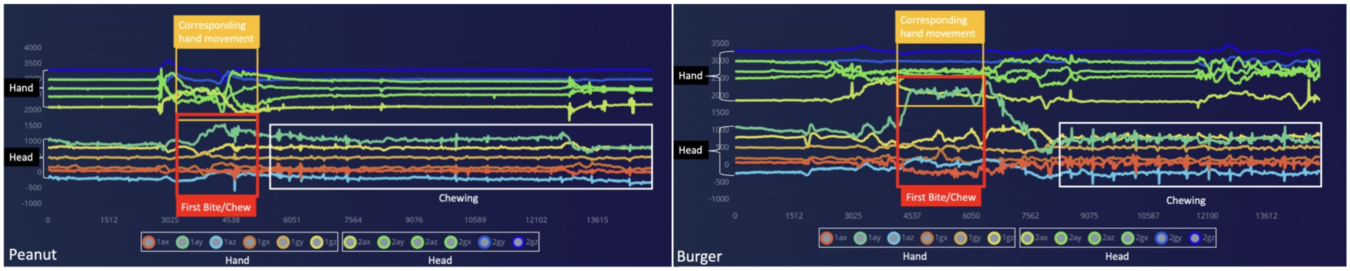

Figure 2: Examples of defining first bite/chew of different types of food.

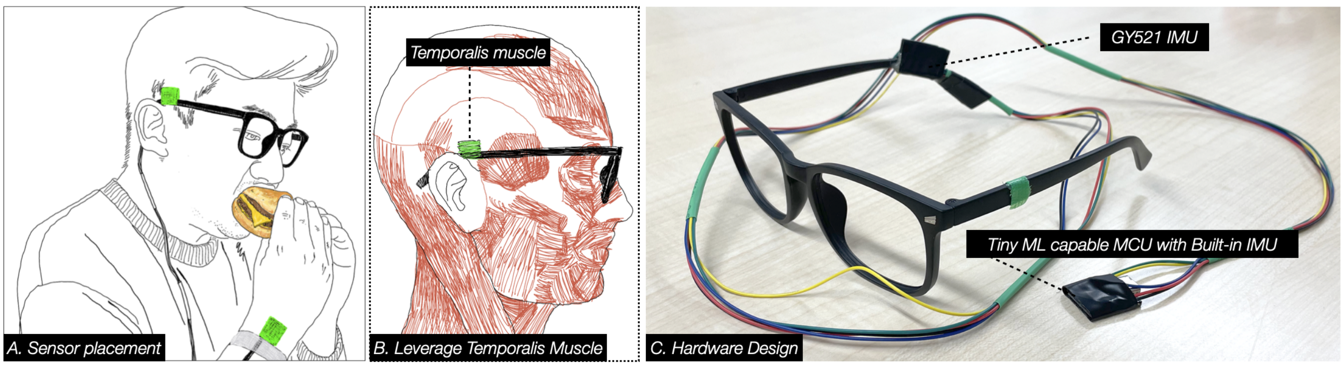

Figure 3: Hardware design and the sensors placement.

Figure 4: Six types of the selected food.

Confusion matrix

	BURGER	EDAMAME	EGG FRIED RICE	NOODLE	PEANUTS	UNKNOWN
BURGER	82.4%	11.8%	2.0%	2.0%	2.0%	0%
EDAMAME	3.6%	84.8%	0.9%	2.7%	3.6%	4.5%
EGG FRIED RICE	0%	1.7%	96.6%	0%	0%	1.7%
NOODLE	1.2%	7.4%	3.7%	87.7%	0%	0%
PEANUTS	0%	5.1%	0%	2.0%	92.9%	0%
UNKNOWN	0%	1.3%	3.9%	0%	0%	94.7%
F1 SCORE	0.86	0.84	0.92	0.90	0.94	0.94

Figure 5: Confusion matrix, F1 score and on-device performance.

6 CONCLUSION

In this work, we proposed a computationally simple and easy-repeatable approach for automatic food intake monitoring by leveraging the First Bite/Chew as the indicator. The initial feasibility evaluation reveals that our approach could distinguish five typical types of allergic food (burger, noodle, peanut, egg fried rice, and edamame) during common eating styles with an average accuracy of 89.7%.

