A DEVICE FOR DETECTING AND COUNTING BITES OF FOOD TAKEN BY A PERSON DURING EATING

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ABSTRACT

We introduce a device capable of detecting in real time information concerning bites taken during a meal. The device can count the total number of bites the user has taken and provide the rate of bites taken (bites per minute) of the user. The device could find use in a number of applications, including helping a user with obesity, eating disorders, or eating rate problems. We have built three prototypes of a bite detector device. Each is based on a different sensor for detecting the motion of the wrist, with particular emphasis given to the rolling motion of the user's wrist. During use, information gathered can be utilized to provide real-time feedback to the user. Information can also be stored to review the motion events as well as to evaluate the performance of the device. Experiments have been conducted to determine the accuracy of the invention. The sensitivity of the device can reach as high as 91%.

ACKNOWLEDGEMENTS

I would like to thank my advisor, Dr. Hoover, for all of the helpful guidance he gave me throughout the Masters' program. I would also like to thank my committee members, Dr. Muth, Dr. Walker and Dr. Birchfield for the time and effort they spent reviewing my thesis. My parents also deserve recognition. Without their time, effort, money, care, and patience throughout my life, I would never have been able to come this far in my education. Thanks also belong to all of my friends (who are too numerous to name) who listened to my complaints and helped me to keep focused on my objectives.

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CHAPTER 1

INTRODUCTION

This thesis introduces a wrist-worn device capable of detecting in real time information with regards to bites taken during a meal. Eating occurs in a variety of environments, including homes, restaurants, places of business, and other social gathering spots. It is very difficult to monitor food intake at all these locations using manual methods. Furthermore, while people eat they may simultaneously engage in a variety of other activities, including talking, reading, watching television, and working. These activities distract from efforts meant to monitor food intake. For example, when 105 participants were asked to manually count the number of bites taken during each meal in a 24-hour period by using an index card and slash system, 43 participants lost count during the meal or forgot to count the number of bites entirely [40].

1.1 Background and motivation

A bite detector device could be used in several applications. First, our proposed bite detector could help overweight or obese people to manage their body weight. Overweight[1] and obesity are a growing concern in the United States. Body weight can be classified by the body mass index (BMI), which is weight (in kilograms) over the square of height (in meters). A person whose BMI is between 25 and 29.9 is overweight; if the BMI is more than 30, the person is obese; if the BMI is above 40, the person is extremely obese [47]. According to this classification and data from the National Health and Nutrition Examination Survey (NHANES), in 2003-2004, 66.3% of US adults were overweight, 32.2% of US adults were obese and 4.8% of US adults were extremely obese. If arranged by sex, in 2003-2004, 70.8% of US men and 61.8% of US women were overweight, 31.1% of US men and 33.2% of US women were obese, 2.8% of US men and 6.9% of US women were extremely obese [45]. In addition, the number did not change much between 2003-2004 and 2005-2006 for men or women [44]. The most recent assessment of global obesity and overweight by the World Health Organization (WHO, 2006) revealed that 1.6 billion adults (ages 15+ years) were overweight and 400 million adults were obese in 2006 according to BMI values [67].

[1] The term "overweight" is most often used as an adjective in vernacular English, but in the medical community, it is also commonly used as a noun.

The reason that overweight and obesity are such a big concern is that they are strongly associated with several major health risk factors. A number of health problems have been linked to a rise in body weight, including heart disease, hypoxia, sleep apnea, hernia, and arthritis. [65]. Table 1.1 shows a survey result that overweight and obesity are related to different health problems. It is based on the largest telephone survey of adults in the United States, the Behavioral Risk Factor Surveillance System (BRFSS), which is a cross-sectional telephone survey conducted by the Centers for Disease Control and Prevention and state health departments. The second row in the table shows there were 195,005 people in this investigation. Using the BMI obesity definition, 84,469 of them are normal weight, 70,231 of them are overweight, 35,767 of them are obese and 4,538 of them are extremely obese. The first column shows different types of health problems. It includes diabetes (DIA), high blood pressure (HBP), high cholesterol (HC), asthma (AS), arthritis (AR) and general health problems (GH). The data shows that both overweight and obesity are significantly associated with diabetes, high blood pressure, high cholesterol levels, asthma, arthritis, and fair or poor health status.

	Total	Normal	Overweight	Obesity	Extreme Obesity
	(N=195,005)	(n=84,469)	(n=70,231)	(n=35,767)	(n=4,538)
DIA(%)	7.9	4.1	7.3	14.9	25.6
HBP(%)	25.7	15.9	27.8	40.9	50.9
HC(%)	31	23.5	34.1	39.4	36.2
AS(%)	11	9.9	10	13.9	22.6
AR(%)	23	17.7	23.7	32.1	44.2
GH(%)	15.2	11.8	14.1	22.5	37.6

Table 1.1 Relation between BMI and health problems (DIA: Diabetes, HBP: High blood pressure, HC: High cholesterol, AS: Asthma, AR: Arthritis, GH: General health problems). Taken from [43].

Flegal et al. [19] found that obese and extremely obese people were linked to increased mortality compared to the normal weight people. In 2000, costs for obesity in the U.S. were estimated at more than $117 billion [34]. So it is very important to successfully manage our body weight.

Terre et al. [63] reviewed several obesity treatments such as pharmacotherapy, very low-calorie diets and surgery. They also mentioned the disadvantage of these methods. For instance, these treatments were costly, had side effects and had disappointing long term results.

A second use for the proposed bite detector could be for helping eating disorders. Eating disorders have also become a serious problem among people. There are two common eating disorders: anorexia and bulimia [18]. "Individuals with anorexia nervosa are unwilling or unable to maintain a body weight that is normal or expectable for their age and height [49]." The activities of anorexia can lead to a variety of medical complications. These include increased physical activity; depression; obsessional preoccupation with food; reductions in heart rate, blood pressure, and metabolic rate; increased cortisol production; and decrease in the production of estrogen (or, in males, testosterone) [64]. On the other hand, "individuals with bulimia nervosa regularly engage in discrete periods of overeating, which are followed by attempts to compensate for overeating and to avoid weight gain [48]." Bulimia nervosa is also associated with a lot of health risk factors, including constipation, tooth decay, irregular menstrualcycles, extremely low blood pressure, depression, and substance abuse [7].

Many methods are suggested to treat eating disorders. Garner et al. [22] discussed several treatments such as psychodynamic, feminist, family approaches, hospital methods, drug treatments and educational approaches. However, Zandian et al. [68] pointed out that the outcome has not improved significantly over a long term and all these treatments are based on very weak evidence and results.

A third use for the proposed bite detector is to control eating rate. Although research has not conclusively shown that slowing down eating rate would reduce food intake [41], several experiments have shown that eating slowly was of great benefit. Otsuka et al. [50] and Sasaki et al. [55] both found that eating fast had a significant positive relationship with BMI. Stuart [60] mentioned that controlling eating rate could help not only reduce the amount of food intake but also help people enjoy the taste.

