TRACKING AND COUNTING MOTION FOR MONITORING FOOD INTAKE BASED ON DEPTH SENSOR

MUHAMMAD FUAD BIN KASSIM

A thesis submitted in
fulfillment of the requirement for the award of the
Degree of Master of Electrical Engineering

Faculty of Electrical and Electronic Engineering
Universiti Tun Hussein Onn Malaysia

JUNE 2020

For my beloved mother and father,

My supervisor,

Lecturers,

Friends,

And everyone who involved in inspired me throughout my journey of completing this project.

ACKNOWLEDGEMENT

In this opportunity, I would like to thank and express my deepest gratitude to my supervisor Ts. Dr. Mohd Norzali bin Hj Mohd. His guidance, ingenious teachings, and most importantly patience made it possible for me to complete this project on time. His sincerest help and generosity towards the sharing knowledge and support has given momentum in driving the project to be successful. Besides, his ambitious idea with numerous excellent suggestions made this project possible to be complete. Secondly, I would like to say thank you to my beloved family members especially my parents; who were always there to encourage and give moral supports. Without them, I would not at this stage. Many thanks for them. To my warm gratitude to all lecturers and FKEE staffs for their knowledge sharing either directly nor indirectly. Finally, to my beloved friends who always be there offer an ultimate support and time. Thank you so much for the teamwork, lessons, and the memories.

ABSTRACT

Obesity has been a serious health concern among people. Moreover, obesity continues to be a serious public health concern in Malaysia and continuing to rise. Nearly half of Malaysians are overweight. Most of the dietary approaches are not tracking and detecting the right calorie intake for weight loss, but currently used tools such as food diaries require users to manually record and track the food calories, making them difficult to be utilized for daily use. Therefore, this project developed a new tool that counts the food intake by monitoring eating motion movement of caloric intake to overcome health issues. The food intake counting method showed a good significance that can lead to a successful weight loss by simply monitoring the food intake taken during eating. The device used was Kinect Xbox One which used a depth camera to detect the motion of a person's gesture and posture during food intake. Previous studies have shown that most of the methods used to count food intake device is worn device type. The recent trend is now going towards non-wearable devices due to the difficulty when wearing devices and it has high false alarm ratio. The proposed system gets data from the Kinect camera and monitors the gesture of the user while eating. Then, the gesture data is collected to be recognized and it will start counting the food intake taken by the user. The system recognizes the patterns of the food intake from the user by following the algorithm design in this thesis to analyze the gesture of the basic eating type and the system get an average accuracy of 96.2%. This system can help people who are trying to follow a proper way to avoid being overweight or having eating disorders by monitoring their meal intake and controlling their eating rate.

ABSTRAK

Obesiti telah menjadi kebimbangan kesihatan yang serius di kalangan orang ramai. Selain itu, obesiti terus menjadi kebimbangan kesihatan awam yang serius di Malaysia dan terus meningkat. Hampir separuh daripada rakyat Malaysia adalah berat badan berlebihan. Kebanyakan pendekatan pemakanan tidak menjejaki dan mengesan pengambilan kalori yang tepat untuk penurunan berat badan, tetapi kini menggunakan alat-alat seperti makanan buku makanan memerlukan pengguna mencatat secara manual dan menjejaki kalori makanan, menjadikannya sukar untuk digunakan untuk kegunaan harian. Oleh itu, projek ini membangunkan alat baru yang mengira pengambilan makanan dengan memantau pergerakan gerakan makan kalori untuk mengatasi masalah kesihatan. Kaedah mengira pengambilan makanan menunjukkan satu kebaikan yang boleh membawa kepada kejayaan penurunan berat badan dengan hanya memantau pengambilan makanan yang diambil semasa makan. Peranti yang digunakan ialah Kinect Xbox One yang menggunakan kamera kedalaman untuk mengesan pergerakan susuk tubuh dan postur badan seseorang semasa pengambilan makanan. Kajian terdahulu telah menunjukkan bahawa kebanyakan kaedah yang digunakan untuk mengira peranti pengambilan makanan adalah jenis peranti boleh pakai. Trend baru-baru ini kini menuju ke arah pengunaan preanti tidak boleh pakai kerana kesukaran memakai peranti mempunyai nisbah kegagalan yang tinggi. Sistem yang dicadangkan mendapat data dari kamera Kinect dan memantau gerakan pengguna semasa makan. Kemudian, data isyarat dikumpulkan untuk diiktiraf dan ia akan mula mengira pengambilan makanan yang diambil oleh pengguna. Sistem ini mengenali corak pengambilan makanan dari pengguna dengan mengikuti reka bentuk algoritma dalam tesis ini untuk menganalisis isyarat jenis pemakanan asas dan sistem mendapatkan purata ketepatan 96.2%. Sistem ini dapat membantu orang yang cuba mengikut cara yang betul untuk mengelakkan berat badan berlebihan atau mengalami gangguan makan dengan memantau pengambilan makanan mereka dan mengawal kadar makan mereka.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS AND ABBREVIATIONS

