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Master's Thesis
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Mouth Movements Based Tracking of Dietary Habits on Smart Glasses

Keio University
Graduate School of Media Design

Xiongqi Wang

A Master's Thesis
submitted to Keio University Graduate School of Media Design
in partial fulfillment of the requirements for the degree of
Master of Media Design

Xiongqi Wang

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Abstract of Master's Thesis of Academic Year 2023

Mouth Movements Based Tracking of Dietary Habits on Smart Glasses

Category: Science / Engineering

Summary

Unbalanced dietary habits can lead to various health issues, including obesity, type 2 diabetes, high blood pressure, elevated cholesterol, and heart disease. The situation can become particularly critical for those with severe food allergies, where accidental consumption of allergenic foods may cause life-threatening reactions or even death. Existing food tracking methods largely fall into four categories: camera-based, on-body sensor-based, microphone-based, and self-reported.

The persisting challenges include detecting commonly allergenic foods, ensuring social acceptance, maintaining a lightweight design, ensuring ease of use, and affordability. Our approach uses a 6-axis IMU on the arm of glasses and a machine learning-enabled MCU on the wrist to identify the user's eating activities and the associated differences. We found that the initial bite or chew can be a consistent and trustworthy signal to differentiate between types of food. Our method can provide information about the actual amount of food consumed.

Our implementation results demonstrate that our technique can distinguish between seven kinds of food with an average accuracy of 93.26% across all four participants. Notably, our method successfully identified and differentiated commonly allergenic foods like burgers (containing wheat), peanuts, and edamame. This suggests our system's potential for both personal and medical applications.

Keywords:

smart eyewear, food intake, diet monitoring, privacy

Keio University Graduate School of Media Design

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This dissertation largely draws upon our earlier works, specifically "First Bite/Chew: Distinguish Different Types of Food by First Biting/Chewing and the Corresponding Hand Movement," published in the proceedings of the 2023 CHI Conference on Human Factors in Computing Systems, and "First Bite/Chew: Distinguish

Typical Allergic Food by Two IMUs," presented at the Augmented Humans Conference in 2023. These studies serve as the bedrock for the research outlined in this dissertation, with segments of their original content being repurposed to elaborate further on the fundamental principles and findings.

Chapter 1
Introduction

Tracking one's food consumption, either utilizing food diaries can be critical to identify potential food allergies or intolerances a person might have. Moreover, these diaries can help manage conditions such as diabetes, obesity, heart disease, high cholesterol, and hypertension. Yet, manual food intake recording methods are notoriously inaccurate, often by as much as 50%. [7]. Traditional Paper-based journalling methods [8] demand significant time and effort, and are often forgotten or abandoned due to these factors [4]. The accuracy of the food intake records largely depends on the individual's dedication to maintaining the diary. [7].

Using smartphones for food tracking has its drawbacks too, as users need to interrupt their meals to input data. Consider instead, an audio-enabled wearable device that could be attached to an earpiece or a pair of glasses. This device could monitor the user's activity and make educated guesses about what the user is eating when it identifies an eating event. [9]. For example, it could inquire, "Are you eating an apple?" The user could confirm or deny by a nod of the head, and if the answer is negative, the device could then ask the user to specify what they are consuming and log the response. Wearable devices [10] have shown the potential to significantly minimize the time gap between a user's intention to perform a task and their actual action [11], leading to a higher probability of user engagement with the interface [12]. Additionally, many users are hesitant to use devices that draw unnecessary attention to themselves or create misconceptions about their abilities [13].

This dissertation introduces a discreet wearable system designed to resemble standard optical glasses, enabling the wearer to differentiate between various foods they consume. The system comprises two IMU (Inertial Measurement Unit) sensors: one captures the vibrations generated during biting and chewing, while the other records the accompanying hand movements during eating activities (refer

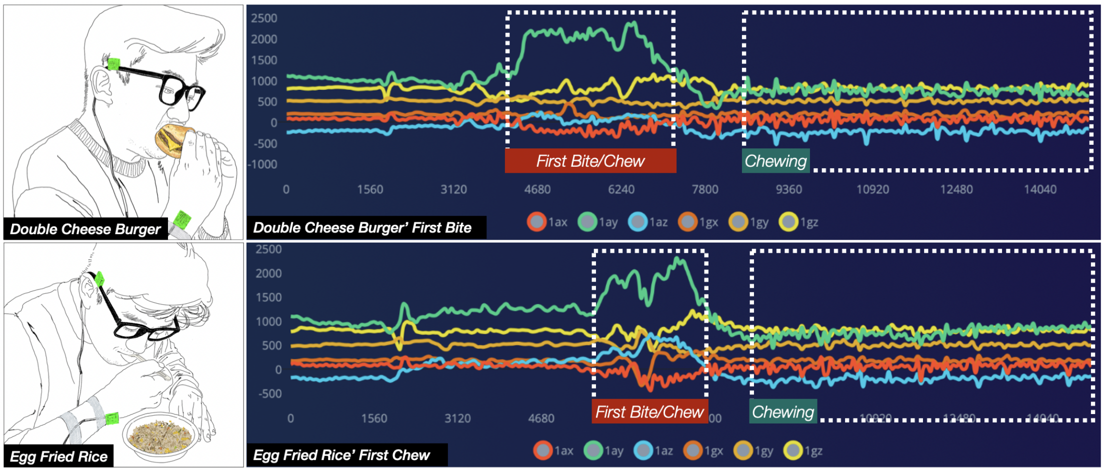


Figure 1.1 First bite/chew are like the white rectangles indicate, they are significantly different from the following bites/chews which are relatively the same among different food types.

to Figure 1.1). In an initial user study, our approach successfully distinguished seven food types with an impressive accuracy of 93.26% (n=4). The foundation of this dissertation significantly draws from my own research work titled "First Bite/Chew: Distinguish Different Types of Food by First Biting/Chewing and the Corresponding Hand Movement," [14], which was published in the proceedings of the 2023 CHI Conference on Human Factors in Computing Systems. Additionally, my other publication titled "First Bite/Chew: Distinguish Typical Allergic Food by Two IMUs" [15] presented at the Augmented Humans Conference in 2023, has also informed this dissertation. These seminal works serve as the cornerstone for the research propounded in this dissertation, with certain sections of their original content being adopted to shed more light on the fundamental principles and discoveries.

The approval of these works by high-ranking academic conferences has bolstered our confidence in the potential and validity of this research approach. The main contribution of this research is the novel concept of First Bite/Chew-based food type detection, which takes into consideration the design of wearable technology and its social acceptability. Our first bite/chew-based approach has several benefits:

1. Precise food intake: In contrast to existing studies that offer calorie estimations for certain foods, our method detects the exact number of bites a user consumes, ensuring more accurate food journaling.

2. Computational simplicity: Our system consists of only two IMUs and an affordable, machine-learning capable MCU (Micro Controller Unit) as the primary components.

3. User-friendly: Monitoring food intake with our approach does not demand extra practice or learning, making it easy for users to adopt.

4. Reproducible: Thanks to its cost-effectiveness and simple design, our approach can be easily replicated by others.

5. Potentially socially acceptable appearance: Our method does not require a camera or bulky battery (i.e., large glasses' legs), maintaining a socially acceptable, standard optical glasses-like appearance.

To validate our claims, this dissertation proposes two main research questions. Firstly, can a wearable system using two IMU sensors and a machine-learning capable MCU distinguish among various types of food accurately and consistently, while maintaining a potentially socially acceptable appearance? Secondly, how does the proposed First Bite/Chew-based approach contribute to the accuracy, usability, and social acceptance of an automatic food intake monitoring system compared to existing solutions? These questions guide our research and system evaluation.

Chapter 2
Background and Related Works

2.1. Human-computer interaction

Human-Computer Interaction (HCI), a vibrant multidisciplinary domain, strives to bridge the gap between users and computing technology. It involves a meticulous study of the interface that forms the point of contact between humans and computers, with a focus on developing designs that facilitate a more intuitive interaction. The primary objective of HCI, as defined by Carroll [16], is to elevate the quality of interactions between users and computers. This is accomplished by ensuring that the computational systems are more receptive to user requirements and are designed in a way that promotes user-friendliness. This objective forms a fundamental principle of our dissertation, guiding the design and development of the proposed system. The discipline of Human-Computer Interaction (HCI) extends beyond the boundaries of the design and application of computer technology, particularly in relation to the interfaces connecting humans and computers. It delves deeper into understanding how computers affect individuals, organizations, and the society at large. HCI research has been phenomenally successful, and its impact on technology, business, and society has been vast [17]. Optimal HCI design focuses on empowering users to interact with technology in a manner that best aligns with their needs and objectives. This necessitates an understanding of how humans engage with computers and consequently, the creation of technologies that enable novel forms of these interactions. HCI involves the study, planning, and design of the interaction between people and computers. HCI is a multidisciplinary domain that synergizes the knowledge from computer science, behavioral sciences, design, among other fields of study [18]. It encapsulates the interactions occurring at an interface, an amalgamation of both hardware and software elements. For example, characters are displayed on a screen by a software program in response to typing on the keyboard. This concept has evolved significantly over the past few decades, from early command-line interfaces to graphical interfaces to today's natural user interfaces. It is shifting towards interaction techniques that allow a more human-centred process, considering both human limitations and advantages in the design process [19]. These shifts are reflected in the interaction design of smartphone applications, computer software, and various technology-enabled devices where ease of use, understanding, functionality, and aesthetics are the cornerstones of the overall user experience. HCI also addresses the socio-technical issues and challenges in the use of computers in the digital era. For example, the design of e-commerce systems should consider trust, security, privacy, and other similar factors. HCI studies such phenomena and devises the best ways to ensure the successful interaction between the user and the computer, which leads to productive, safe, and satisfying user experiences [20]. Moreover, HCI's role extends to the design of user interfaces, creating systems and technologies that are accessible, easy to use, and efficient. This aspect is especially critical in the development of systems for people with disabilities or those who may not be technically inclined. HCI principles help designers create interfaces that cater to a broader audience, making technology more inclusive and available to all [21]. As we continue to evolve and innovate, the importance of the field of HCI grows more apparent. There is still much to explore and understand about how humans interact with the growing array of digital technologies that are becoming an integral part of everyday life. With this, the demand for effective HCI design is more critical than ever. As technology continues to evolve and permeate our lives, the importance of human-computer interaction (HCI) becomes even more evident. It is vital to consider the human aspect in the design and use of these digital systems, leading to an increased emphasis on user experience (UX). The UX domain focuses on understanding and enhancing people's experiences, perceptions, and responses when interacting with products and services [22]. The understanding of UX is crucial in HCI as it shapes the design principles and decision-making processes, which subsequently leads to more intuitive, efficient, and enjoyable products.

One key challenge in HCI is to manage the complexity of the increasingly sophisticated digital systems. As we are presented with an overwhelming amount of data and options, the role of HCI is to design interaction techniques and interfaces that make these systems accessible and usable. This involves leveraging cognitive psychology to understand how humans process information and how this can guide the design of information displays and interaction mechanisms [23].