1.2 Related work

1.2.1 Food intake detection

In a more general view, the goal in all of these problems (the overweight problem, the eating disorder problem, and the eating rate problem) is to balance consumption and expenditure. Currently, there are no widely used tools for monitoring food intake.

The most common way to monitor food intake is to manually track the food eaten and calculate the number of the food calories. Beidler et al. [8] established a system, called Personal Nutrition Assistant Project, which provided web-based tools using a search engine interface to the USDA database for clients to get their intake analysis. Clients could select their daily diet entry in the database. Then, they could go to the next browser to enter diary entry with measurement units. Siek et al. [58] presented a study about electronic intake monitoring application for chronic kidney disease patient who had low literacy and low income. The application, Barcode Ed, was designed with an off-the-shelf Palm OS Tungsten T3 PDA and Socket In-Hand SDIO card scanner. In this three-week study, participants scanned barcode or voice recorded what, when, and how they ate. The result of this study showed barcode scanning would be helpful for recently diagnosed CKD patients in learning about diet entry strictly. However, these types of systems force the user to input, scan, or voice-record food eaten into a system. People often forget or dislike doing this sort of task after every meal.

Another method to measure the amount of food intake is to weigh the amount of food before and after eating. So the difference of the weight is the amount of food intake. Westerterp-Plantenga [66] monitored food intake using an electronic built-in table with a weighing scale under the plate. The food intake details, the amount eaten, the eating time, the average eating rate, the average bite size, and the average bite frequency, were recorded by a digital computer that was connected to the scale. They developed cumulative food intake curves that can be used as adequate tools to analyze the dietary and clinical interventions on meal size. Chang et al. [13] proposed a dining table which could measure the food intake. The table consisted of weighing sensors and Radio Frequency Identification (RFID) sensors. The food should be placed in the container which also had a RFID tag. Different foods should be placed in different table cells so that the RFID sensors would be able to identify it. By recognizing the RFID tag on the container and the existed database, the table could analyze the food intake by weighing the container. However, these methods can only monitor people when they eat at the instrumented table, and for example it can not be used to monitor people when they dine at a restaurant or at a friend's house.

In other methods, instead of weighing the pre-eaten food and post-eaten food, people take photos before the eating and after the eating and use image processing to tell the amount of food intake. Takeda and colleagues [62] [20] [54] discussed such a concept. First, they took images of the dish before and after intake. Second, they used thresholds to convert the image into black and write images. Third, they applied a network algorithm to measure the intake calorie. Zhu et al. [69] also used image processing to evaluate the amount of food intake. They used a PDA with a camera inside. After taking a picture of the food, the user needed to label the food manually. Then the system would analyze the food by image segmentation, feature extraction and image classification and measure the amount and nutrient of the food. However, these sorts of systems require carefully constructed environments similar to the dining tables with built-in scales. The foods measured must also be restricted due to the difficulty of using image processing techniques to detect pre and post-eaten differences.

Some researchers studied the sound made by chewing the food. Drake [17] recorded the chewing sound and crushing sound through a microphone and a sound recorder-reproducer. Then he used tools such as spectrum recorder, voltmeter, attenuator, oscillograph and audio generator to analyze the amplitude, frequency and duration of the sound. He also compared chewing sounds made by different foods and chewing sounds produced by different people. DeBelie et al. [9] also studied the sounds made by chewing food. They recorded the chewing sounds of four different dry-crisp snacks (potato chips, prawn crackers, cornflakes and low calorie snacks) and they compared them using FFT analysis and multi-way data analysis. They found that different people had different chewing sounds. After calibrating the sound of different people, they could almost distinguish the sound from different types of food though it is hard to identify the potato chips because of their irregular shape. Amft et al. [3] discussed the chewing sounds and the best position to put the microphone. They concluded that when they put the microphone in an inner ear, they could get high chewing signal intensity but low speech signal intensity. After getting the signal of the chewing sound, they used chewing segmentation and classification to tell different food products apart. However, these methods have poor precision in differentiating many kinds of food due to low signal to noise ratio. Furthermore, the recording procedures are very expensive.

The sound caused by swallowing food has also been investigated. Logan et al. [39] analyzed the spectrograms of four kinds of sounds, deglutition, respiration, voluntary cough, and vocalization. Sound was amplified from a microphone and recorded on a tape recorder for later analysis. It was found that deglutition sounds performed a particular spectrographic pattern which was different from those three. Limdi et al. [38] used the electrodes near the neck to record the surface electromyography. After amplifying and filtering the signal, they could detect the swallowing rate. If the rate was too high, they would give feedback to the user. Recently, Amft et al. [4] put a microphone sensor on the neck to record the sound and used gel electrodes to transduce the surface electromyography. With the continuous data, they detected the swallowing events by using a sliding-window and bottom-up algorithm and a feature similarity search. Because of the same problem as analyzing chewing sound, these methods are inaccurate and costly.

Other technologies have also been involved. Some studies have been undertaken to measure the fat content of meat using near-infrared (NIR) spectroscopy [33] and nuclear magnetic resonance (NMR) imaging [24] [6]. These methods are targeted towards meat and food inspection rather than individual user consumption. In addition, most of these methods require the use of large equipment.

1.2.2 Wrist worn device

All of the methods discussed so far are not applicable for general, everyday-use for food intake monitoring. The device should be able to be worn casually, and its feedback and recording capabilities should not embarrass the user. Towards this goal, we now look specifically at wrist-worn devices and what they have been used to measure in previous works.

Wrist-worn devices can be used for many applications. Sharples and Beale [57] reviewed a variety of monitoring devices that could be worn, including many that are wrist-worn. Such devices have been proposed or built to measure environment and health properties, including temperature, barometric pressure, altitude, and heart rate.

Many applications are concerned with some aspects of health. Harland et al. [26] described a wrist-worn device for ambulatory monitoring of the human electrocardiogram (ECG). They used two wristwatch style sensors to acquire high resolution ECG and displayed it on a laptop computer through a wireless transceiver. Gagnadre et al. [21] proposed a wrist-worn device using an optic fiber sensor to measure heart rate, breathing frequency, blood pressure variations and breathing amplitude. With these parameters, they could detect different sleep phases. Ching et al. [14] designed a circuit connected to a microphone on the wrist to calculate heart rate. From a survey of the subject including gender, age, body weight and the linear relationship between the heart rate and oxygen consumption, they could tell if the subject was in bad health. Sugimoto et al. [61] had the same idea as Ching et al. [14]. They presented a wrist-worn device which can measure the heart rate. By sending the data wirelessly through a Bluetooth technology, they calculated the oxygen consumption, and estimated the energy expenditure. Ouchi et al. [52] [51] used a wrist-worn device which mainly comprised of four different sensors, pulse meter, thermometer, galvanic skin reflex electrodes and 3-axis accelerometer, to acquire pulse wave, skin temperature, perspiration and movement. Sending these measuring data to a PDA through a Bluetooth connection, they could estimate the user's health condition.