ANN	-	Artificial Neural Network
API	-	Application Program Interface
CNN	-	Convolutional Neural Network
FN	-	False Negative
GPU	-	Graphics Processing Unit
GUI	-	Graphical User Interface
HAC	-	Hand at Chin
HAE	-	Hand at Ear
HAH	-	Hand at Head
HAN	-	Hand at Nose
HAP	-	Hand at Phone
HD	-	High Definition
HMMs	-	Hidden Markov Models (HMMs)
IR	-	Infrared Camera
KPFIf	-	Kilocalories per food intake female
KPFIm	-	Kilocalories per food intake male
LHM	-	Left Hand at Mouth
PWM	-	Pulse Width Modulation
RAM	-	Random Access Memory
SDK	-	Software Development Kit
SeMG	-	Surface Electromyography
TADA	-	Technology Assisted Dietary Assessment
TN	-	True Negative
TP	-	True Positive
TPR	-	True Positive Rate
USB	-	Universal Serial Bus

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

The study of the food intake counting is carried out due to the escalating interest in its immense potential in reducing weight. Obesity is the 5th major cause of death worldwide and about 2.8 million people died each year from a disease related to obesity [1]. Mostly all the diet plan approaches rely on calories from food label and this is not effective because not all food at the grocery has calories label on packaged food. There is an ongoing debate of obesity recognition as a condition or a disease, motivated at least in part by the desire of researchers to increase options for its treatment and reduce the stigma and discrimination experienced by the obese. It has been shown that monitoring and counting food intake count reduce overweight people drastically [2].Technology is all about helping people, which created a new opportunity to take serious action in managing their health care. Moreover, most of the dietary approach is not tracking and detecting the right calorie intake for weight loss, but currently used tools such as food diaries require users to manually record and track the food calories, making them difficult to be utilized for daily use.

Despite the many efforts to encourage healthier diets, obesity continues to be a serious public health concern in Malaysia and across the world. Weight control can be assisted by self-monitoring of intake consumption, which has been consistently related to successful weight loss. Self-report tools for measuring energy intake in free-living include diet records, 24-hour recalls, food frequency questionnaires, and food photography methods. These methods require time-consuming data entry, recording food types and portion sizes, and linking data with extensive dietary databases.

The Bite Counter is a device to measure how much people eat, was created by Eric Muth, a psychologist, and Adam Hoover, an electrical engineer, both at Clemson University. Muth and Hoover launched their own company, Bite Technologies, and licensed the technology from Clemson University Research Foundation (CURF) in 2010 [3].

This thesis presents a food intake non-wearable system of counting motion consisting of a simple algorithm that is capable of detecting in real time information with regards to food intake during a meal. The algorithm focuses on detecting the user hand gesture motion movement using Kinect sensor to determine their food intake count. With the algorithm created and GUI design, it can tell that the target intake has been reached and it is time to stop eating, thereby helping people to create long-term healthy eating patterns and can prevent obesity

In this project, a new method was used to measure food intake. The food counting is measured using wrist joint motion during eating using Depth-Sensing Cameras which is Kinect Xbox One. By detecting a characteristic pattern, it can identify when a food intake has been taken. The GUI can monitor food intake in real-time and provide feedback to the user. The feedback gives information to tell the user to stop eating after a target intake had been reached a specific threshold which being set at the startup on the GUI and can help the user track long-term eating patterns. Target intake is being calculated using formula of kilocalories per food intake (KPFI).

Generally, hand is aimed downwards to pick something up and sideways to place it into the mouth. This pattern holds regardless of the type of food or utensil. Figure 1.1 shows the illustration of wrist roll when taking a food intake bite.