Moreover, HCI plays a crucial role in improving accessibility and inclusivity in technology. As digital technology has become an essential part of our lives, it is critical to ensure that everyone, including people with disabilities and the elderly, can use these technologies effectively. This includes designing interfaces that are easy to see, hear, and manipulate, and developing adaptive technologies that can cater to different user abilities and preferences [24].

HCI is also involved in addressing the "digital divide" — the gap between those who can access and benefit from digital technology and those who cannot. This is not just about providing physical access to technology, but also about ensuring that people have the skills and knowledge to use these technologies effectively. HCI researchers are investigating ways to make technology more accessible and understandable to a broader range of users, including those with low digital literacy [25].

As artificial intelligence (AI) and machine learning (ML) technologies are increasingly integrated into digital systems, HCI also needs to deal with the unique challenges and opportunities that these technologies present. This includes designing interfaces that can effectively communicate the capabilities and limitations of AI/ML systems, and understanding how these systems can support human decision-making [26]. HCI researchers are also exploring ethical issues related to AI/ML, such as data privacy, algorithmic bias, and the impact of automation on jobs and society [27].

In the era of social media and online communities, HCI is also concerned with how people interact with each other through digital platforms. This involves understanding how people present themselves online, how they form relationships and communities, and how these interactions can be facilitated and supported by technology [28]. HCI researchers are also investigating the impact of social media on society, including issues like online harassment, misinformation, and the impact on mental health [29].

In conclusion, HCI is a multifaceted field that lies at the intersection of technology, human behavior, and society. It plays a crucial role in shaping the way we interact with technology and the impact that technology has on our lives. As digital technologies continue to evolve and become more integrated into our lives, the importance of HCI will continue to grow.

2.2. Food intake

The importance of knowing and remembering food intake is extremely significant, especially for individuals with certain medical conditions like diabetes and gout, for those who suffer from bad eating habits , and for the elderly.

For example, diabetes is a condition that requires careful dietary management. According to the American Diabetes Association, a balanced diet is crucial in maintaining blood glucose levels [30]. This is not only about the types of food eaten, but also the quantity, as excessive intake of even “healthy” foods can cause sugar levels to spike. For people with diabetes, it is essential to remember what and how much they have eaten, in order to calculate insulin doses correctly. If they forget, they risk taking too much or too little insulin, leading to dangerously high or low blood glucose levels [31].

In a parallel context, dietary habits have a profound influence on conditions like gout, a form of inflammatory arthritis. Gout is primarily instigated by the accumulation of uric acid crystals in the joints, a phenomenon frequently triggered by the intake of foods rich in purines [32]. Consequently, accurate recollection of food consumption becomes a pivotal aspect for individuals with gout, as it aids in managing their condition and averting the occurrence of painful flare-ups. This illustrates yet another scenario where our proposed wearable technology, which facilitates precise food intake tracking, could prove invaluable.

Overworking of muscles, such as the masseter and temporalis involved in chewing, can have detrimental consequences. When these muscles are consistently stressed beyond their capacity, it can lead to muscle strain. This strain can present itself as discomfort or pain in the jaw region, sometimes extending to the neck and shoulders. Over time, if the overuse continues, these muscles may undergo hypertrophy, where they become enlarged and stiff, further exacerbating discomfort [33].

As for the elderly, especially those with cognitive decline or dementia, remembering what they have eaten can be challenging. Yet, it is essential to ensure adequate nutrient intake and prevent malnutrition. In such cases, remembering food intake could help caregivers to plan meals and track nutritional status [34].

Furthermore, monitoring and remembering food intake is not only crucial for disease management, but it also plays an integral role in preventing the onset of certain medical conditions. Overeating and consuming foods high in fats, sugars, and salts are major risk factors for conditions such as obesity, hypertension, and cardiovascular diseases [35, 36]. These conditions are preventable and can be mitigated with a healthy diet, reinforcing the significance of understanding and recalling food intake.

The importance of monitoring food intake is amplified in the context of weight management. Evidence has shown that keeping track of dietary intake can contribute to successful weight loss and maintenance [37]. Individuals who can accurately recall what and how much they have eaten can make necessary adjustments to their eating habits and physical activity to achieve their weight goals.

Moreover, in the context of maintaining healthy masticatory muscles and promoting good eating habits, understanding and remembering food intake extends beyond the individual to caregivers, particularly parents of young children. Children may not yet have the understanding or capacity to monitor their own food intake accurately and could unintentionally consume foods that are detrimental to the health of their masseter and temporalis muscles, or contribute to the development of bad eating habits [38]. Parents and caregivers need to be vigilant about what their child eats, especially in social settings where foods associated with poor muscle health or bad eating habits, such as fast food or sugary snacks, may be present.

This is further relevant in the case of the elderly, where food intake monitoring can aid in identifying nutritional deficiencies and rectifying them promptly. This is of utmost importance in conditions like osteoporosis, where sufficient calcium and vitamin D intake is crucial [39]. Furthermore, for the elderly living independently, monitoring food intake can also help identify changes in eating habits, which could be early indicators of cognitive decline, depression, or other health issues [40].

In light of these insights, it's evident that the significance of knowing and remembering food intake extends to various aspects of human health, encompassing individuals in every stage of life. This includes children and adults striving to maintain healthy masticatory muscles and promote good eating habits, as well as those managing chronic conditions or trying to ensure adequate nutrition during aging [41, 42].

As we progress in the era of technology and data, innovative solutions that assist individuals in monitoring their food intake will prove invaluable in promoting healthier lifestyles and managing medical conditions. Such methods can play a crucial role in curbing the negative effects of poor eating habits on muscle health and overall well-being.

In conclusion, monitoring food intake is not only vital for managing the health of masticatory muscles and preventing the adverse consequences of bad eating habits, but it can also have life-saving implications. With the growing prevalence of conditions linked to muscle health and dietary choices, there is a pressing need for new technologies that aid individuals in accurately tracking and remembering their food intake, thus empowering them to make informed choices for better health.

2.3. Personal privacy

Navigating the terrain of personal privacy protection is paramount in our digitally interconnected era. With the boundaries between personal and public life becoming increasingly indistinct, the inherent human right to privacy—endorsed by the UN Declaration of Human Rights, the ¡International Covenant on Civil and Political Rights¿, along with numerous international and regional treaties—faces escalated vulnerability [43]. Protecting this right is essential as it serves as the foundation for many democratic societies' valued liberties, such as "freedom of speech, freedom of thought, and freedom of association" [44].

In the digital age, personal privacy protection takes on added significance. The extensive use of digital technologies, such as social media, online banking, and e-commerce platforms, has led to an unprecedented volume of personal data being collected, stored, and shared online [45]. This data, encompassing everything from financial information to health records to location data, can be extremely sensitive.

If mishandled, it can be exploited for a range of nefarious purposes, including identity theft, online harassment, and more sophisticated forms of cybercrime [46].

But privacy is not solely about safeguarding ourselves from harm; it also concerns preserving our autonomy. In his landmark study on privacy, renowned legal scholar Alan Westin posited that privacy fundamentally pertains to an individual's entitlement to determine the circumstances, manner, and extent to which their personal information is shared with others [43]. This influential concept underscores the critical role of personal agency and informed consent in the discourse on privacy, particularly in the age of digital information sharing and consumption. In essence, privacy is about autonomy – our capacity to make decisions about our lives, free from unwelcome interference from others.

However, this autonomy is increasingly under siege in the digital age. The proliferation of digital technologies has afforded corporations, governments, and other entities unprecedented access to our personal data, often without our knowledge or consent [27]. This invasion can result in numerous adverse consequences, ranging from discrimination and stigmatization to a loss of trust in digital technologies and broader institutions [47].

Personal privacy protection is also integral to preserving our democratic institutions. Democracy is founded on principles of transparency and accountability, which can only be maintained if individuals can freely express their thoughts and opinions without fear of retribution or surveillance. Yet, the extensive collection and utilization of personal data can undermine this freedom, instigating a chilling effect on free speech and democratic participation [48].

Moreover, privacy concerns in wearable devices such as Google Glass have garnered significant attention. As these technologies become more deeply woven into the fabric of our lives, they encroach upon our personal and private spaces, often without our full knowledge or consent [49]. Google Glass, while lauded for its advanced technical capabilities and potential applications, has elicited criticism due to its implications for privacy. This wearable technology's capacity to capture photos, record videos, and access information hands-free raises numerous questions about consent, surveillance, and the balance between public and private spaces [50].

Challenges revolve around consent, especially in public spaces. Traditional recording devices make it clear when someone is recording or taking a photo, but Google Glass renders this less obvious, enabling recording individuals without their knowledge or consent [51]. This capability can have serious implications for personal privacy, as individuals may lose control over when or how they are recorded. Additionally, the integration of a camera into a wearable device like Google Glass transforms the wearer into a walking surveillance camera [52]. Consequently, individuals might find themselves under constant surveillance, altering their behavior due to the potential for constant observation [53].

Besides, Google Glass can blur the distinction between public and private spaces. Its ability to record and share experiences in real-time exposes traditionally private or intimate moments to a wider public, often without the consent of those involved [54]. Furthermore, the integration of facial recognition technology with Google Glass introduces additional privacy concerns. Third-party developers have created apps capable of identifying individuals and accessing their personal information [55], potentially leading to misuse of personal data [56].

Various solutions have been proposed in response to these privacy concerns. Some advocate for regulation to protect privacy, including restrictions on recording without consent and stronger data protection laws [57]. Others propose technological solutions, such as "privacy by design," where privacy protections are integrated into the technology itself [58]. For instance, Google Glass could be designed to make it more evident when it is recording or to give individuals the option to opt-out of being recorded.

In conclusion, while technologies like Google Glass hold immense potential, they also pose significant challenges to personal privacy. As these technologies become more prevalent, it will be critical to navigate these challenges to protect individuals' rights to control their personal information and preserve their private spaces. We must prioritize privacy protections and advocate for policies and practices that respect and uphold this fundamental right in this digital era.

2.3.1 Food related privacy

While the world is increasingly moving towards a digital future where data is ubiquitous, the importance of privacy, particularly in personal matters such as dietary habits, is paramount [59]. As our understanding of health and nutrition evolves, there is an understandable interest in collecting and analyzing dietary data. However, this interest must be balanced against individuals' rights to privacy and freedom of choice.

Many people enjoy junk food as part of their diet. While there are undeniable health implications related to the excessive consumption of such foods, individuals also have the right to enjoy their preferred foods without public scrutiny or shame [60]. People's food choices can be personal and can be influenced by numerous factors including cultural background, personal preferences, economic situation, and psychological factors [61].

The pressure and stigma associated with dietary choices can have significant psychological impacts. Shaming people for their food choices can lead to a variety of negative outcomes, including body dissatisfaction, decreased self-esteem, and even disordered eating [62]. It is therefore crucial to approach the topic of diet with sensitivity and respect for personal choices and privacy.