Wrist-worn devices have also been used in non-health-monitoring applications. Heil et al. [27] used a wrist-worn light to document that indoor lighting for a particular day-shift work environment could serve as the primary light exposure dosage for humans. Maurer and colleagues [42] [59] developed an E-watch. This E-watch had a lot of applications. It can be used as a normal watch to show the current time. It could also use light sensors and a microphone to recognize the location and use a temperature sensor to detect the temperature. In addition, it had a calendar function which could communicate with a cell phone or a computer. Blasko et al. [10] used a small wrist-worn projector and projected a large image onto surfaces.

A very important reason researchers prefer putting a non-invasive device on the wrist instead of on other parts of the body is because the wrist-worn devices can be used to study hand motion and gesture recognition in various domains. Howard et al. [29] designed a lightglove, a virtual typing and pointing system, which was worn around the wrist. This wrist-worn device sent out beams of fan shape light directing from the wrist. While descending a finger into the light beam, there was a key closure generated that provided the host system with visual feedback to complete the input. This keyboard/mouse mimicry visual control mitigated constraint of posture and position and allowed other hand operations. Ogris et al. [46] used ultrasonic sensors, accelerometers and gyroscopes to measure the distance and the motion to determine the gesture of a pre-defined bicycle repair task. Schmidt et al. [56] conducted a study about a wrist-worn computer and platform, named eWatch, which could detect light and acceleration data. The analysis of velocity and gesture recorded by the eWatch was similar to analysis of orchestra beating. They confirmed that the eWatch was a suitable input device for acceleration based gesture recognition for the virtual orchestra system. Chambers et al. [12] used accelerometers to detect the acceleration and used a hidden Markov model to recognize the gestures. Lementec et al. [37] used sensors to recognize the arm gestures. They used four sensors in different parts of the body: upper part of the left arm, upper part of the right arm, the left wrist, and the right wrist. They defined three states: the steady state, the oscillation state and the unclassified state. They also defined five positions: high, medium-high, medium, medium-low and low. With the combination of the sensors states and positions, they could classify the different motion gestures. Amft and colleagues [2] [32] used wrist-worn sensors in combination with sensors on the upper arms, head, and ears, to classify an eating action taken by a person. Their methods searched for pre-defined patterns in the signals conveyed by all the sensors in order to classify a motion pattern as one of drinking, using a spoon, using cutlery, or using fingers to eat. In contrast, we are interested in a simpler problem. We use a single wrist-worn sensor to detect a bite taken by a person regardless of the type of food or motion involved in the bite.

1.2.3 Related patent

There are some patents related to our bite detector device. Some devices can be used to monitor the amount of food and calorie intake that one consumes during a given day.

U.S. Patent No. 4,321,674 to Krames et al. [35] described such a system. People entered the food items into the device, and the device would calculate the total calories and the nutritional values. If the calories exceeded the daily calorie limit, a warning would be shown.

U.S. Patent No. 4,686,624 to Blum et al. [11] described a device to calculate the calorie of the food input by the user as well. Furthermore, this device included the time when the user recorded the food and the device could transfer the data to a remote computer so it could be reviewed by the doctor.

U.S. Patent No. 4,575,804 to Ratcliff [53] and U.S. Patent No. 4,911,256 to Attikiouzel [5] also developed a device with the same idea. In addition, their device included a weighing scale. With the weighing scale and the food items input by the user, the device could calculate the calorie and protein value.

Unfortunately, such devices usually lack the ability to provide real time feedback to a user. Also, many of these devices require the user to enter information into a computer which takes time and effort. It is a tedious job to manually track or note in a diary every meal consumed, and manual tracking provides obvious opportunities for bias and misreporting. Moreover, devices developed for clinical or hospital or research monitoring of food intake are not applicable for everyday use by an average person.

Devices that offer real time feedback to a user have also been described. For instance, U.S. Patent No. 5,398,688 to Laniado [36] described a device that could detect changes in physiological variables such as heart rate, stroke volume, and blood pressure corresponding to initiation of eating. A detected change in a physiological variable started a timer and after a predetermined amount of time had passed, the device would notify the user to stop eating.

U.S. Patent No. 5,864,518 [23] to Geiser described a device and method for analyzing a swimmer's swim stroke. He used two metallic sensors in the watch to count the stroke. When the hands were in the water, it would form a short circuit. When the hands were out of the water, it would form a open circuit; therefore it was counted as one stroke.

U.S. Patent No. 5,563,850 [25] to Hanapole described a device that alerts the user when it was acceptable to take another bite based upon the time interval between individual bites. The device utilized a wrist motion detector that activated a timer upon wrist motion.

U.S. Patent No. 6,135,950 [1] to Adams described a device that included a first sensor placed on a user's throat to monitor swallowing and a second sensor that was placed near the user's heart. Feedback from the two sensors allowed better quantification of the amount of food ingested.

Other sensors have been developed to monitor other bodily functions. For instance, U.S. Patent Application Publication No. 2005/0245793 [28] to Hilton, et al. described an apparatus and methodology that may be used to measure and store physiological parameters indicative of sustained activity by a user including walking, sleeping, exercising, or other activities.

1.3 New solution - the idea of a bite detector

While the above methods offer improvements in the art, room for additional improvements exist. What is needed is a non-invasive, inexpensive, easy to operate, and discreet device that can measure food intake. Thus, we envision a bite detector device that is worn like a watch and can detect individual bites and count them when the person wearing it eats. We demonstrate three different prototypes of the bite detector. Each device is placed on the person's wrist and connected to an external computer. During use, the device can gather and interpret information with regard to the motion of the user's wrist during a meal, with particular emphasis given to the rolling motion of the user's wrist. Information gathered can be utilized to provide real-time feedback to the user. Information can also be stored to maintain a long term record of eating, so as to better examine the user's eating habits over time. The following chapter will introduce the bite detector device, the bite detection algorithm, the experiments conducted, and the performance of the bite detector in detail.

CHAPTER 2

METHODS

2.1 Overview

This chapter covers in greater detail the actual implementation of our bite detector device. First, we introduce three sensor prototypes we built for our bite detector. They are based on the wired InertiaCube3 sensor, the wireless InertiaCube3 sensor and the STMicroelectronics LIS3L02AL sensor respectively. Each sensor can detect the orientation data in degrees in real time. For the first two prototypes, we just need to directly connect the sensors to the computer's RS-232 port or USB port via a wired or wireless connection. For the third prototype, we need to design a circuit board and then connect the LIS3L02AL sensor to the computer through an analog input-to-digital I/O board. Second, we introduce our algorithm of bite detection. It includes collecting the orientation data, controlling the record frequency, selecting the useful orientation, dealing with the bound problem, smoothing the signal, calculating the derivative, defining the coordinate system of wrist motion, and defining the bite period. Then we will describe the video capture scene and we will develop two graphical user interfaces (GUI) for our bite detector device. The first graphical user interface is used to detect the bite information and give feedback to the user in real time. The second graphical user interface can be used to review the stored information of sensor data and synchronous recorded video. It can detect the bite offline with regard to different parameter settings. It can also evaluate the bite detector after marking the ground truth bite manually by reviewing the data and the synchronous video. At last, we will discuss how to evaluate our bite detector.