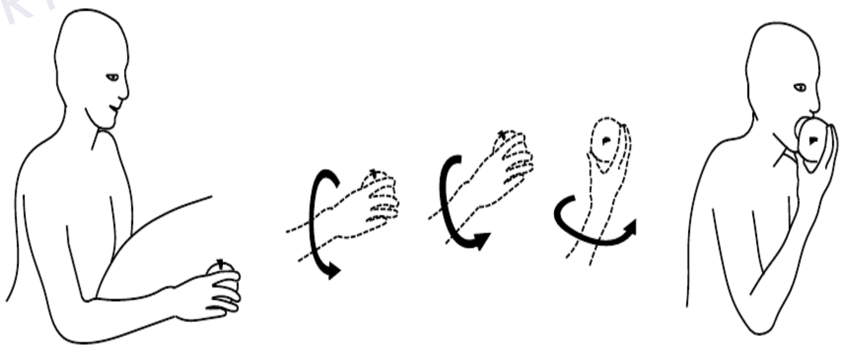

Figure 1.1: Wrist roll when taking a bite [4]

1.1 Problem statement

The study of the food intake counting motion monitoring using Kinect is carried out due to the escalating interest in its immense potential in reducing weight. Obesity continues to be a serious public health concern across the world. Mostly all the dietary approaches rely on detailed individual tracking calories which is long-term and challenging and ineffective. First, overweight and obesity are a growing concern in the Malaysia which has been described among the most overweight countries in South-East Asia [5]. Body weight is classified as Body Mass Index (BMI), that is commonly used as a screening tool to determine people who are underweight, overweight and obesity. A big reason why obesity is such a big concern is it is being linked with major health concerns such as Diabetes mellitus (DM), High Blood Pressure (HBP), High Cholesterol and asthmas (AS). The problem of the previous food counting method is that it mostly uses wearable device where such systems design is not suitable and prone to error for long term monitoring. The difference of it in reference to current project developed is that we use simple algorithm with non-wearable sensor attached on body and making the user comfortable while taking their meal. Next, the proposed food gesture counting could help to avoid eating disorders which already become a serious problem among people. People with eating disorders resulted from the unhealthy way of food intake which can lead to problems in their health. The most common type of eating disorders are Anorexia Nervosa and Bulimia Nervosa [6]. Lastly, the previous problem of bite counting device is the battery and the device mostly not able to count and display properly. Thus, this project uses a Graphical User Interface (GUI) system that display the user food count daily limit and can monitor user BMI.

1.2 Aim

This research aims to develop a system that can monitor and count food intake during eating.

1.3 Objectives

The aim of the research is to monitor the bite of food intake to help person tracking their intake while losing their weight. The objectives proposed as follows:

1. To create system that monitors the motion of food intake using non wearable sensor
2. To create a food intake counting algorithm based on simple gesture algorithm.
3. To develop a Graphical User Interface (GUI) that display the user food count daily limit.

1.4 Scope

This thesis presents an automatic detection of food intake in the presence of physical activity and motion:

1. Monitor food counter with specific food with hand eating and no drinking involved in this experiment.
2. The experiment takes place in a laboratory area to provide as normal a space as possible for eating while enabling as much data collection.
3. Kinect Xbox One camera is positioned in front the user eating areas with specific distance from user.
4. Single normal adult person is being monitored.

1.5 Summary

This chapter demonstrated the background of the research topic with a discussion on different approaches previously used for food intake counting. The objectives of this study were derived to develop a simple and accurate food intake counting detection system that can solve overweight problem and the scope and significance of the study conducted were also discussed. The current issues in food intake counting system were briefly discussed. Counting food intake is hard since people will lost track of their daily food intake and to manual counting of calories intake is time-consuming and highly prone to error as such procedure is laborious and depends on the expert's skill.

In fact, it produced similar result in weight loss, and it is also a safe way rather than counting calories or other diet method. This diet method is proven by previous research [3] that do the tracking on several people and the result of weight loss is proven. This diet is not forcing people on strict diet and beside user can eat anything on plate but based on counting intake. Thus, this project aims to solve the problem by using depth camera since it can track the joint of human body to monitor the eating gesture and count their intake without the use of any other sensor. The next chapter describes in detail on the food intake count techniques applied in the related studies.

CHAPTER 2

LITERATURE REVIEW

In this section, a detailed review process of food intake mechanism system which is chewing, swallowing and intake gesture. The type of meal intake, hand gesture recognition, body joint detection, quaternion of joint orientation, and previous research based on this project are explained. To begin studying this idea, a various way of eating tracking monitoring to be discussed.