In this light, digital health technologies that monitor dietary habits should be designed with privacy and consent as central considerations [63]. Users should have full control over who has access to their dietary data and how it is used. The privacy design should also consider the potential for unintentional shaming or pressure based on the data collected.

In conclusion, while junk food consumption can have health implications, individuals have the right to enjoy their dietary preferences without being subjected to shame or stigma. Respect for dietary privacy is an essential aspect of personal freedom and dignity. Technological advancements, while offering exciting possibilities for health and wellness, should also respect and uphold this right to privacy [64].

2.4. How We Eat

The process of eating is a remarkably intricate one, requiring coordinated movements from various parts of the body. This intricate dance of actions involves everything from major gross motor movements such as the use of our hands and arms to the fine motor control exhibited by our facial muscles and tongue.

The act of eating commences with the hand movements involved in food pickup, guided by the eyes, and then bringing it to the mouth. This movement requires intricate coordination involving several muscles and joints. Specifically, the movements incorporate the shoulder's ball-and-socket joint, the hinge joint at the elbow, and the complex structure of the wrist and hand. The action is controlled by the cerebellum and the motor cortex in the brain [65].

Once the food is near the mouth, a complex symphony of facial and oral muscle movements begins. Opening the mouth is facilitated by the depressor muscles of the mandible, most notably the digastric muscle, which pulls the lower jaw downward [66]. At the same time, muscles such as the masseter and temporalis, some of the strongest muscles in the body for their size, prepare to close the mouth and begin the process of chewing [67].

The temporalis muscle, situated on the skull's side, exhibits a broad, fan-like structure. This muscle is crucial for mandibular elevation and retraction, thereby playing a pivotal role in the process of mastication. When we chew, the temporalis muscle undergoes contraction, drawing the mandible upwards. This action contributes substantially to the teeth's crushing and grinding function, integral to the process of breaking down food for digestion [67].

Simultaneously, the tongue plays a significant role in the eating process. It not only aids in food manipulation within the mouth, but also assists in the formation of a bolus, the ball of food ready to be swallowed [68]. The intricacy of this action calls for exacting control and coordination of the tongue's numerous muscles. These include intrinsic muscles, responsible for modifying the tongue's shape, and extrinsic muscles, which adjust the tongue's position. Together, these sets of muscles facilitate the intricate movements and functionality of the tongue during various activities, including speech and ingestion [66].

The process of mastication, commonly known as chewing, commences as soon as the food enters the mouth. The primary role of the teeth at this stage is to fragment the food into more manageable pieces, thereby expanding the surface area exposed to the digestive enzymes present in the saliva. This crucial action is enabled by the synergistic function of masticatory muscles, namely the masseter, temporalis, and the medial and lateral pterygoids, which collectively manage and guide the process of breaking down food in the mouth [69].

Throughout mastication, a series of complex inter-mouth movements take place.

The tongue, lips, and buccinator muscles in the cheeks work in team to keep the food between the teeth, moving it around so it can be efficiently broken down. Additionally, these intricate movements aid in integrating the food with saliva, a crucial step in creating the bolus — a small rounded mass of food ready for swallowing [70].

The bolus is then ready for swallowing, also known as deglutition. This act of swallowing necessitates a sophisticated procedure involving the concerted efforts of the pharyngeal muscles and the esophagus. The tongue pushes the bolus towards the back of the oral cavity and into the pharynx, triggering the swallowing refle [71]. Simultaneously, the soft palate ascends to restrict the bolus from accessing the nasal cavity, while the larynx rises allowing the epiglottis to shield the tracheal entrance, thereby averting any aspiration [72]. An essential component of the eating process is the hand-to-mouth movement. This seemingly simple action is a complex ballet of coordinated muscle contractions and relaxations. The hand-to-mouth movement starts with the flexion of the arm at the shoulder and elbow joints. Simultaneously, there is a subtle rotation at the wrist to orient the hand and fingers appropriately. Muscles like the biceps brachii, brachialis, and brachioradialis primarily manage the bending of the elbow, while deltoid and pectoralis major control shoulder flexion [73]. The complex structures of the carpal bones, the arrangement of the wrist and hand's flexor and extensor muscles, and the intricate web of nerves and tendons all contribute to the dexterity and flexibility of the hand and fingers [66].

The hand, guided by the somatosensory and visual feedback, is key to identifying, securing, and manipulating the food. This process involves the movements of numerous joints in the hand, coordinated by the activity of various muscle groups [65]. In this, the muscles of the hand — such as the flexor digitorum superficialis and profundus, the flexor pollicis longus, and the intrinsic muscles of the hand — play a crucial role. They enable the fine motor control that allows us to manipulate food objects of various sizes, textures, and shapes [73].

During this action, the head's movement ensures proper positioning for the food's acceptance. The neck muscles, such as the sternocleidomastoid and the scalenes, play a significant role in providing stability and movement to the head [66]. In most cases, the head remains relatively stable to facilitate easier hand-to-mouth coordination, but slight adjustments can be made by flexing, extending, or tilting the head, depending on the context.

One particular movement that is noteworthy is the anticipatory opening of the mouth as the hand approaches with the food. The opening of the mouth in anticipation of the food is a complex coordination of muscles in the face, specifically those associated with the mandible. The digastric muscle, in coordination with the mylohyoid, geniohyoid, and lateral pterygoid muscles, is primarily responsible for opening the mouth [73].

In essence, the action of eating is not just a simple reflex but a sophisticated symphony of numerous coordinated actions. The understanding of these movements has significant implications for rehabilitation in conditions where these movements might be compromised, such as in stroke, Parkinson's disease, or after some types of surgery. The process of eating is an extraordinary feat of coordination and control, involving a myriad of different muscles and numerous intricate movements. From the first reach of the hand towards the food to the final act of swallowing, the act of eating demonstrates the incredible complexity and sophistication of the human body.

2.5. Food Intake Monitoring Approaches Overview

Current food intake monitoring methods can be roughly categorized as Motion sensor-based,sound-based, Image-based, Glass-based, and Self-report Based.

2.5.1 Motion Sensor Based Methods

The use of Inertial Measurement Unit (IMU) technology has proved to be successful in detecting food intake, specifically through monitoring the wearer's hand movements [1, 74, 75]. This methodology involves attaching the IMU to a wristband, allowing the sensor to trace and analyze hand gestures. Upon identifying distinct hand-to-mouth movements, the device signals the occurrence of food intake.

Despite their success in food intake detection, these techniques exhibit certain limitations. One key challenge is their inability to accurately identify the types of food consumed, let alone the calorie content. Kim et al. attempted to address this issue with a smartwatch-based method that recognizes different eating patterns associated with specific food types. However, their tests were only limited to rice and noodles [2]. Another challenge that arises from reliance on hand movements is the considerable variations in eating habits, both within individuals and across different groups. For instance, the techniques for consuming food can greatly vary, such as eating with one's hand(s), using chopsticks, forks, knives, or other types of tableware [74].

Considering these limitations, other researchers have explored the combination of IMU and Piezoelectric sensors on eyeglasses to track the user's chewing action. They achieve this by detecting Jaw Elevation and temporalis muscle contraction [3]. Nevertheless, while these approaches offer valuable insights, our method proves to be more superior in detecting a wider range of food types. Our technique goes beyond merely tracking food intake or recognizing limited food types. Instead, it provides a more comprehensive understanding of eating habits by identifying a broad spectrum of food types, thus offering a more complete picture of dietary patterns.

2.5.2 Sound Based Methods

Sound-based detection of food intake primarily employs two methodologies. One extensively studied method involves using microphones incorporated into headsets, hearing aids, or earphones to capture the chewing noise generated by the user. This noise serves as a sign of intaking food [4]. The other technique utilizes a laryngophone Tied to the neck of the user to identify swallowing sounds [76]. This method also incorporates IMUs to capture throat vibrations for further clarification of the swallowing action.

Despite their effectiveness, sound-based detection techniques face challenges in accurately identifying food types and their respective caloric content. Moreover, they are highly dependent on environmental factors, thereby limiting their real-world applicability.

Various studies have attempted to compare the efficiency of audio-based and IMU-based chewing detection techniques. For instance, Lotfi et al. reported that their in-ear IMU method surpasses the audio-based method in detecting chewing activity [5]. Meanwhile, Drake's work investigated the acoustics of chewing and

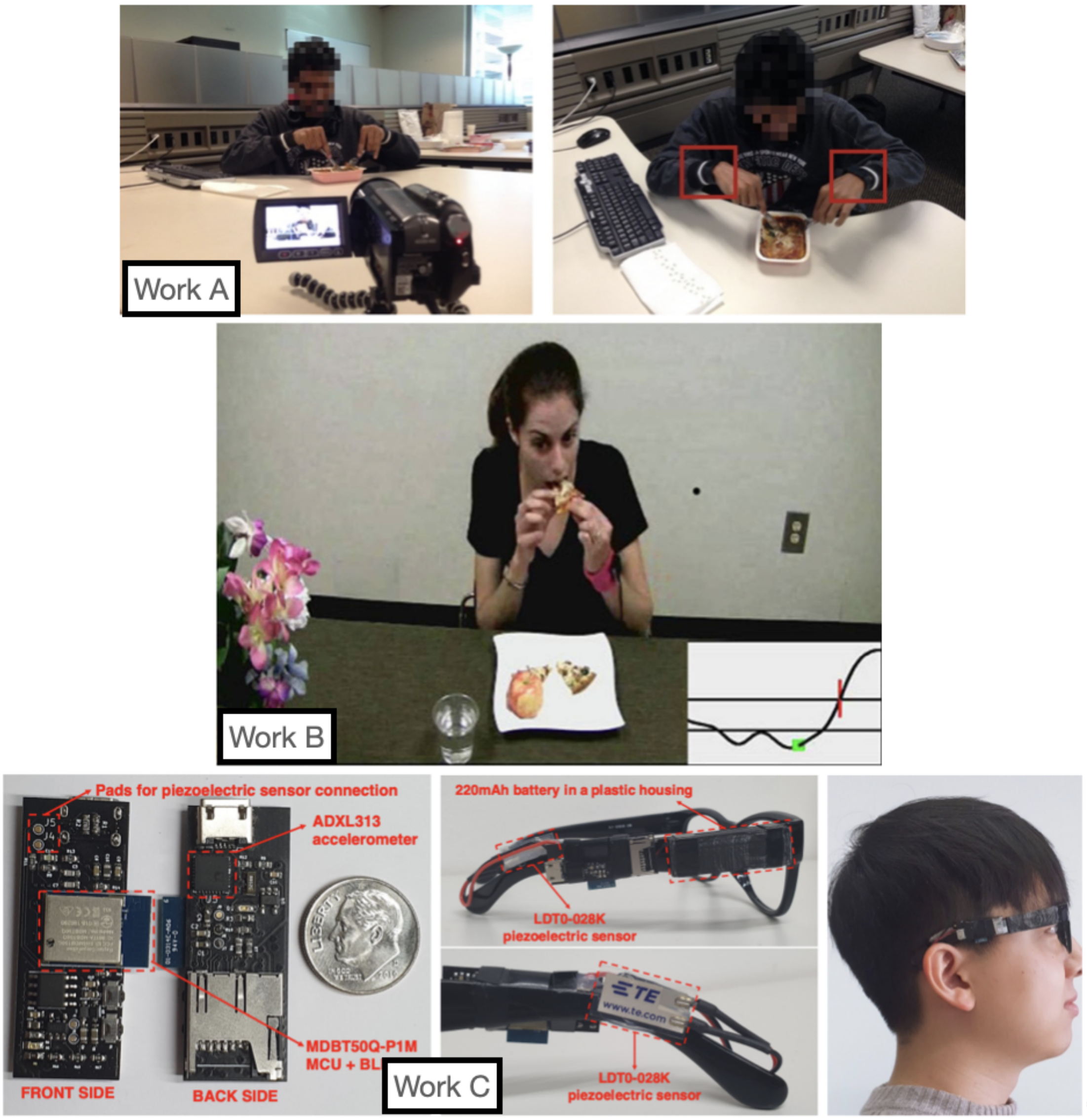


Figure 2.1 Motion Sensor Based Methods. Work A is from [1].Work is from [2].Work C is from [3]

crisp food [77], and Amft further expanded sound-based detection to include both eating and drinking behavior in healthy individuals [78]. Shuzo et al. also offered their insights into sound-based detection methods [6].