2.2 Sensor prototypes

We have built three prototypes for the bite detector device. Each uses a different sensor for detecting the motion of the wrist. The sensor is used to calculate the motion of the user's wrist in order to identify individual bites during a meal. These sensors can sense the angular rate of roll, pitch and yaw. The three different kinds of sensors are the wired InertiaCube3 sensor, the wireless InertiaCube3 sensor and the STMicroelectronics LIS3L02AL sensor. Figure 2.1 shows a picture of two of the sensors. Both InertiaCube3 sensors are the same size (the left side of Figure 2.1), the difference being that the one pictured uses a wire to connect to a computer while the other is wireless but needs a battery. The STMicroelectronics sensor in the middle is much smaller compared to the other two.

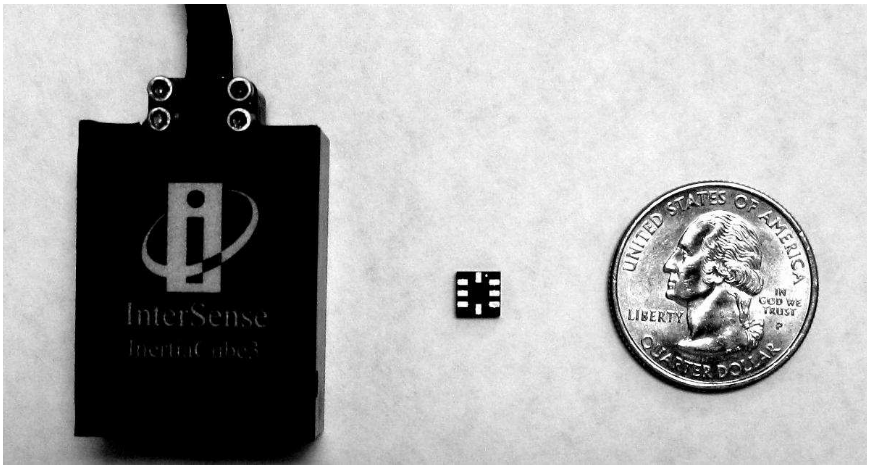

Figure 2.1 The InterSense InertiaCube3 sensor and the STMicroelectronics LIS3L02AL sensor

2.2.1 Wired InertiaCube3 sensor

The first prototype is based upon a wired InertiaCube3 sensor produced by InterSense Corporation (InterSense, Inc., 36 Crosby Drive, Suite 150, Bedford, MA 01730, www.isense.com). The wired InertiaCube3 sensor is an inertial 3-DOF (Degree of Freedom) orientation tracking system. It is based on micro-electro-mechanical systems (MEMS) technology. It contains an accelerometer, a gyroscope and a magnetometer on each of the 3 axis so it can provide 360 degree measurement in all three orientations: pitch, yaw and roll [30]. The whole sensor package includes the orientation sensor, the RS-232 serial interface, the AC power cable and the AC/DC +6VDC power supply. All of these parts are shown in Figure 2.2.

To get the orientation data from the wired InertiaCube3 orientation sensor, we need to link the sensor to the computer. First, we attach the orientation sensor to the RS-232 serial interface connector. Then we plug the serial interface connector into a personal computer's RS-232 port. After that, the AC to DC power is connected to the main power and the +6VDC power is connected to the RS-232 serial interface connector.

The InterSense company also provides a library file ISENSE.DLL and a header file ISENSE.H so that the user can initialize and retrieve data from the wired InertiaCube3 sensor by using development software Microsoft Visual Studio C++ 6.0. To initialize the sensor, the function

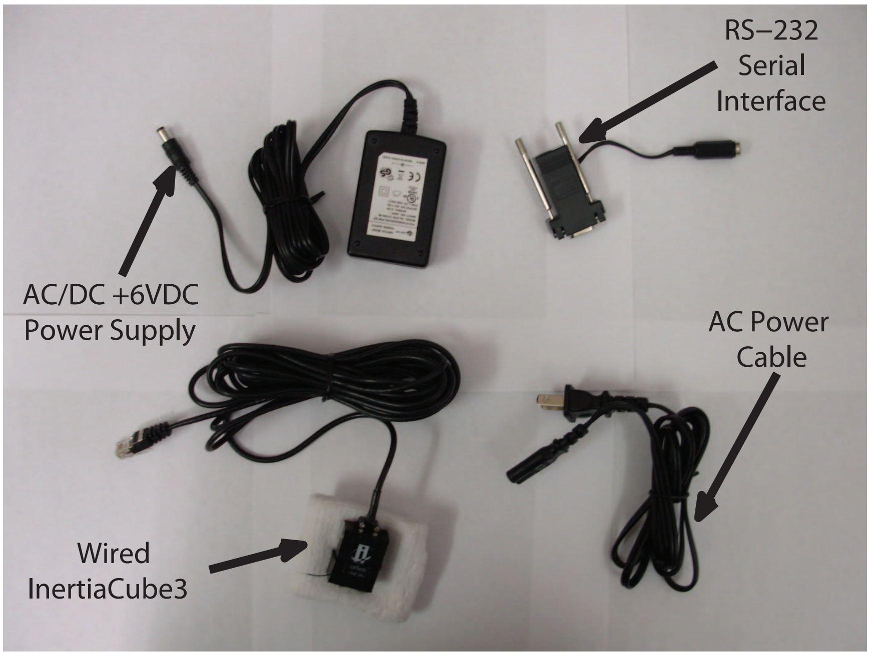

Figure 2.2 The components of the InterSense wired InertiaCube3 Sensor

ISD_OpenTracker in the ISENSE.H header file should be used. If the function return value is TRUE, it means the sensor has been opened successfully through the RS-232 port. After that, we can use the function ISD_GetData to get the orientation data in yaw, pitch, and roll from the configured sensor. At last, we can use the function ISD_CloseTracker to shut down the sensor, close the communication port and release all the resources allocated by the sensor.

2.2.2 Wireless InertiaCube3 sensor

The second prototype is mainly based on a wireless InertiaCube3 sensor which is also produced by the InterSense Corporation (InterSense, Inc., 36 Crosby Drive, Suite 150, Bedford, MA 01730, www.isense.com). The wireless InertiaCube3 sensor is also an inertial 3-DOF (Degree of Freedom) orientation tracking system as the wired InertiaCube3 sensor. The main difference between these two sensors is that the wireless InertiaCube3 sensor can connect to the computer wirelessly and it allows up to 16 different channel selections [31]. It consists of a wireless InertiaCube3 sensor and an InertiaCube3 receiver which uses the same channel. The wireless InertiaCube3 sensor and the InertiaCube3 receiver are shown in Figure 2.3.