2.1 Introduction to Kinect sensor

Kinect created by Microsoft is available on market for gaming purposes. The first device was X-Box 360 which has fewer features compared to the new version of Kinect X-Box One that has many features to be explored. The unique potential of Kinect is the incredible data capturing specifically for motion monitoring moving things in real life. The Kinect sensor contains a feature to detect motion and image using RGB color, VGA video, and depth sensor. The depth camera contains a sensor that captures the 3D imagery and it can measure the point of user body joint using Time of Flight (ToF) camera. The principle of ToF refers to the process of measuring the depth of a point image by quantifying the changes that an emitted light signal encounters when it reflects back from objects in a point image. The Kinect Xbox One are much more precise than the old Kinect v1. Kinect Xbox One uses “time of flight” technology to determine the features and motion of certain objects. The Kinect for Window software development kit (SDK) version 2.0 allows the developers with enough tools, drivers, APIs and device interfaces; allowing the development of Kinect based applications easily made. The body tracking features in SDK make it easier for developers to track up to six people and it supports 25 joints detection. The sensors together with the SDK, can be create and develop applications using method suggested and able to capture as well as react to a person's movement and gestures to give output. The Kinect overview is as shown in Figure 2.1.

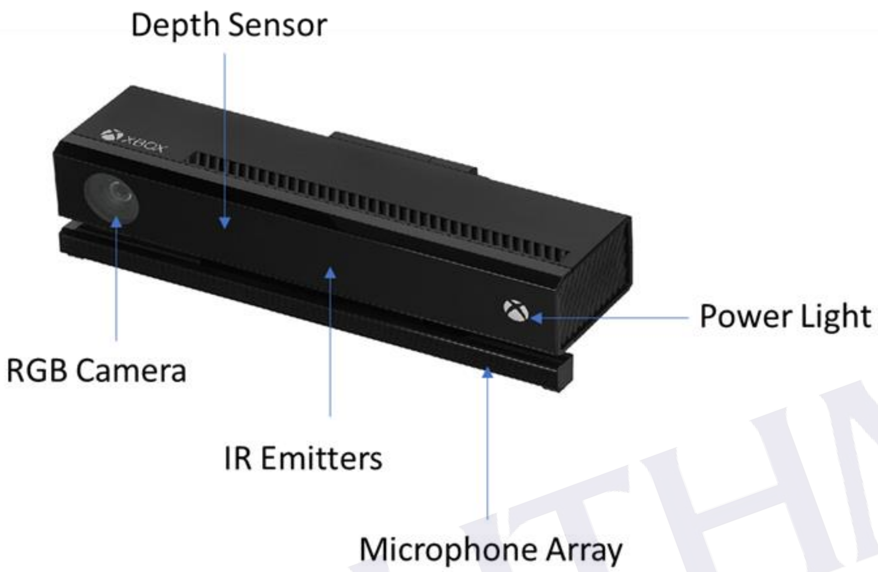

Figure 2.1: An overview of Kinect sensor

2.2 The Significance of gesture recognition

Gesture recognition is the process to describe movement by which gestures are made by the user such as upper limb joints, facial face and lower limb joints which give information and control electronic device. Previously there was a device that able to track and detect a gesture from users to give information that can be used in 2-D and 3-D cameras using camera system [7]. Gesture Recognition has solved many problems such as sign language [8], activity action recognition [9] and human-computer interaction [10]. Most of the literatures related to gesture focused on the field where emotions are from face and also hand joint human gesture. This gesture can be trained using machine learning such as neural network, Hidden Markov Machine (HMM) and decision trees which can predict the gesture accurately. Wearable device has also been widely used for gesture classification. Specifically, accelerometers and gyroscopes that can read and analyze data for joint orientation such as roll, pitch, and yaw was included too. Chakravarthi [11] developed a low power wearable accelerometer wrist band gesture that used mobile monitoring that trains an Artificial Neural Network

(ANN). Hong [12] also used accelerometer data called MGRA that developed 27 features motion which achieved high accuracy with less time and energy consumption. Chouhan [13] developed a glove with the combination of accelerometers, bend sensor and hall sensor to give information of sign language to an easier translation. Jiang et al. [14] combined Surface Electromyography (sEMG) and inertial measurement unit (IMU) to recognize air hand gestures based on wristband movements. Krasoulis [15] used a myoelectric and inertial measurements-based system for upper-limb gesture recognition. The system sensors are distributed along arm with raw sensor values from IMUs which measured the orientation. Most of the gesture sensor describe from the previous researcher not focusing on food intake gesture monitoring. Gesture recognition can help computers to understand and learn human behavior as input. More discussion on different sensor elaborated below.