However, the usage of devices such as hearing aid packages, which might give the impression of a disability, or conspicuously wired devices may raise concerns among users [4]. In comparison, our method provides a more comprehensive approach. We are not only able to detect a wider variety of food types, but our system also respects user privacy by avoiding constant audio recording. This way, our users can feel comfortable knowing that their dietary habits are being monitored without compromising their privacy.

2.5.3 Image Based Methods

Image-based approaches for monitoring food intake involve various steps, including image segmentation, food recognition, and portion size estimation, which collectively enable effective evaluation of food consumption [8]. Nevertheless, these processes typically demand substantial computational resources and may necessitate users to follow precise guidelines when preparing image source files [79, 80].

Computer vision-based studies, while being capable of offering estimated nutrition or caloric content for specific types of food, fall short in providing information on the actual quantity of food consumed by the user [8, 81]. The complexity increases when dealing with images that feature a full meal [8].

An alternate approach involves the attachment of a camera to eyeglasses to record the user's mouth area. Upon detecting food intake, the device begins to record the food and the user's eating actions. The user can then review these videos to recall their daily food intake [82].

While the use of cameras or smartphone cameras for food intake detection is relatively well-studied, their application varies significantly. Some methodologies employ these cameras attached to wearable devices to identify food by the use of computer vision [83, 84].

To handle the complexities associated with image-based methodologies, Hassannejad et al. suggest the provision of practical guidelines or interactive procedures as potential solutions [79].

In comparison to these techniques, our method offers a significant advantage

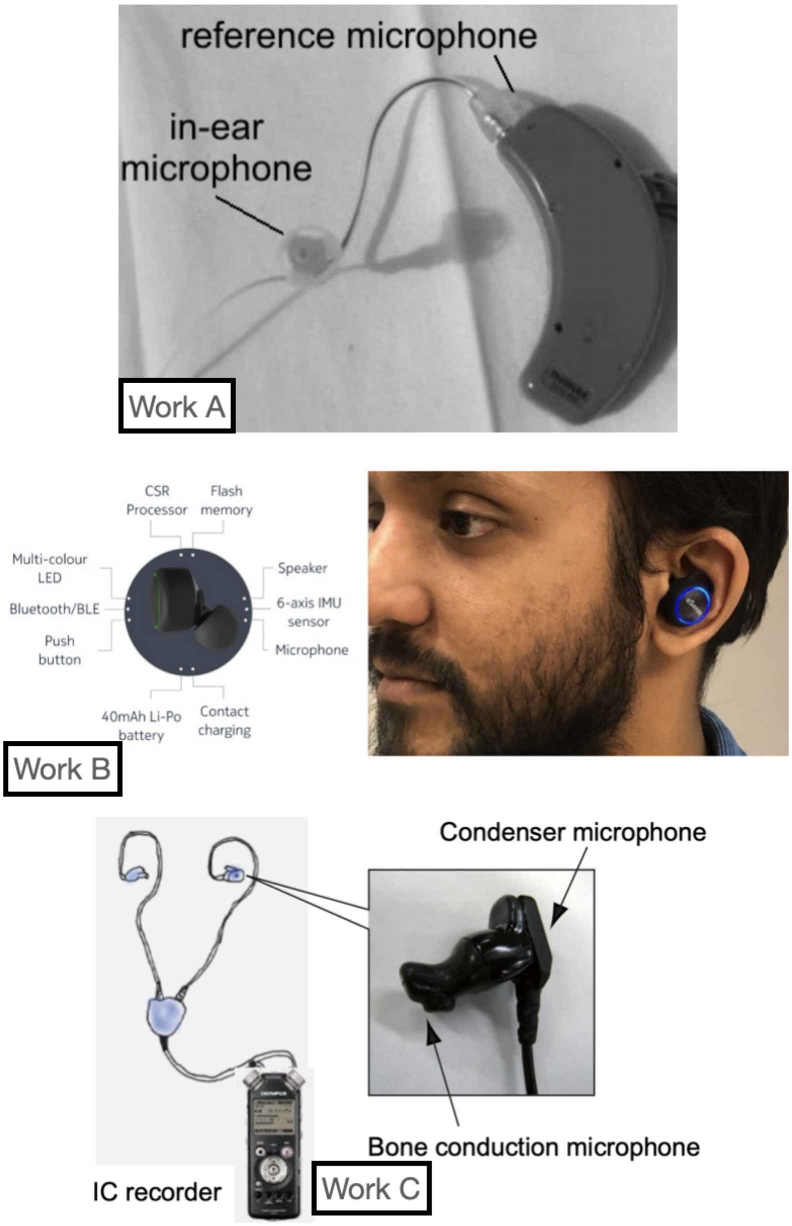


Figure 2.2 Different Sound Based Methods: Work A is from [4].Work is from [5].Work C is from [6]

in preserving user privacy. By avoiding the continuous recording or capturing of images, our method eliminates the privacy concerns associated with image-based methods, thus ensuring a user-friendly, secure, and efficient food intake monitoring system.

2.5.4 Glasses Based Chewing Detection

Mertes et al. [85,86] developed a glasses-based approach to detect chewing motion in elderly individuals. Similarly, Chung et al. [87] devised smart glasses capable of classifying food intake movements from physical activities. Additionally, Bedri et al. [82] introduced multi-modal sensor-based glasses with a camera to detect food intake events, even in noisy environments. However, to the best of our knowledge, none of these existing studies utilizing smart glasses have been able to differentiate between various types of food, particularly those associated with compromised muscle health and unhealthy eating habits.

Expanding on this, the ability to differentiate between various types of food, especially those that can lead to poor muscle health and reinforce bad eating habits, is a critical and unique feature of our method. While existing solutions may detect the act of eating or measure the volume of food intake, they lack the capability to identify the specific type of food consumed. This limitation is significant, especially for users seeking to improve their muscle health and dietary habits.

Our method aims to address this limitation by not only monitoring food intake but also classifying the types of food consumed. This additional layer of information provides a more comprehensive understanding of a user's eating habits and patterns, enabling more accurate dietary tracking and potential assistance in managing and preventing poor muscle health. In essence, our approach adds a new dimension to the application of smart glasses in the context of dietary monitoring and promoting better eating habits.

2.5.5 Self-report Based Methods

Self-reported methods [8] can be in the form of a physical notebook or diary, or they can be digital using smartphone apps or online platforms. Users typically write down the details of each meal or snack, including the time of consumption and any relevant information like the location or company.

While food journals can be effective in providing detailed information about dietary habits, they do have some limitations. Firstly, they rely on the individual's memory and accuracy in recording the information, which can lead to errors and omissions. Additionally, manually tracking food intake can be time-consuming and cumbersome, which may result in users forgetting or giving up on the practice [4].

Chapter 3
Designed solutions

3.1. Hardware Design

The design of a device's hardware constitutes a pivotal aspect in the successful implementation of any system, be it in the realm of HCI, or other sectors of technology. In the case of our system, which involves an amalgamation of wearable technology and advanced sensor arrays, the hardware configuration is of vital importance. Our hardware configuration includes a dual setup of Inertial Measurement Unit (IMU) sensors. This setup yields a robust 12-axis sensorial feedback system that effectively captures movement data [88].

Our sensor configuration comprises two IMUs. The first IMU is the LSM6DS3, integrated directly into the Microcontroller Unit (MCU) of the device. The LSM6DS3 is a system-in-package featuring a 3D digital linear acceleration sensor and a 3D digital angular rate sensor. This sensor's advanced features and compact size make it an ideal choice for incorporation into our wearable device [89].

The second IMU, the GY521, is an external sensor that we have attached to the right leg of our glasses. The GY521 is a cost-effective, yet highly efficient IMU featuring a 3-axis gyroscope and a 3-axis accelerometer. This sensor uses the MPU-6050 chip, which has gained widespread acceptance in the field of motion-enabled devices [90].

These two IMUs provide a 6-axis motion tracking system each, combining to a total of 12 axes, which helps us to gather a comprehensive range of data on user movement. This multi-axial setup enables us to accurately capture a broad spectrum of movements, including but not limited to, head movements, leg movements, and subtle shifts in posture, thereby providing a rich dataset that can be used for various HCI applications [91].

We have further discussed the intricacies of our hardware configuration, including the sensor placement and signal processing methodology in the previous section on hardware design. These aspects are of utmost importance in our device as they determine the accuracy and reliability of the data that our system can capture, and hence, the efficacy of the overall system.

3.2. Design Ideation

Design ideation is a central component of any hardware project, particularly when the goal is to generate novel, usable, and efficient technology. Our design process was iterative and exploratory, with several stages of concept development, prototyping, testing, and revision.

The development of our wearable technology hinged on the successful integration and accurate data collection from two Inertial Measurement Unit (IMU) sensors: the built-in LSM6DS3 on the Microcontroller Unit (MCU) and the external GY521 sensor. These sensors, providing 12 axes of data in total, were critical to our goal of capturing a comprehensive range of motion data.

One of the significant challenges in our design process was identifying the optimal location for sensor placement on the glasses. Initially, we explored several possible locations for the GY521 IMU sensor. This exploration was necessary because the placement of the sensor would significantly impact the type and quality of data that we could collect.

In our investigations, we discovered that positioning the sensor on the temporalis muscle, located on the side of the head, provided superior data quality. This muscle is one of the primary muscles involved in the complex movements of chewing and swallowing. By positioning the sensor here, we could capture more nuanced data about these movements. This discovery was a key turning point in our design ideation process.