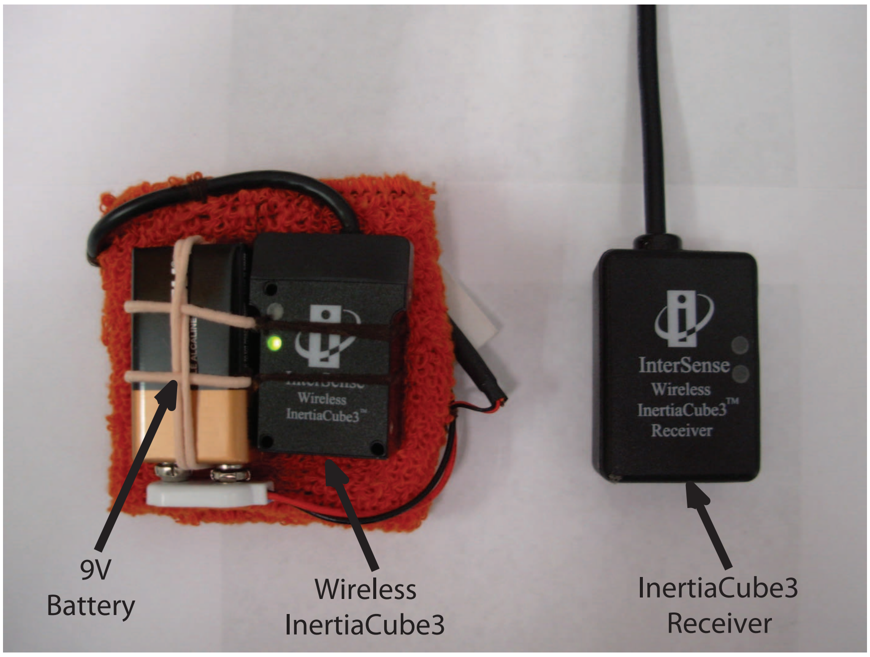

Figure 2.3 The components of the InterSense wireless InertiaCube3 Sensor

To get the orientation data from the wireless InertiaCube3 sensor, we attach a 9 volt battery to the wireless InertiaCube3 sensor and connect the receiver to the computer through a USB port.

After that, we use the software “DeviceTool” provided by the InterSense company to configure the wireless InertiaCube3 sensor and the InertiaCube3 receiver. The software will search for all linked receivers and the paired wireless InertiaCube3 sensor. After the link is established, the green LED on the battery will stay on steady. As said in [31], if the voltage is below 5.2 Volts, the green LED will flash until the voltage goes back to at least 5.5 Volts. If the voltage is below 4.5 Volts, the communication will be disconnected. At last, we can use the same library ISENSE.DLL and the same functions as the wired InertiaCube3 sensor to read the orientation data from the sensor wirelessly.

2.2.3 STMicroelectronics LIS3L02AL sensor

The third prototype uses a MEMS inertial sensor LIS3L02AL produced by STMicroelectronics Corporation (STMicroelectronics, 39 Chemin du Champ des Filles, C.P.21, CH 1228 Plan-Les-Ouates, Geneva, Switzerland, www.st.com). The sensor is shown in the middle of Figure 2.1.

The LIS3L02AL is a 3-axis linear capacitive accelerometer. It is small, has low power consumption and has a bandwidth of 1.5 KHz.

Figure 2.4 shows the circuit design for a STMicroelectronics LIS3L02AL sensor that we built. The design guide is taken from the user manual of the LIS3L02AL sensor [16]. A power supply decoupling capacitor (100 μF ceramic or polyester + 10 μF aluminum) should be connected to the Vdd leg of the device. The LIS3L02AL allows to band limit V_{out_x}, V_{out_y} and V_{out_z} through the use of external capacitors. The frequency range should be less than 1.5 KHz. The equation for the cut-off frequency (f_t) of the external filter is given using Equation 2.1:

$$f_t = \frac{1}{2\pi \cdot R_{out} \cdot C_{load}(x, y, z)} \tag{2.1}$$

R_{out} has a nominal value equal to 110 $k\Omega$, so we can simplify the Equation 2.1 into Equation 2.2.

$$f_t = \frac{1.45\ \mu F}{C_{load}(x, y, z)}\ [Hz] \tag{2.2}$$

In our design, we have chosen a 22 nF capacity as C_{load}(x), C_{load}(y), and C_{load}(z), thus calculating from Equation 2.2, the cut-off frequency of the external filter is 66 Hz. We have also built the test mode of the circuit. In Figure 2.4, if the wire from ST is connected to Vdd, it is in test mode;

otherwise it is in normal mode. The final STMicroelectronics LIS3L02AL sensor circuit is shown in Figure 2.5.

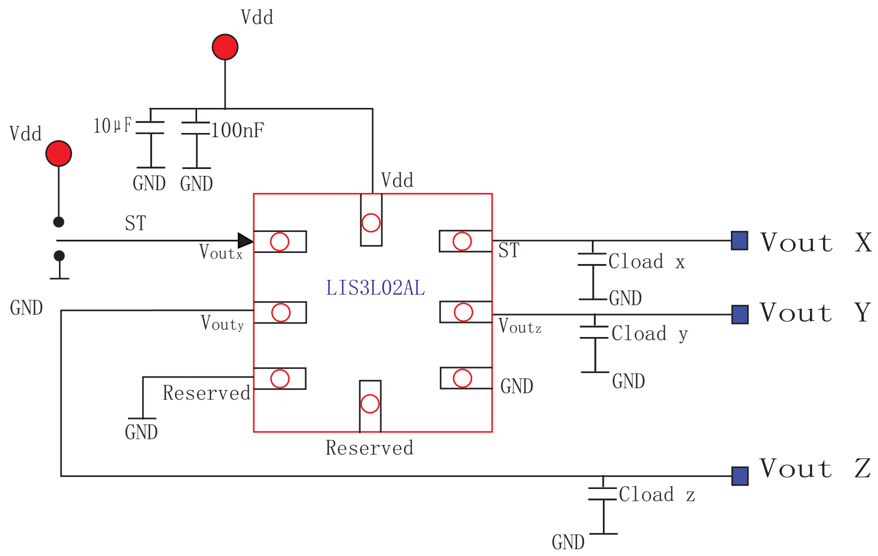

Figure 2.4 Circuit design for the STMicroelectronics LIS3L02AL sensor

We have attached the LIS3L02AL sensor to an analog input-to-digital I/O board in a computer. We used the PCI-DAS08 produced by Measurement Computing Corporation (Measurement Computing Corporation, 10 Commerce Way, Norton, MA 02766, USA, www.measurementcomputing.com). The analog input-to-digital I/O PCI-DAS08 board is shown in Figure 2.6.