2.3 Related works of eating activity

Recently a lot of researches have been discussing the techniques for eating activity monitoring method in terms of feature extraction and classification. The depth camera sensor will be used in this project since the depth camera from Kinect v2 can track the gesture motion of hand. Previous method also used embedded sensor on body to track the gesture such as accelerometer and gyroscope to track the user orientation rotation of hand gesture when eating. Kinect v2 can also measure the rotation of the human body joints. Therefore, by using the joint point of hand for tracking its orientation movement of roll, pitch, and yaw, we can track the user's rotation when eating food without using any external sensor attached to body.

2.3.1 Chewing recognition activity

Chewing recognition is a chewing and biting involving the movement motion of the jaw bone. Detecting the sound of chewing has a potential for the development of food intake monitoring. Mostly, the research in this field used a different algorithm such as a microphone in ear and sound wave detection of bite to evaluate chewing event. Recently, Olubanjo et al.[16] focused on a noisy surrounding area similar to this paper where restaurant background noise was implemented to ensure the accurate data of the clean signal for performance for evaluation purposes. Chewing recognition sensor research based not suitable for used in daily life therefore most of the researcher not focused on this sensor method type.

2.3.2 Swallowing recognition activity

Swallowing recognition is a process of breaking food in small chunks while food is being swallowed in digestive system. While food enter mouth the vocal folds in throat close to keep food and liquid from entering the swallowing stage. The noises that you hear when swallowing is the result of the food entering the vocal folds. There are many studies that have taken advantage of this way to detect food while swallowing. Wearable sensing has been used in detecting food or liquid intake. Dong[17] created a system that observed a person's breathing process by detecting swallows for liquid monitoring intake. Chun [18] used tracking Jawbone Movements that uses a proximity sensor that needs to be wore like a necklace which is better compared to neckbone sensor that needs to be wore around the neck while eating. The disadvantages of this approach are it relies to motion and sound approach and it can be affected by other noise when eating and drinking. However, the wearable device for monitoring based on any of these methods may not be convenient due to their characteristic which is uncomfortable when being worn and is deemed as possibly unsafe equipment that may harm user. To overcome this issue, a non-wearable sensor can be proposed to monitor the swallowing process occurring during the food intake. For example, a device which detects gesture motion that is used to capture jaw and throat vibrations using microphones during swallowing and this device does not need to be wearable. Some of these sensors have their own advantages and disadvantages. The use of accelerometers has been proposed for low-cost alternative and simple algorithm. The problem is sensor location and placement may not be suitable for obese individuals due to high body fat under the chin and different size of everyone. Figure 2.2 shows the swallowing example of food intake method.

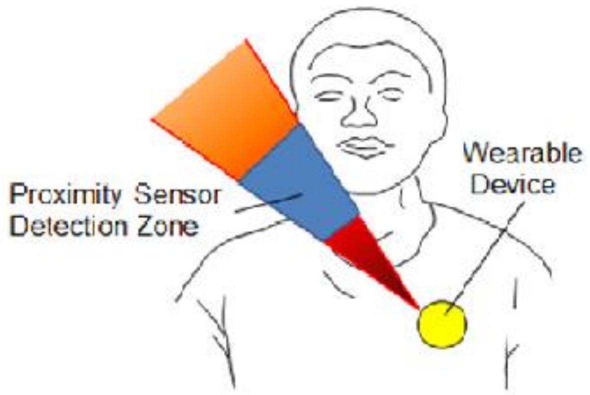

Figure 2.2: Swallowing example of food intake. [18]

2.3.3 Acoustic approach of eating activity

Generally, food intake sound can be categorized into two which i.e. chewing and swallowing since both processes correlate with each other. Acoustic based swallowing and chewing usually use wearable sensor placed around neck or in-ear for monitoring. Bedri [19] created an Ear Bit algorithm which use Inertial measurement unit (IMU) sensor, proximity and microphone to detect eating sound and they also have camera visual to track food bite. Fontana [20] evaluated both technique of chewing and swallowing device for 30 different people to wear the sensor during eating, the result showed that chewing was greater than swallowing thus indicating that swallowing sensor is more comfortable to be used. Sebastian [21] used microphone attached to the outer ear canal and record the process of eating. The recorded sound is compared using two datasets which contains 60 thousand chew events. The disadvantage of acoustic-based swallowing detection systems suffers from environmental noise and presence of surrounding voice. Kalantarian [22] created a smartwatch that has the features of identification of bites and swallows from sound signal. The system was able to detect the presence of chewing sound with an average accuracy of 94% in a laboratory setting. To the best of our knowledge, no system has been tested for the detection of food intake when participants were physically active. The wearable device developed in the previous work is acceptable since it is unobtrusive and non-invasive. This has developed a new way of tackling obesity since the device has the potential in reducing the weight. Figure 2.3 shows the illustration for hierarchical analysis by Sebastián.