Once we had confirmed the placement of the sensors, we then proceeded to the integration and testing phase. We adjusted and calibrated the sensors to ensure reliable and accurate data capture. We designed the hardware to be compact, lightweight, and comfortable to wear, as these were crucial factors in a successful wearable device.

The nitty-gritty details of the hardware configuration, including our considerations for sensor placement, data acquisition, and signal processing, were thoroughly described in the hardware design section. Throughout the design ideation process, our focus remained on creating a device that was user-friendly, efficient, and able to provide valuable insights into human movements and behaviors.

In the complex task of interpreting human movements and behaviors, data accuracy and precision are paramount. When developing our glasses-based technology, we initially relied on the IMU sensors located on the glasses. However, during our testing phases, we discovered certain limitations in our system. One of the most notable was the difficulty in distinguishing between specific activities such as eating and talking, due to the overlapping movements in both actions.

Our initial sensor placement on the temporalis muscle of the head could accurately record the muscle's movements involved in chewing and swallowing. Still, it had the limitation of picking up facial movements associated with speech. This is because many of the muscles used for chewing are also engaged during talking. Hence, our system sometimes misinterpreted conversation as eating. For instance, in one scenario, after a discussion while wearing the glasses, the system deduced that I had consumed three burgers and two apples.

Recognizing this limitation, we sought to enhance our system's accuracy and discernment. The idea to add an additional IMU sensor to the wrist emerged as a potential solution. The rationale was that while eating activities often involve distinct hand-to-mouth movements, conversational gestures are usually different. The sensor at the wrist would allow us to capture these hand-to-mouth movements, adding an additional layer of data for analysis. This would help differentiate between eating activities and other actions involving facial muscles, like talking.

We carefully integrated the IMU sensor into a wristband, ensuring that it was comfortable, lightweight, and non-intrusive. We designed it to communicate seamlessly with the other sensors, creating a synchronized multi-sensor system. This wrist sensor provided critical context to the data obtained from the glasses. It offered a more complete picture of the user's activities by combining data on head movements, facial muscle activity, and now, hand movements.

Upon incorporating this wrist-based IMU sensor, we noticed a significant improvement in the system's ability to distinguish between eating and talking. This improvement reiterated the fact that the human body works in a complex, interconnected manner. Our multi-sensor approach, combining data from different points of activity, indeed added a new dimension of accuracy to our system. It highlighted the importance of multi-point data capture in creating a more comprehensive, nuanced, and accurate understanding of human behavior.

3.3. Our Approach: First Bite/Chew Based Foods Intake Monitoring

Our method capitalizes on the varying textures of food, or more specifically, the distinct reactions different foods have to biting and chewing, as well as the unique hand movements associated with eating each food type, to differentiate between various kinds of food.

To capture detailed data pertaining to biting, chewing, and the corresponding hand movements during eating, we developed a device that comprises a pair of standard glasses and a wristband. As illustrated in figure 3.1, an Inertial Measurement Unit (IMU)[1] was affixed to the inner side of the right leg of the glasses (closest to the head), strategically positioned near the superior auricular and temporalis muscles when the glasses are worn. Additionally, an IMU-embedded Microcontroller Unit (MCU)[2] was incorporated into the wristband and linked to the glasses' IMU via a four-wire connection using the IIC-Bus.

Broadening this concept, the unique design and strategic placement of the IMUs allow for precise capture of both facial muscle movements related to chewing and biting and the hand motions associated with food consumption. This multifaceted approach provides a more holistic understanding of the eating process, offering nuanced data that contribute to the accurate identification of different food types.

Moreover, the use of wearable tech, like ordinary glasses and wristbands, offers

1 We used a module based on the MPU6050 IMU.

2 We used the Seeeduino Xiao BLE sense MCU. `https://www.seeedstudio.com/Seeed-XIAO-BLE-Sense-nRF52840-p-5253.html`

a non-intrusive and socially acceptable way to monitor food intake, significantly increasing user compliance and usage in day-to-day life. This feature enhances the real-world applicability and usability of our system, making it a promising tool for dietary monitoring and management.

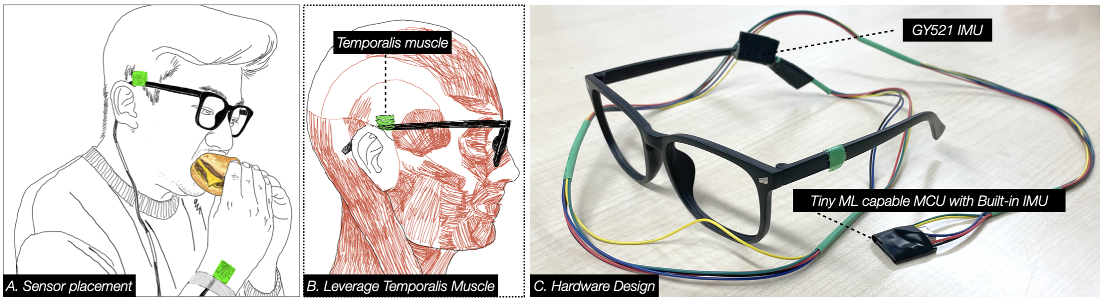


Figure 3.1 A. The placement of the two IMU sensors is as follows: one is affixed to the right leg of the glasses, and the other is securely attached to the wrist of the dominant hand. B. We utilize the temporalis muscle as one of our data sources in the monitoring process. C. The hardware design is depicted in Figure C, illustrating the arrangement and configuration of the sensors and glasses.

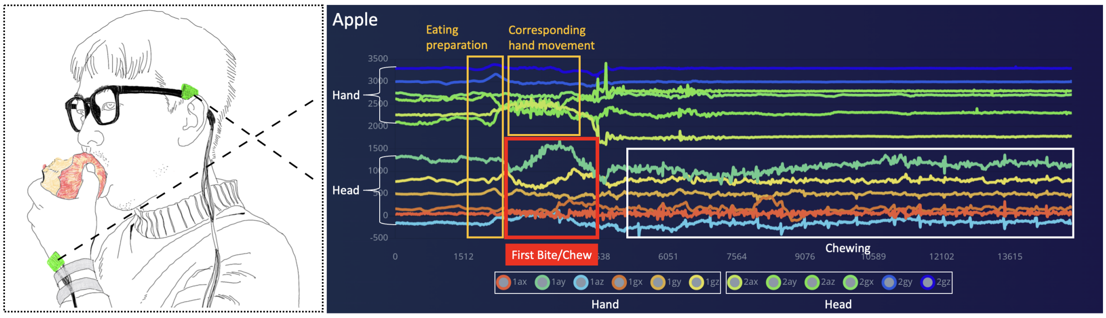


Figure 3.2 When a participant consumes an apple, we collect 12 axes of IMU data related to their eating movements, as shown in the Waveform plot on the right side. The length of the red rectangle represents the portion we define as the first bite/chew, while the thin yellow rectangle indicates the preparation of hand and head movements before eating.

Chapter 4
Experiment

4.1. Method

4.1.1 Participants

For the purposes of our study, we gathered data from four participants, two males and two females, ranging in age from 23 to 32 years. Each participant was individually recorded while they ate meals on campus. The duration of each meal recording varied between 40 and 70 minutes. We recorded five meals for each participant over three consecutive days, including two lunches and three dinners.

Each participant was asked to read, understand, and sign two forms. The first form was a consent form that explained the nature of our study, and the second was an allergy checklist. This list included common allergens such as peanuts, milk, pork, beef, and various types of seafood. In addition to this, we asked the participants about any specific food or drink allergies, intolerances, and restrictions (due religious beliefs, personal dislikes or others) they had to ensure that no one would unintentionally consume any food that could be unwanted, harmful, or even fatal to them. This measure ensured the safety and well-being of our participants throughout the study.

Further expanding on this, the collection of allergy and dietary restriction information before the commencement of the study underscores the seriousness with which we treated participants' safety. Not only did we record and analyze the participants' eating habits, but we also ensured that the food provided adhered to their dietary restrictions. This careful attention to detail is crucial in research studies and signifies our commitment to ethical research practices.

Foods Selection

To facilitate our method's ability to detect different types of food, we intentionally selected seven types of food to be tested under two main categories - typical daily foods, and foods commonly associated with poor muscle health. The typical daily foods category includes hamburger, instant noodles, apples, and nuggets, while the group associated with poor muscle health comprises peanuts, egg fried rice, and edamame.

These foods were selected in line with reports highlighting the potential effects of certain foods on oral and muscle health. For instance, the consumption of fast and processed foods, such as hamburgers, instant noodles, and nuggets, has been associated with inadequate chewing, leading to underdevelopment or weakening of the masseter and temporalis muscles [92]. Peanuts, while nutrient-rich, can pose a risk when consumed frequently in large amounts due to their high fat and calorie content, potentially leading to obesity and associated health problems [93]. Eggs and soy, such as in egg fried rice and edamame, are high in protein but can contribute to an imbalance diet when over-consumed, affecting overall health and potentially leading to muscle strain or discomfort [94, 95].

It's worth noting that maintaining a balanced and varied diet is crucial not just for the health of the masseter and temporalis muscles, but for overall well-being. Therefore, our method aims to promote healthier eating habits by providing insights and feedback on food choices that may impact muscle and oral health.

One asked the subjects whether they have any allergic reaction to the food that were provided, and if they prefer not to eat some food due to religious and culture reasons. The other one is consent form, in this form we explained our experiment, informed their participants rights, confidentiality and anonymity, and use of their data. We found out from the first form that subject#3 don't eat pork, but the egg fried rice we provided have pork as ingredient, so we removed egg fried rice from his meal list.

Before the experiment, we queried the subjects about potential allergic reactions to the food provided and whether they had any dietary restrictions due to cultural or religious reasons. Additionally, a consent form was provided, which outlined the details of our experiment, informed participants about their rights, assured them of confidentiality and anonymity, and explained the usage of their data. The responses to the first form revealed that subject #3 did not consume pork. Since the egg fried rice included in the meal list contained pork as an ingredient, we made sure to exclude this item from his meals.

Expanding on this, our method's ability to detect and classify different types of food could have wider applications beyond individual users. For instance, it could be employed in clinical and research settings to study eating habits and their relation to various health outcomes. This would further our understanding of nutrition and its links to diseases such as obesity, diabetes, and heart disease.

Our method could also aid in public health efforts by providing data on population-level eating patterns. This could guide policies aimed at promoting healthier eating habits and addressing common nutritional deficiencies.

Moreover, as concerns regarding poor muscle health and bad eating habits are prevalent among many individuals, our method could be a significant step forward in managing these conditions. It could provide reassurance to users and their caregivers by helping them avoid foods that could lead to strain or imbalance in the masseter and temporalis muscles. This proactive approach to monitoring food intake can contribute to promoting healthier muscle function and overall well-being, reducing the risk of discomfort and chronic conditions associated with poor eating habits.

Finally, the ability to customize the food list based on individual dietary restrictions, as in the case of subject #3, ensures our method is adaptable and considerate of diverse dietary preferences and needs.