The PCI-DAS08 is a multifunction measurement and control board designed to operate in computers with PCI bus accessory slots. All hardware configuration options on the PCI-DAS08 are software controlled. There are no switches or jumpers to set [15]. The board uses a 37-pin male "D" connector. The main connector pinout of the analog input-to-digital I/O PCI-DAS08 board and the connection with the STMicroelectronics LIS3L02AL sensor are shown in Figure 2.7.

2.3 Bite detection algorithm

The key ability of the bite detector device is to detect a bite in real time during a meal. In this section, we describe the algorithm of bite detection. We have developed the bite detection algorithm in Microsoft Visual C++ 6.0. Figure 2.8 shows the flow diagram of our bite detection algorithm. Before the loop, we initialize *Bite_Count* as 0 and two time parameters, $T1$ and $T2$, also as 0 where $T1$ is the old time and $T2$ is the current time. When we update the time from the system, if the

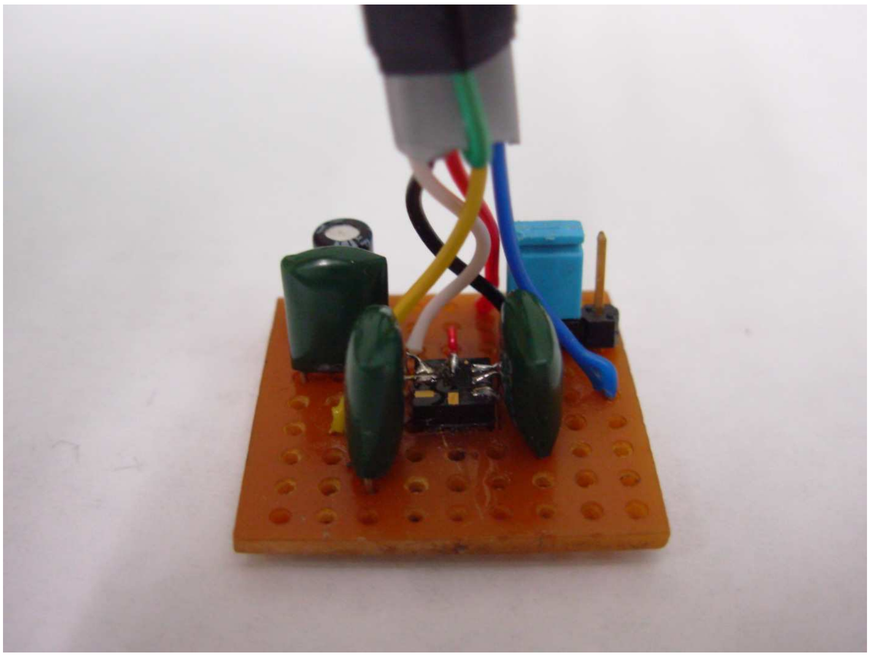

Figure 2.5 Circuit board for the STMicroelectronics LIS3L02AL sensor

Figure 2.6 Analog input-to-digital I/O PCI-DAS08 board

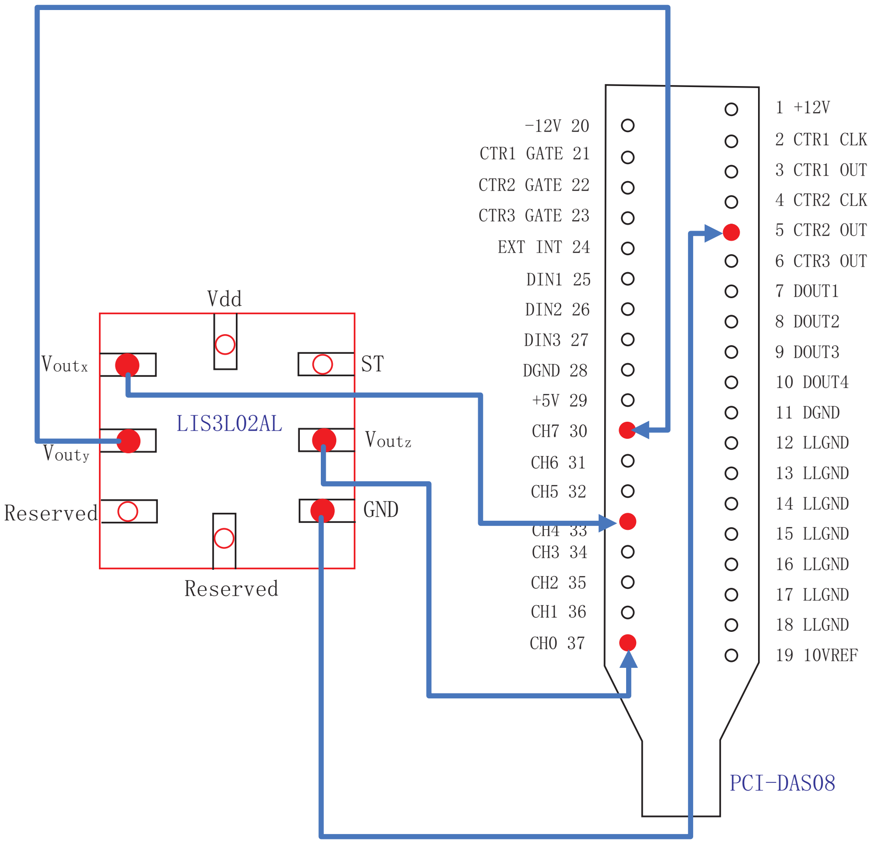

Figure 2.7 Main connector pinout of the analog input-to-digital I/0 PCI-DAS08 board and the connection with the STMicroelectronics LIS3L02AL sensor

current time is more than $\frac{1}{60}$ second plus the old time, we replace the old time with the current time and get one sensor orientation data from the sensor. After that, we handle the bound problem, then smooth the data, calculate the derivative data, and judge if a bite has happened at this specific time. If so, the parameter $Bite\_Count$ will increase by 1 and then we get the current time again. Otherwise, we just get the current time again. All the steps are discussed in detail in the following subsections.