ACKNOWLEDGMENTS

This work is partly supported by IoT Accessibility Toolkit JST Presto Grant Number JPMJPR2132; JST SPRING, Grant Number JPMJSP2123.

REFERENCES

[1] Barbara K Ballmer-Weber and Stefan Vieths. 2008. Soy allergy in perspective. *Current opinion in allergy and clinical immunology* 8, 3 (2008), 270–275.
[2] S Allan Bock and FM Atkins. 1989. The natural history of peanut allergy. *Journal of Allergy and Clinical Immunology* 83, 5 (1989), 900–904.
[3] Jean-Christoph Caubet and Julie Wang. 2011. Current understanding of egg allergy. *Pediatric Clinics* 58, 2 (2011), 427–443.
[4] Jungman Chung, Wonjoon Oh, Dongyoub Baek, Sunwoong Ryu, Won Gu Lee, and Hyunwoo Bang. 2018. Design and evaluation of smart glasses for food intake and physical activity classification. *JoVE (Journal of Visualized Experiments)* 132 (2018), e56633.
[5] Abul Doulah, Tonmoy Ghosh, Delwar Hossain, Masudul H Imtiaz, and Edward Sazonov. 2020. "Automatic ingestion monitor version 2"–a novel wearable device for automatic food intake detection and passive capture of food images. *IEEE Journal of Biomedical and Health Informatics* 25, 2 (2020), 568–576.
[6] Hamid Hassannejad, Guido Matrella, Paolo Ciampolini, Ilaria De Munari, Monica Mordonini, and Stefano Cagnoni. 2017. Automatic diet monitoring: a review of computer vision and wearable sensor-based methods. *International journal of food sciences and nutrition* 68, 6 (2017), 656–670.
[7] Susan L Hefle, Julie A Nordlee, and Steve L Taylor. 1996. Allergenic foods. *Critical Reviews in Food Science & Nutrition* 36, S1 (1996), 69–89.
[8] Hyun-Jun Kim, Mira Kim, Sun-Jae Lee, and Young Sang Choi. 2012. An analysis of eating activities for automatic food type recognition. In *Proceedings of the 2012 asia pacific signal and information processing association annual summit and conference*. IEEE, 1–5.
[9] Gert Mertes, Hans Hallez, Tom Croonenborghs, and Bart Vanrumste. 2015. Detection of chewing motion using a glasses mounted accelerometer towards monitoring of food intake events in the elderly. In *International Conference on Biomedical and Health Informatics*. Springer, 73–77.
[10] Gert Mertes, Hans Hallez, Bart Vanrumste, and Tom Croonenborghs. 2017. Detection of chewing motion in the elderly using a glasses mounted accelerometer in a real-life environment. In *2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 4521–4524.
[11] Sebastian Päßler, Matthias Wolff, and Wolf-Joachim Fischer. 2011. Food intake recognition conception for wearable devices. In *Proceedings of the First ACM MobiHoc Workshop on Pervasive Wireless Healthcare*. 1–4.
[12] Halley Profita, Reem Albaghli, Leah Findlater, Paul Jaeger, and Shaun K Kane. 2016. The AT effect: how disability affects the perceived social acceptability of head-mounted display use. In *proceedings of the 2016 CHI conference on human factors in computing systems*. 4884–4895.
[13] Hugh A Sampson, Louis Mendelson, and James P Rosen. 1992. Fatal and near-fatal anaphylactic reactions to food in children and adolescents. *New England Journal of Medicine* 327, 6 (1992), 380–384.
[14] Jessica H Savage, Allison J Kaeding, Elizabeth C Matsui, and Robert A Wood. 2010. The natural history of soy allergy. *Journal of Allergy and Clinical Immunology* 125, 3 (2010), 683–686.
[15] Dale A Schoeller. 1995. Limitations in the assessment of dietary energy intake by self-report. *Metabolism* 44 (1995), 18–22.
[16] Thad Starner. 2013. Project glass: An extension of the self. *IEEE Pervasive Computing* 12, 2 (2013), 14–16.
[17] Thad E Starner. 2002. Wearable agents. *IEEE pervasive computing* 1, 2 (2002), 90–92.
[18] Thad E Starner, Cornelis M Snoeck, Benjamin A Wong, and R Martin McGuire. 2004. Use of mobile appointment scheduling devices. In *CHI'04 Extended Abstracts on Human Factors in Computing Systems*. 1501–1504.