4.1.2 Procedure

Prior to commencing data recording, experimenters assisted each participant in wearing the device and verified that it was generating data correctly. Specifically, the wristband was placed on the participant's dominant hand.To avoid undesired displacement of the sensors, we used two additional elastic bands to fasten the sensor and the cables to the participant's arm. After everything was set up, we made sure the device was not causing any discomfort to subjects. All subjects were asked to bring to typical meal we designed which consisted of one main course and two starters. They were given three instructions before the recording started: 1)eat one type of food at a time, only start a new type after the last one was finished 2)eat one bite of food after receiving cue from researcher, and only start the next bite after receiving the next cue 3)regarding the last bite of the food, if the food left is too small that the participant will generally put it in their mouth without biting, the data will not be recorded.

After the recording started, the researcher would wait for 2 to 3 seconds before giving the cue with gesture and voice to avoid missing out on desired data. After the cue, Participants were given the freedom to consume their meal in the manner that felt most natural and customary to them. We recorded the time of eating preparation movement and first bite/chew as ground truth annotations. All the accelerometer and gyroscope data of their hand and mouths were recorded for 15 seconds each time with a sampling rate of 80 HZ. We found out from a pilot study that 15 seconds of sample length is suitable for most people eating most types of food, which covers a whole eating cycle of one bite without involving too much-unwanted data. The sampling rate of 80 Hz is limited by hardware, which we found out has a sampling rate floating around 80 Hz.

The data is 12 axes in total generated by two IMU sensors, one is the built-in LSM6DS3 on the MCU, and another is the GY521 IMU sensor that we attached to the right leg of our glasses. Hardware details we described in the previous hardware design section.

4.2. Result

	Participant #1		Participant #2		Participant #3		Participant #4	
Food list	Times	Bites Count(AVG)	Times	Bites Count(AVG)	Times	Bites Count(AVG)	Times	Bites Count(AVG)
Instant Noodle	3	12.3(SD=0.47)	3	17.7(SD=1.70)	2	26(SD=1)	2	18.5(SD=1.5)
Double Cheese	4	8(SD=0)	1	16(SD=0)	1	32(SD=0)	3	7(SD=0)
Nuggets(plece)	15	2(SD=0)	15	2.07(SD=0.25)	8	4.13(SD=0.33)	15	2(SD=0)
Apple	1	32	1	35	1	30	2	17(SD=3)
Edamame	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Peanuts	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Egg Fried Rice	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A

Table 4.1 Bites needed for eating up 7 types of food. Food such as edamame peanuts and egg fried rice are heart to Control the amount and how may does the participants want to eat. Therefor documented as N/A.

We successfully recorded in total 916 valid samples as our dataset. For apple, total of 125 samples were recorded, from participant #1 to #4, each participant was recorded 28, 35, 28, 34 samples respectively. For double cheese burger, total of 76 samples were recorded, from participant #1 to #4, each participant was recorded 21, 14, 22, 19 samples respectively. For edamame, total of 179 samples were recorded, from participant #1 to #4, each participant was recorded 53, 45, 44, 37 samples respectively. For instant noodle, total of 139 samples were recorded, from participant #1 to #4, each participant was recorded 37, 36, 38, 28 samples respectively. For nugget, total of 123 samples were recorded, from participant #1 to #4, each participant was recorded 30, 28, 32, 33 samples respectively. For peanut, total of 169 samples were recorded, from participant #1 to #4, each participant was recorded 41, 48, 39, 41 samples respectively. For egg fried rice, total of 105 samples were recorded, from participant #1 to #3, each participant was recorded 33, 42, 30 samples respectively.

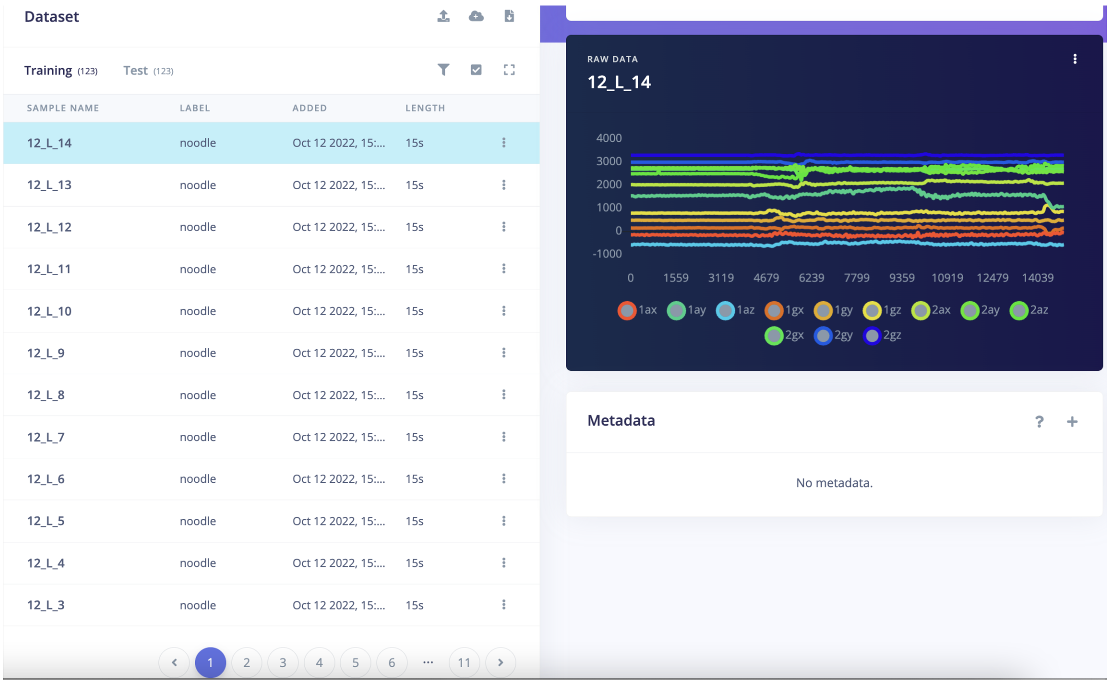


Figure 4.1 Participant's raw data

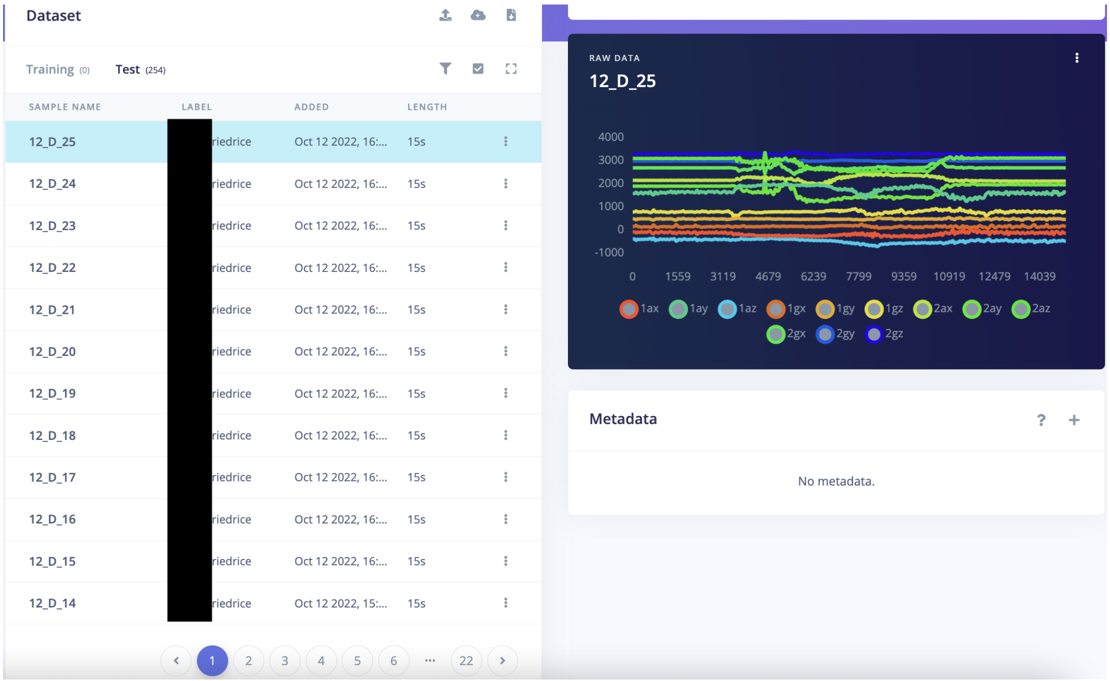
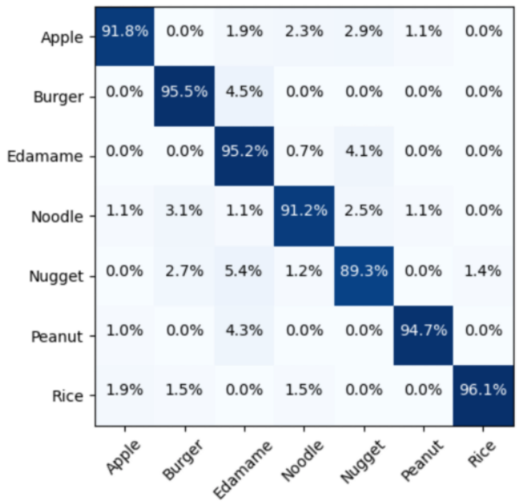


Figure 4.2 For Participant's privacy name is blocked

Based on our observations, we identified both similarities and unique characteristics in the eating motions and gestures of the four participants. Similarities include the following: 1) All participants open their mouths when the food is halfway moved toward their mouth. 2) For foods like burgers and apples, participants tend to hold the food close to their mouths in preparation for the next bite, making the hand-to-mouth motion less obvious. 3) The eating preparation period for instant noodles is longer than for other foods, with participants often blowing on the noodles for a few seconds before taking bites.

Regarding individual characteristics, participant #1 tends to inspect and spin the apple before eating. Participant #2 has a habit of holding her phone with her left hand and browsing while eating. Participant #3 looks down at her phone on the table while eating. Participant #4 sometimes requires clarification from researchers before taking bites. Additionally, participant #4 reported religious restrictions on consuming pork, leading him to exclude pork-containing egg-fried rice from his food choices during data collection. As a result, participant #4



Food	F1 Score
Apple	0.94
Burger	0.91
Edamame	0.90
Noodle	0.93
Nugget	0.85
Peanut	0.97
Rice	0.96

Figure 4.3 The average confusion matrix and F1 score were computed by taking the mean value of each entry across the four participants.

consumed only the remaining six types of food for the data collection process.

4.3. ML Model Structure

For food category recognition, we utilized a multiclass Support Vector Machine (SVM). The classifier was trained and tested using each subject's own data, with 80% of the data used for training and the remaining 20% for testing. As depicted in Figure 4.3, the classifier achieved an impressive average accuracy of 93.3% and an average F1 score of 0.92 across all food types and participants. Specifically, the average accuracy for Apple was 91.8%, Burger was 95.5%, Edamame was 95.2%, Egg fried rice was 96.1%, Instant noodle was 91.2%, Nuggets was 89.3%, and Peanuts was 94.7%. Though our initial study showed a promising result that it is feasible to detect different types of food using a combination of the first bite/chew and the corresponding hand movement from two IMUs, there are challenges remain.