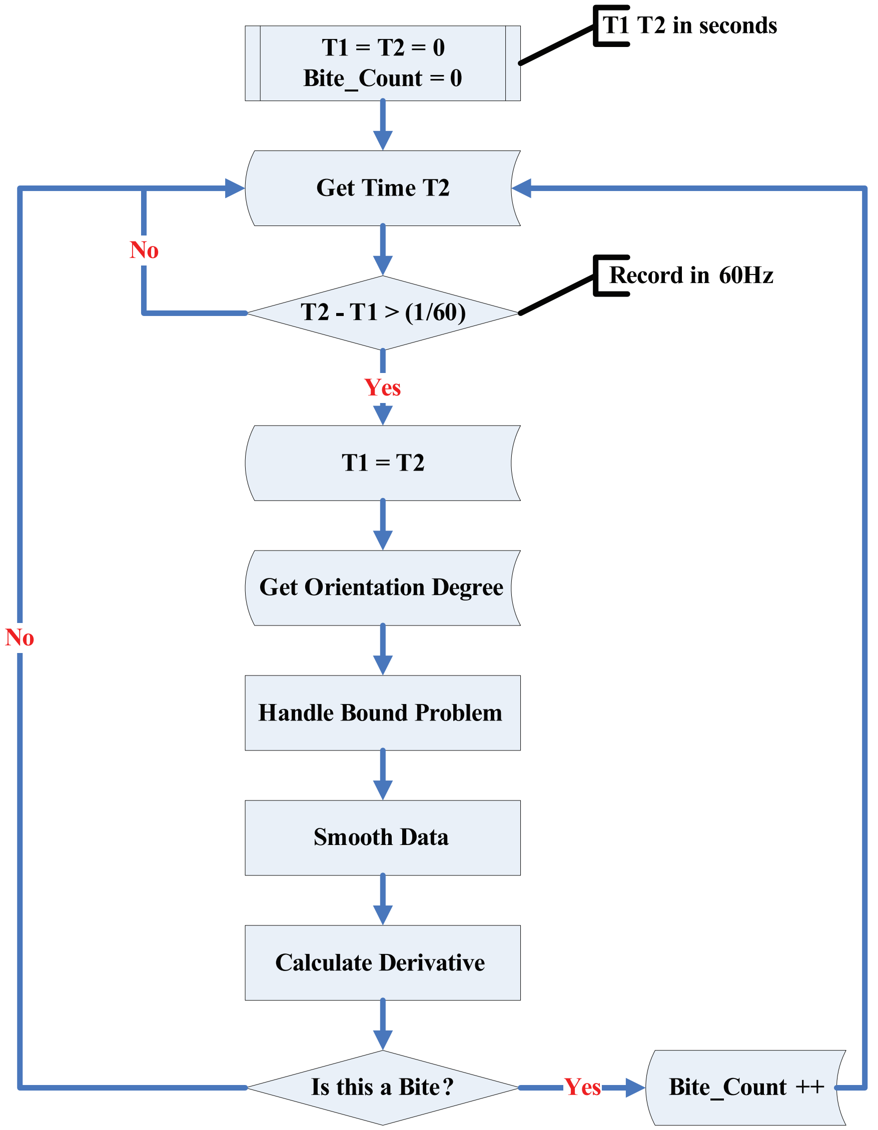

Figure 2.8 Flow diagram of bite detection algorithm

2.3.1 Data collection and orientation selection

All data streams are recorded at 60Hz. We have observed that the sensor can update the data at approximately 100Hz without any time control. The issue of data rate will be discussed more later in the next chapter.

To record sensor data stream at 60Hz, the following algorithm is performed:

```
start = clock();                %time in milliseconds
data_count = 0;
loop:
  update sensor data;
  data_count++;
  while ((clock() - start) < data_count * 1000 / 60);
```

Next, it needs to be decided which data is useful. For each meal, all three prototype sensors can record the movement of the wrist in three orientations: pitch, yaw, and roll. Figure 2.9 shows the data of three orientations recorded by three different people on three different days 11-17-2007, 11-18-2007 and 11-24-2007 respectively. From Figure 2.9 the data look meaningless in time domain, so we perform the DTFT (Discrete Time Fourier Transform) of the original data to transfer the data into frequency domain. The transformed data is shown in Figure 2.10. We can see from this figure that although the DTFT of the original data is still very noisy, unlike the other two orientations, the roll data has some peaks other than 0. For example, the first subject has some peaks around 0.18 Hz, 0.24 Hz and 0.35 Hz, the second subject has a peak around 0.14 Hz and the third subject has a peak around 0.2 Hz. It means the subjects have rolled their hands periodically every few seconds. From these data in frequency domain, we can make the hypotheses that although we cannot detect a bite only depending on the orientation frequency, we can use the roll data while discarding the yaw data and the pitch data to detect bites during a meal. As a result, we will only use the roll orientations to develop the bite detection in our algorithm.

2.3.2 Bound problem

Note that when the sensor records the orientation data, the orientation range is from -180° to 180°. If the data goes past 180°, it will suddenly change to -180°, and vice versa. Because of this, the signal may be discontinuous. In order to smooth the data signal in the next step, we have to transform this discontinuous signal to a continuous signal. We use a common approach (for example,

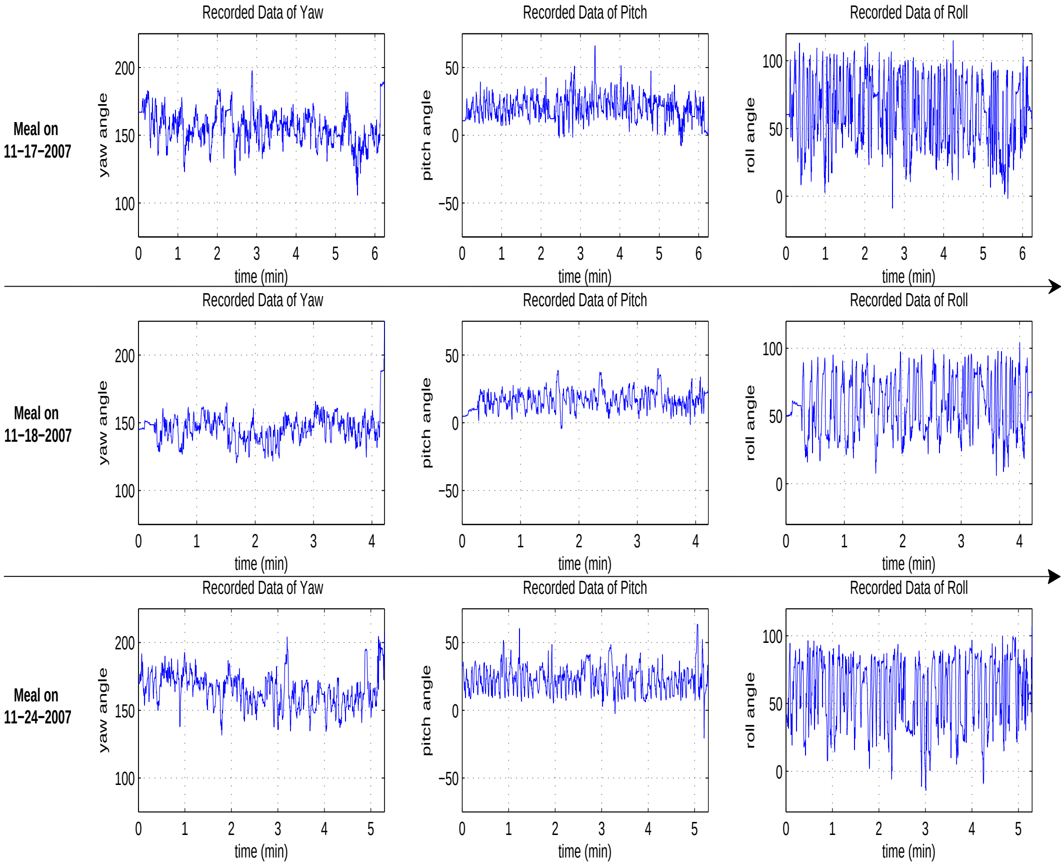

Figure 2.9 Original pitch, yaw, and roll orientation data in three different meals recorded by the InterSense InertiaCube3 sensor