There are three steps and they are intake cycle classification, food intake recognition, and food intake activity detection. The algorithm detects and classifies single chew event where food intake occurred and estimated the intake cycle event occurred. Table 2.1 shows the summary of the acoustic approach.

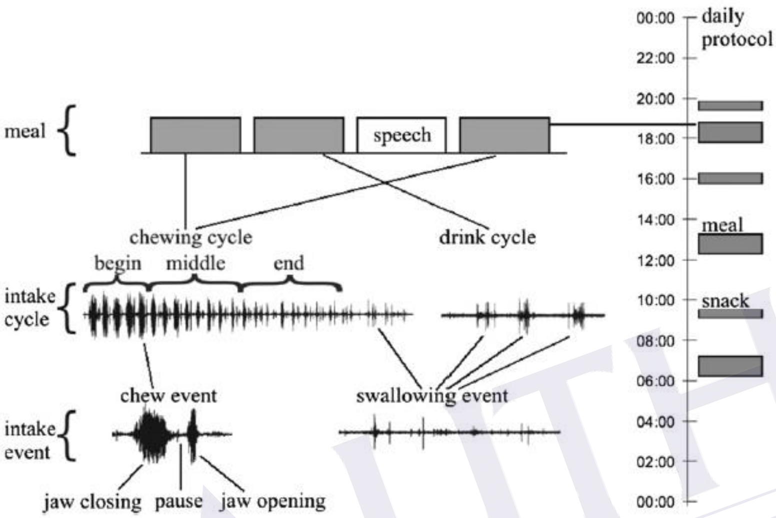

Figure 2.3: Sound Chewing example of food intake.[21]

Table 2.1: Summary of acoustic approach

No	Year	First Author	Techniques	Classification	limitations
1	2013	J. M. Fontana	-Piezoelectric film strain sensor and throat microphone [20]	self-reporting	wearable sensor system to assess eating behaviors
2	2014	S. Päßler	-In-ear microphone placed in the outer ear canal [21]	HMM training	Using microphone sound which affect surrounding sound
3	2015	Bedri	-Outer Ear Interface (OEI) [23]	HMM	Cannot recognize all food

REFERENCES

[1] K. Kearns, A. Dee, A. P. Fitzgerald, E. Doherty, and I. J. Perry, "Chronic disease burden associated with overweight and obesity in Ireland : the effects of a small BMI reduction at population level," *BMC Public Health*, vol. 14, no. 1, pp. 1–10, 2014.

[2] M. Wilson, "Assessing the Bite Counter as A Weight Loss Tool," *All Theses.1995*, p. 98, 2014.

[3] J. L. Scisco, E. R. Muth, and A. W. Hoover, "Examining the utility of a bite-count-based measure of eating activity in free-living human beings," *J. Acad. Nutr. Diet.*, vol. 114, no. 3, pp. 464–469, 2014.

[4] J. L. Scisco, "Sources of Variance in Bite Count," *All Diss.*, vol. 914, no. May, p. https://tigerprints.clemson.edu/all_dissertations/, 2012.

[5] L. K. Ghee, "A Review of Adult Obesity Research in Malaysia," *Med. J. Malaysia*, vol. 71, no. June, pp. 1–19, 2016.

[6] K. Tsuboi, "Eating Disorders in Adolescence and Their Implications," *J. Japan Med. Assoc.*, vol. 129, no. 10, pp. 1586–1590, 2005.

[7] S. Berman and H. Stern, "Sensors for Gesture Recognition Systems," *IEEE Trans. Syst. Man. Cybern.*, vol. 42, no. 3, pp. 277–290, 2012.

[8] S. Goldin-meadow, D. Brentari, and C. H. Development, "Gesture, sign and language: The coming of age of sign language and gesture studies," *Behav Brain Sci*, 2017.

[9] M. Asadi-aghbolaghi *et al.*, "Deep learning for action and gesture recognition in image sequences : a survey To cite this version : HAL Id : hal-01678006," 2018.