Chapter 5
Discussion and Future Works

5.1. Segmentation and Annotation

A previous study focused on two main aspects of an eating cycle: the movements of the hand and mouth approaching each other and the biting/chewing motion. Ye et al. further categorized hand-to-mouth motions into three phases: hand ascending period, biting period, and hand descending period [96]. Upon closer examination, we discovered that for specific types of food, the eating preparation motion involves the mouth reaching for the hand-held food, rather than moving the food to the mouth by hand. Integrating insights from previous research and our own observations, we identified three key steps in an eating cycle:

1. The phase when the hand and mouth come closer to each other in preparation for eating.

2. The initial biting or chewing motion.

3. The regular chewing period.

During our data recordings of the seven types of food, we observed a close temporal relationship between the subjects' first bite and the convergence of their hand and mouth movements. To label the ground truth for the eating preparation period, we utilized recorded timestamps during the observation process. Subsequently, we identified the start of the first bite segment immediately after the eating preparation period. However, for certain types of food, the first distinct bite motion was not present in the data, as some participants directly put a bite of food into their mouths. In such instances, we substituted this action with the first chewing motion. The chewing segment was randomly selected from the subsequent regular chewing period. Each segment was precisely 2 seconds in duration, allowing sufficient time to capture all relevant data.

5.1.1 Pre-Processing

For feature extraction and training, we employed a sliding window of 1600 ms with 12.5% overlap. Within each window, a total of 132 features were extracted from both the time domain and frequency domain. Specifically, for each axis of the accelerometer and gyroscope, the following features were computed: 1) root mean square, 2) skewness, 3) kurtosis, and 4) the first 8 coefficients from the discrete Fourier transform.

5.1.2 Future Work

Exact Food Types

While our initial findings indicate that utilizing a combination of the first bite/chew and its corresponding hand movement could serve as a straightforward and dependable method to differentiate food types, we acknowledge some limitations in our current prototype. As the current design prioritizes a socially acceptable appearance and does not incorporate a camera, there is a possibility that certain food types with similar textures may exhibit similar corresponding hand movements. This limitation highlights the need for further improvements and considerations in future iterations of our approach.

Extending to New Users

The current model is individually trained for each user, which poses challenges in adapting to new users due to variations in eating patterns even for the same type of food. For instance, when observing participants eating noodles, participant #1 tends to bow the head to reach the bowl, while others prefer to lift the noodles to their mouth. These distinct differences result in varying patterns in terms of amplitude and frequencies. In future endeavors, we plan to address this issue by expanding our dataset to include a larger user group as our base model. By incorporating more diverse scenarios, the model can better accommodate individual variations. Techniques like transfer learning can then be utilized to facilitate adjustments for new users, potentially reducing the effort required for adaptation.

Extending to New Food

At the moment, our method is capable of distinguishing only seven types of food. Despite the possibility of incorporating more categories in future work, it remains infeasible to include all possible food types a user might encounter in their daily life during the training phase. A promising solution to this challenge lies in the application of few-shot learning techniques, which are a focus of current research. This approach involves training a model to assess the similarity between two input signals, rather than directly mapping signals to categories.

Consequently, the user only needs to gather a few samples of a new food category for reference. Whenever a new real-time signal is received by the system, it's compared against all the reference points. The food type associated with the closest match, based on similarity, is then identified as the category of the new signal. This approach eliminates the need for additional training and significantly reduces the burden on the user, as only a few reference samples are required.

Building on this, the application of few-shot learning can pave the way for a more flexible and user-friendly system. It makes our method adaptable to a wider range of food types and eating scenarios, thereby enhancing its real-world applicability.

Furthermore, by continuously updating and refining the reference samples based on the user's diet, our method can potentially evolve into a personalized food intake detection system. This individualized approach could enhance the accuracy and relevance of the system, contributing to more effective diet management.

In the long run, the use of few-shot learning could also enable our method to incorporate other relevant factors such as the user's eating speed, chewing patterns, and other unique eating habits. This would add a layer of depth to the system's capability, allowing it to provide even more comprehensive and nuanced insights into the user's eating behavior.

In an effort to discover the full range of possibilities offered by our method, we present three potential scenarios where users could benefit from our proposed approach.

Participant 1	APPLE_FB	BURGER_FB	EDAMAME_FB	NOODLE_FB	NUGGET_FB	PEANUT_FB	RICE_FB
APPLE_FB	80.8%	0%	7.7%	0%	11.5%	0%	0%
BURGER_FB	0%	100%	0%	0%	0%	0%	0%
EDAMAME_FB	0%	0%	85.3%	2.9%	11.8%	0%	0%
NOODLE_FB	0%	4.5%	4.5%	86.4%	4.5%	0%	0%
NUGGET_FB	0%	0%	0%	0%	100%	0%	0%
PEANUT_FB	3.8%	0%	3.8%	0%	0%	92.3%	0%
RICE_FB	0%	0%	0%	0%	0%	0%	100%
F1 SCORE	0.88	0.97	0.87	0.90	0.69	0.96	1.00

Participant 2	APPLE_FB	BURGER_FB	EDAMAME_FB	NOODLE_FB	NUGGET_FB	PEANUT_FB	RICE_FB
APPLE_FB	90.9%	0%	0%	9.1%	0%	0%	0%
BURGER_FB	0%	100%	0%	0%	0%	0%	0%
EDAMAME_FB	0%	0%	95.5%	0%	4.5%	0%	0%
NOODLE_FB	0%	3.7%	0%	96.3%	0%	0%	0%
NUGGET_FB	0%	0%	5.6%	0%	94.4%	0%	0%
PEANUT_FB	0%	0%	3.4%	0%	0%	96.6%	0%
RICE_FB	0%	4.5%	0%	4.5%	0%	0%	90.9%
F1 SCORE	0.95	0.90	0.93	0.93	0.94	0.98	0.95

Participant 3	APPLE_FB	BURGER_FB	EDAMAME_FB	FRIEDRICE_FB	NOODLE_FB	NUGGETS_FB	PEANUTS_FB
APPLE_FB	95.5%	0%	0%	0%	0%	0%	4.5%
BURGER_FB	0%	100%	0%	0%	0%	0%	0%
EDAMAME_FB	0%	0%	100%	0%	0%	0%	0%
FRIEDRICE_FB	5.6%	0%	0%	94.4%	0%	0%	0%
NOODLE_FB	4.2%	4.2%	0%	0%	87.5%	0%	4.2%
NUGGETS_FB	0%	5.6%	11.1%	5.6%	0%	77.8%	0%
PEANUTS_FB	0%	0%	10%	0%	0%	0%	90%
F1 SCORE	0.93	0.91	0.88	0.94	0.93	0.88	0.92

Participant 4	APPLE_FB	BURGER_FB	EDAMAME_FB	NOODLE_FB	NUGGET_FB	PEANUT_FB
APPLE_FB	100%	0%	0%	0%	0%	0%
BURGER_FB	0%	81.8%	18.2%	0%	0%	0%
EDAMAME_FB	0%	0%	100%	0%	0%	0%
NOODLE_FB	0%	0%	0%	94.7%	5.3%	0%
NUGGET_FB	0%	5%	5%	5%	85%	0%
PEANUT_FB	0%	0%	0%	0%	0%	100%
F1 SCORE	1.00	0.86	0.93	0.95	0.89	1.00

Figure 5.1 The accuracy confusion matrix of 4 participants (participant #4 can't eat egg fried rice due to religion background)

	Food Types	Sensors	Device Type	Operation Method	Food Classification
IMU Based	**I.** N/A[9] **II.** N/A[26]	**I.** Gyroscope[9] **II.** Piezoelectric Sensor & Accelerometer[26]	**I.** Wristband **II.** Eye glasses	**I.** Automatic **II.** Automatic	**I.** N/A **II.** N/A
Microphone Based	7 Types [19]	Electret microphones	Hearing aids	Automatic	Applicable
Camera Based	N/A[16]	Smart phone	Smart phone	N/A	N/A
Multi-sensor Based	**I.** 19 Types[1] **II.** N/A[**4**] **III.** 2 Types (Steamed rice with dishes, and Noodle-Ramen)[14]	**I.** Inertial sensors, Ear-worn microphone, Electromyography, EMG, Stethoscope microphone, Temperature sensor[1] **II.** One camera, One proximity sensor, and Six IMUs[4] **III.** Accelerometer Sensor and Micro Camcorder[14]	**I.** Motion sensor jacket, Earphone, Collar **II.** Eye glasses **III.** Wrist Worn Type	**I.** Automatic **II.** Manual **III.** Automatic	**I.** Applicable **II.** N/A **III.** Applicable
Our Device	**7 Types (Instant Noodle, Double Cheese, Nuggets, Apple, Edamame, Peanuts and Egg Fried Rice)**	**Two IMUs (One on the glasses another on the wrist)**	**Eye glasses & Wristband**	**Automatic**	**Applicable**

Figure 5.2 Comparison between our approach and existing works

Our goal is to broaden the scope beyond merely detecting food intake. We aim to enhance the functionality of our approach by incorporating food classification features, which could be a vital aid for individuals dealing with the challenges of maintaining proper muscle health and managing bad eating habits. Moreover, we aspire that our research will encourage future studies in food intake detection to pay special attention to these groups, namely, those suffering from poor muscle health and dietary-related issues.

To expand on this, consider the first scenario where an individual is prone to bad eating habits that could compromise the health of their masseter and temporalis muscles. With our innovative method, users could receive alerts when they are about to consume foods that may negatively impact these critical muscles, such as overly hard, sticky, or fast food that requires less chewing. This approach could help users avoid foods that might lead to muscle strain or underutilization, thus promoting healthier muscle function. By acting as a dietary guide, our method aids in correcting poor eating habits, thereby reducing the risk of muscle imbalance, strain, and associated disorders. This not only ensures better muscle and oral health but also contributes to the overall well-being of the user.

In the second scenario, our method could assist individuals suffering from memory loss, particularly those who have difficulty remembering what they ate. By providing accurate records of past meals, our device could help these individuals maintain a balanced diet and ensure they are meeting their nutritional needs.

Lastly, in a more general context, our method could serve as a comprehensive dietary tracking tool. By accurately identifying and recording the type and amount of food consumed, it could help users monitor their eating habits and make healthier food choices, contributing to their overall well-being.

In conclusion, we believe our method has the potential to significantly enhance individual health management. By addressing various user scenarios, from concerns related to poor muscle health and bad eating habits to memory loss, we aim to inspire a new direction in the field of food intake detection and management. Our approach not only promotes better muscle health and dietary habits but also contributes to the overall well-being of users, offering valuable insights and guidance for maintaining a healthier lifestyle.

Chapter 6
Applications

6.1. Eating Habits Correction

Bad eating habits can have detrimental consequences for various aspects of health, including the muscles involved in mastication. The masseter and temporalis muscles, key muscles used in chewing, can be significantly affected by poor dietary choices.

Chewing hard, sticky, or crunchy foods regularly can put undue stress on the masseter and temporalis muscles. Foods like hard candies, sticky caramels, or tough meats can require excessive force to break down, leading to muscle strain. Over time, excessive use of these muscles can lead to hypertrophy (an increase in muscle size) or tightness, potentially causing pain and discomfort [94]. This is particularly evident in individuals who habitually chew gum or clench their teeth, as they are engaging these muscles frequently, often without realizing the cumulative strain [97].

Moreover, the way one eats can also affect these muscles. Consuming large chunks of food without cutting them into smaller pieces can force the masseter and temporalis muscles to work harder than necessary. Additionally, eating rapidly without adequately chewing food can place sudden and repetitive strain on these muscles. Bad eating habits like the consumption of sugar-rich foods and drinks can lead to tooth decay [98]. When teeth become compromised due to cavities, this can affect the way people chew, which in turn places an additional strain on the masseter and temporalis muscles. People may try to compensate for discomfort or pain by chewing on one side, leading to an imbalance in muscle usage. This imbalance can cause one muscle to become overworked, potentially leading to muscle strain, discomfort, or Temporomandibular joint disorders (TMJ) [95].

Moreover, the consumption of heavily processed and fast foods, which are often softer and require less chewing, can result in underuse of these muscles. Similar to any other muscle in the body, lack of use can lead to muscle weakening over time. Inadequate chewing due to the consumption of softer foods can result in the underdevelopment or weakening of the masseter and temporalis muscles [92].

Furthermore, the nutritional quality of the food we consume has a direct impact on muscle health. Lack of essential nutrients and vitamins can affect muscle function and overall health. For instance, deficiency in Vitamin D is associated with muscle weakness and pain, which could potentially impact the health of masseter and temporalis muscles [99].

The lack of masseter and temporalis muscle health can have profound effects on an individual's overall well-being. If these muscles are weakened or strained due to poor eating habits, they can cause a range of uncomfortable symptoms. This can include difficulty chewing, jaw pain, headaches, and even changes in facial appearance due to muscle hypertrophy or atrophy [94]

Moreover, imbalance or dysfunction in these muscles can lead to Temporomandibular joint disorders (TMJ), a group of conditions that cause pain and dysfunction in the jaw joint and muscles controlling jaw movement. Symptoms of TMJ include difficulty opening the mouth wide, jaw locking when talking, eating or yawning, and difficulties in biting or chewing [95].

In severe cases, the constant pain and discomfort can even affect mental health, leading to conditions such as anxiety or depression. There's also evidence that chronic pain, such as persistent jaw pain, can interfere with sleep, cognitive function, and work productivity, significantly reducing the quality of life [100].

Our method presents a unique approach to monitoring and improving eating habits, particularly with respect to the health of the masseter and temporalis muscles.

By capitalizing on the varying textures of food and the different reactions they elicit during biting and chewing, this method provides a nuanced understanding of the masticatory process. The device comprising standard glasses and a wristband embedded with Inertial Measurement Units (IMUs) strategically captures data related to facial muscle movements (specifically near the superior auricular and temporalis muscles) and hand movements during eating. This information can provide insights into the eating habits of the individual and help identify areas of improvement.

For instance, if the data reveals frequent consumption of hard or tough foods that require excessive force and consequently strain the masticatory muscles, individuals can be guided to diversify their food choices to include softer foods. This modification would reduce muscle strain and promote a balanced use of these muscles. Similarly, the analysis of hand movements can guide individuals to cut their food into smaller, more manageable sizes, reducing the workload on the masticatory muscles.

Moreover, the wearable technology design, using standard glasses and wristbands, provides a non-intrusive and socially acceptable means of monitoring food intake. This feature enhances user compliance, making the device a practical tool for real-world dietary monitoring and management. By tracking eating habits in this manner, individuals can be more aware of their patterns, understand the impact of their choices on muscle health, and make necessary adjustments to promote healthier habits.

In conclusion, the adverse effects of poor eating habits on the masseter and temporalis muscles extend beyond mere strain, leading to muscle imbalance, underdevelopment, nutrient deficiencies, and overall decreased muscle health. Maintaining the health of these muscles through proper eating habits is not just crucial for the mechanical process of eating but also for overall health and well-being. A lack of muscle health can lead to discomfort, chronic conditions, and potentially significant decreases in quality of life. Our innovative method presents a promising tool for monitoring and improving these eating habits, thus promoting the health of these muscles. Maintaining balanced and healthy eating habits is imperative not only for optimal muscle function but also for overall oral health. Through effective monitoring and conscious modifications, individuals can mitigate the negative consequences of poor eating habits, ensuring the well-being of their masticatory muscles, and contributing to better oral health.

6.2. Precise Calories Intake Estimation

Instead of relying on camera recording or requiring the user to manually input the quantity of a certain food, we discovered that the number of bites taken can provide a practical estimation of food consumption. As Table 4.2 illustrates, the number of bites required to finish a particular type of food tends to remain constant. For instance, participant #1 consistently took eight bites to finish a double cheeseburger, a pattern that persisted over four such burgers consumed across three days. Similarly, a cup of instant noodles always required 12 bites (SD = 0.47). This pattern appears to be consistent among different individuals, albeit with slight variations.

By extension, this bite count method offers a number of advantages for the estimation of caloric intake. Firstly, it provides a user-friendly and efficient way to track food consumption without the need for intrusive measures such as video recording or time-consuming manual entry.

Secondly, it brings in a higher level of precision in dietary tracking by linking the bite count to the type of food consumed, thereby giving us a more accurate understanding of the calorie intake.

Thirdly, this method could potentially be expanded to other eating behaviors and serve as an interesting avenue for further research into dietary habits and their relationship with health outcomes.

Finally, the adaptability of this approach across different individuals suggests its potential for wider application in dietary tracking, allowing more people to monitor their eating habits effectively and, by extension, manage their health better.

Such that if we can get the user's needed bites for each kind of food in advance and count the actual bites the user takes, we believe our approach can be extended to a precise calorie intake monitoring system by multiplying calories per food unit by the food amount.

6.3. Remote Elderly Food Intake Monitoring

Alterations in appetite and dietary habits are often observed in the elderly, particularly those suffering from age-related diseases. Research has shown that there is a noticeable escalation in hunger and a decline in satiety among individuals with Alzheimer's disease. For example, one case study reported an 84-year-old man diagnosed with Alzheimer's disease who was consuming larger meals more frequently, despite not experiencing feelings of fullness [101].

Our system offers an innovative approach to remotely monitor the dietary habits of older adults by being capable of identifying the kind and amount of food consumed by the user. This method potentially enhances current remote monitoring strategies in a number of ways. Firstly, it is designed to be a wearable device, which makes it convenient for continual usage and less intrusive than conventional methods. Secondly, it does not rely on camera-based technology for its operation, making it a more discreet and privacy-friendly solution.

Additionally, our system could serve as a valuable tool for healthcare professionals who are managing the dietary needs of their elderly patients. The ability to monitor the eating habits of individuals, especially those with Alzheimer's disease, can lead to more personalized dietary plans and interventions. This could potentially alleviate some of the complications related to improper nutrition in older adults.

Furthermore, the system could also provide important insights into the relationship between eating habits and the progression of age-related diseases. This could help researchers understand these conditions better, potentially leading to more effective treatments in the future.

Chapter 7
Conclusion

In this research, we have put forward a solution for automated food intake monitoring that is both effective and socially acceptable, taking advantage of the concept of the First Bite/Chew. To start with, we carried out a preliminary study to determine the appropriate hardware design and to assess the feasibility of our approach. This was followed by a rigorous testing phase where we evaluated the performance of our system using real-time eating data collected from four participants, with subsequent comprehensive analyses.

Interestingly, our findings indicate that despite the use of just two IMUs to track the movements of the hand and mouth, our approach still yields substantial results in terms of both accuracy and F1 score, two key metrics in performance assessment. This suggests that our system offers a robust solution for monitoring food intake, and does so in a way that users would be comfortable with in a social setting.

In the conclusion of our study, we presented a range of potential user scenarios that could significantly benefit from our system. These examples aim to inspire further investigations and innovations in the field of food intake monitoring. For instance, individuals concerned about their muscle health and wanting to avoid bad eating habits could utilize our technology to ensure they make informed food choices that promote healthier masticatory muscles and overall well-being. Additionally, dieticians and health professionals could leverage the system to gain valuable insights into a patient's eating habits, assisting them in providing personalized advice for improving muscle health and dietary patterns.

Furthermore, given its ease of use and non-invasive nature, our system has immense potential for widespread adoption. It could be particularly beneficial for those aiming for weight loss or managing chronic conditions like diabetes or high cholesterol, where consistent monitoring of food intake is crucial.

Moving forward, we hope our work serves as a foundation for future research, leading to further improvements and broader applications in the field of automatic food intake monitoring. We believe this direction of research has the potential to significantly contribute to improving individual and public health.

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Appendices

A. PARTICIPANT CONSENT FORM

PARTICIPANT CONSENT FORM

PARTICIPANT CONSENT FORM

You are being asked to take part in a research study on remote learning scenarios. The research is conducted under supervision by Kai Kunze from Keio University.

INFORMATION SHEET

In this study, you will be asked to record your physiological data which are your body movement via the eye-glasses your wear and the wristband passed to you. The participants in this study are not exposed to any risk beyond the risks of everyday life. You may terminate your participation in the study at any time without giving any reason and without any disadvantages. In the event of termination, all data collected up to that point will be deleted.

PARTICIPANTS' RIGHTS

You may terminate your participation in the study at any time without giving any reason and without any disadvantages. In the event of termination, all data collected up to that point will be deleted. If you have any questions as a result of reading this information sheet, you should ask the researcher before the study begins.

CONFIDENTIALITY/ANONYMITY

The data we collect do not contain any personal information about you except the information that you filled in the following. No one will link the data you provided to the identifying information you supplied (e.g., name, address, email). Up until the point at which your data have been anonymized, you can decide not to consent to having your data included in further analyses. Once anonymized, these data may be made available to researchers via accessible data repositories and possibly used for novel purposes.

DATA STORAGE

The data collected with this study will be stored at the GEIST research group at KMD and deleted after three years at the latest. The data is stored in a form that does not allow any conclusion to be drawn about your person. This consent form shall be kept separate from the other test materials and documents.

By signing below, you are agreeing that: (1) you have read and understood the Participant Information Sheet, (2) questions about your participation in this study have been answered satisfactorily, (3) you are aware of the potential risks (if any), (4) you are taking part in this research study voluntarily (without coercion), and (5) anonymized data only may be shared in public research repositories.

Participant Number*.	Date*
________________________________	________________________________
Participant's Name (Printed)*	Participant's signature*
________________________________	________________________________

If you have any questions, please do not hesitate to contact: Xiongqi Wang
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