[10] A. Haria, A. Subramanian, N. Asokkumar, and S. Poddar, "ScienceDirect ScienceDirect Hand Gesture Recognition for Human Computer Interaction," *Procedia Comput. Sci.*, vol. 115, pp. 367–374, 2017.

[11] M. K. Chakravarthi, R. Kumar, and S. Handa, "Accelerometer Based Static

Gesture Recognition and Mobile Monitoring System Using Neural Networks," *Procedia Comput. Sci.*, vol. 70, pp. 683–687, 2015.

[12] F. Hong, S. You, M. Wei, Y. Zhang, and Z. Guo, "MGRA: Motion Gesture Recognition via Accelerometer," *Sensors (Basel).*, vol. 16, no. 4, p. 530, Apr. 2016.

[13] T. Chouhan, A. Panse, A. K. Voona, and S. M. Sameer, "Smart Glove With Gesture Recognition Ability For The Hearing And Speech Impaired," *2014 IEEE Glob. Humanit. Technol. Conf. - South Asia Satell.*, pp. 105–110, 2014.

[14] S. Jiang, B. Lv, X. Sheng, C. Zhang, H. Wang, and P. B. Shull, "Development of a real-time hand gesture recognition wristband based on sEMG and IMU sensing," *2016 IEEE Int. Conf. Robot. Biomimetics*, pp. 1256–1261, 2016.

[15] A. Krasoulis, "Improved prosthetic hand control with concurrent use of myoelectric and inertial measurements," *J. Neuroeng. Rehabil.*, pp. 1–14, 2017.

[16] T. Olubanjo, E. Moore, and M. Ghovanloo, "Detecting food intake acoustic events in noisy recordings using template matching," *3rd IEEE EMBS Int. Conf. Biomed. Heal. Informatics, BHI 2016*, pp. 388–391, 2016.

[17] B. Dong and S. Biswas, "Wearable sensing for liquid intake monitoring via apnea detection in breathing signals," *Biomed. Eng. Lett.*, vol. 4, no. 4, pp. 378–387, 2014.

[18] K. S. Chun, S. Bhattacharya, and E. Thomaz, "Detecting Eating Episodes by Tracking Jawbone Movements with a Non-Contact Wearable Sensor," *Proc. ACM Interactive, Mobile, Wearable Ubiquitous Technol.*, vol. 2, no. 1, pp. 1–21, 2018.

[19] A. Bedri *et al.*, "EarBit: Using Wearable Sensors to Detect Eating Episodes in Unconstrained Environments," *Proc. ACM interactive, mobile, wearable ubiquitous Technol.*, vol. 1, no. 3, p. 37, Sep. 2017.

[20] J. M. Fontana and E. S. Sazonov, "Evaluation of Chewing and Swallowing Sensors for Monitoring Ingestive Behavior.," *Sens. Lett.*, vol. 11, no. 3, pp. 560–565, 2013.

[21] S. Päßler and W. J. Fischer, "Food intake monitoring: Automated chew event detection in chewing sounds," *IEEE J. Biomed. Heal. Informatics*, vol. 18, no. 1, pp. 278–289, 2014.

[22] H. Kalantarian and M. Sarrafzadeh, "Audio-based detection and evaluation of

eating behavior using the smartwatch platform," *Comput. Biol. Med.*, vol. 65, pp. 1–9, 2015.

[23] A. Bedri, A. Verlekar, E. Thomaz, V. Avva, and T. Starner, "A wearable system for detecting eating activities with proximity sensors in the outer ear," *Proc. 2015 ACM Int. Symp. Wearable Comput. - ISWC '15*, pp. 91–92, 2015.

[24] P. Pouladzadeh, S. Shirmohammadi, S. Member, and R. Al-maghrabi, "Measuring Calorie and Nutrition From Food Image," *IEEE Trans. Instrum. Meas.*, vol. 63, no. 8, pp. 1947–1956, 2014.

[25] H. L. Mcclung *et al.*, "Digital food photography technology improves ef fi ciency and feasibility of dietary intake assessments in large populations eating ad libitum in collective dining facilities," *Appetite*, vol. 116, pp. 389–394, 2017.

[26] F. J. Pendergast, N. D. Ridgers, A. Worsley, and S. A. McNaughton, "Evaluation of a smartphone food diary application using objectively measured energy expenditure," *Int. J. Behav. Nutr. Phys. Act.*, vol. 14, no. 1, p. 30, 2017.

[27] P. J. Stumbo, "New technology in dietary assessment: a review of digital methods in improving food record accuracy," *Proc. Nutr. Soc.*, vol. 72, no. 1, pp. 70–76, 2013.

[28] Y. He, N. Khanna, C. J. Boushey, and E. J. Delp, "Image Segmentation for Image-Based Dietary Assessment: A Comparative Study," *International Symposium on Signals, Circuits and Systems ISSCS2013*. pp. 1–4, Jul-2013.

[29] C. Liu, Y. Cao, Y. Luo, G. Chen, V. Vokkarane, and Y. Ma, "DeepFood: Deep Learning-Based Food Image Recognition for Computer-Aided Dietary Assessment," *CoRR*, vol. abs/1606.0, 2016.

[30] B. L. Daugherty *et al.*, "Novel technologies for assessing dietary intake: Evaluating the usability of a mobile telephone food record among adults and adolescents," *J. Med. Internet Res.*, vol. 14, no. 2, pp. 156–167, Apr. 2012.

[31] Z. Huang, "An Assessment of the Accuracy of an Automated Bite Counting Method in a Cafeteria Setting," *Dissertation*, no. August, 2013.

[32] J. N. Salley, A. W. Hoover, M. L. Wilson, and E. R. Muth, "Comparison between Human and Bite-Based Methods of Estimating Caloric Intake," *J. Acad. Nutr. Diet.*, vol. 116, no. 10, pp. 1568–1577, Oct. 2016.

[33] S. Sharma, P. Jasper, E. Muth, and A. Hoover, "Automatic Detection of Periods of Eating Using Wrist Motion Tracking," *Proc. - 2016 IEEE 1st Int. Conf.*

Connect. Heal. Appl. Syst. Eng. Technol. CHASE 2016, pp. 362–363, 2016.

[34] X. Ye, G. Chen, and Y. Cao, "Automatic Eating Detection using head-mount and wrist-worn accelerometers," *2015 17th Int. Conf. E-Health Networking, Appl. Serv. Heal. 2015*, pp. 578–581, 2016.

[35] M. L. Magrini, C. Minto, F. Lazzarini, M. Martinato, and D. Gregori, "Wearable Devices for Caloric Intake Assessment: State of Art and Future Developments," *Open Nurs. J.*, vol. 11, pp. 232–240, Oct. 2017.

[36] S. Sen, V. Subbaraju, A. Misra, R. K. Balan, and Y. Lee, "The case for smartwatch-based diet monitoring," *2015 IEEE Int. Conf. Pervasive Comput. Commun. Work. PerCom Work. 2015*, pp. 585–590, 2015.

[37] S. Manton, G. Magerowski, L. Patriarca, and M. Alonso-Alonso, "The 'Smart Dining Table': Automatic Behavioral Tracking of a Meal with a Multi-Touch-Computer," *Front. Psychol.*, vol. 7, 2016.

[38] L. Costa, P. Trigueiros, and A. Cunha, "Automatic Meal Intake Monitoring Using Hidden Markov Models," *Procedia Comput. Sci.*, vol. 100, pp. 110–117, 2016.

[39] S. Gaglio, G. Lo Re, and M. Morana, "Human Activity Recognition Process Using 3-D Posture Data," *IEEE Trans. Human-Machine Syst.*, vol. 45, no. 5, pp. 586–597, 2015.

[40] E. Cippitelli, S. Gasparrini, E. Gambi, and S. Spinsante, "Unobtrusive intake actions monitoring through RGB and depth information fusion," *Proc. - 2016 IEEE 12th Int. Conf. Intell. Comput. Commun. Process. ICCP 2016*, pp. 19–26, 2016.

[41] C. F. Liew and T. Yairi, "Human Head Pose Estimation and Its Application in Unmanned Aerial Vehicle Control," in *The Malaysia-Japan Model on Technology Partnership*, 2015, pp. 327–336.

[42] Y. Nizam, M. N. H. Mohd, and M. M. A. Jamil, "Human Fall Detection from Depth Images using Position and Velocity of Subject," *Procedia Comput. Sci.*, vol. 105, no. Iris 2016, pp. 131–137, 2017.

[43] R. Roberto, P. Lima, V. Teichrieb, and T. Araújo, "Evaluation of Motion Tracking and Depth Sensing Accuracy of the Tango Tablet," *2016 IEEE Int. Symp. Mix. Augment. Real. (ISMAR-Adjunct), Merida*, pp. 231–234, 2016..