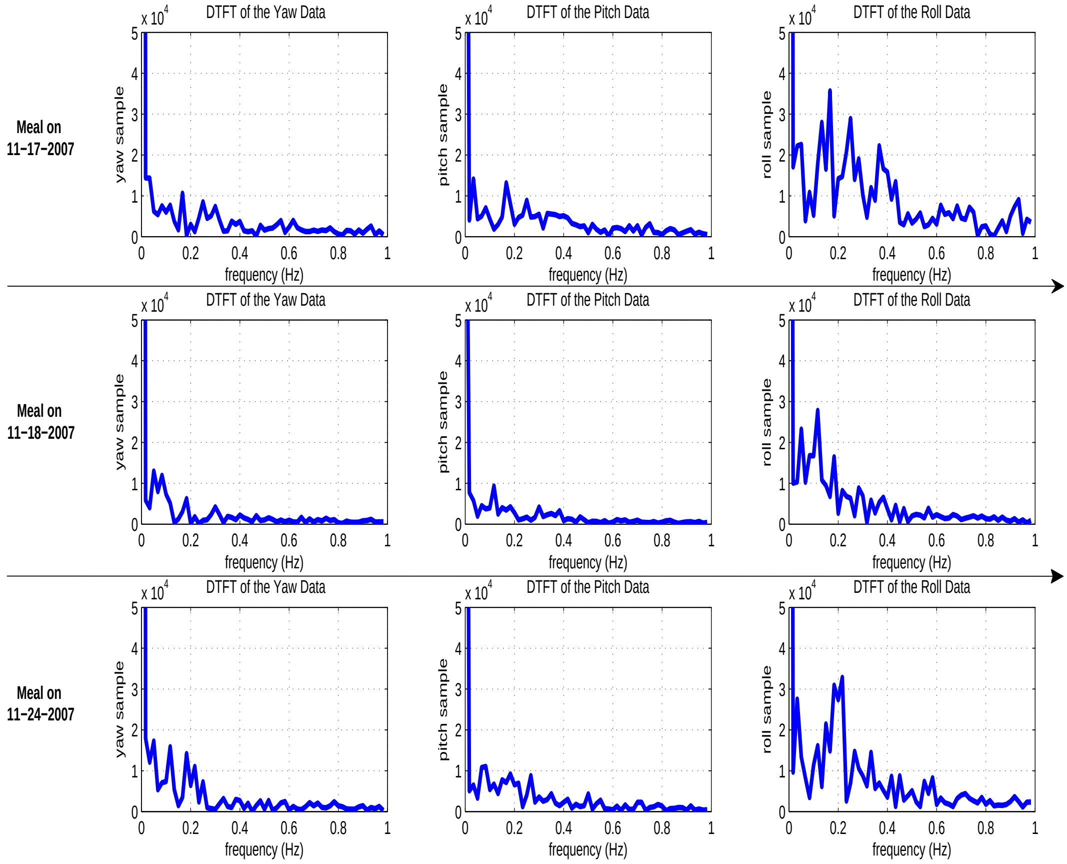

Figure 2.10 Discrete time Fourier transform of the original pitch, yaw, and roll orientation data in three different meals recorded by the InterSense InertiaCube3 sensor

[37]). Considering that a person cannot rotate his or her hand 180° in a very short time (less than 0.1 seconds), a simple and effective way is shown below:

```
if (R_t - R_(t-1) > 180)
  new_R_t = R_t - 360;
else if (R_t - R_(t-1) < -180)
  new_R_t = R_t + 360;
else
  new_R_t = R_t;
```

Where R_t is the roll data at time t and $R\_(t-1)$ is the roll data at time t-1.

2.3.3 Smooth the roll data

As in Figure 2.9, the raw sensor data is noisy. To remove the noise, we have applied a Gaussian-weighted window. A normalized Gaussian distribution is shown in Figure 2.11. The midpoint of the window corresponding to the peak of the Gaussian is centered on the current measurement, so that only a half of a Gaussian distribution is used for smoothing. This half of the Gaussian distribution is marked as $*$ in Figure 2.11. Equation 2.3 shows how we compute the smoothed roll data. In this equation, O_t is the original roll orientation measured at time t and S_t is smoothed data at time t, N is the Gaussian-weighted window size and R is the Gaussian standard deviation. In our implementation, the default value of N and R are 120 and 20 respectively.

$$S_t = \sum_{i=-N}^{0} O_{t+i} \times \frac{e^{-\frac{(t-N)^2}{2R^2}}}{\sum_{x=0}^{N} e^{-\frac{(x-N)^2}{2R^2}}} \tag{2.3}$$

2.3.4 Compute the derivative of smoothed roll data

Different people may wear the sensor at a different angle. If we use the absolute value of the roll data, it is difficult to define a bite period. Therefore, we compute the derivative of the smoothed roll data. Using the derivative data, the behavior of rotation by different people will be the same.

The derivative is computed simply as the difference between consecutive smoothed measurements:

$$d_t = s_t - s_{t-Q} \tag{2.4}$$

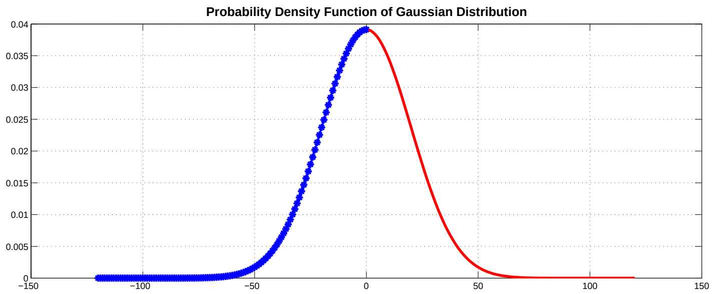

Figure 2.11 Probability density function of Gaussian distribution

The default value of Q is 120. To calculate the derivative data, we just simply use the Equation 2.4 where d_t is the derivative data and s_t is the smoothed data at time t. Because the default Q is 120 and our data collection frequency is 60 Hz, the value for $d_t/2$ is the roll velocity (degrees/second). In order to smooth the original roll data and compute the derivative of the smoothed roll data, the computer must buffer the most recent Q measurements. The contents of the buffer are updated after each new measurement, shifting out the previously stored oldest measurement.

2.3.5 Bite detection

We have discovered that while eating, the wrist of a person undergoes a characteristic rolling motion that is indicative of the person taking a bite of food. Referring to Figure 2.12, the roll motion takes place about the axis extending from the elbow to the hand. We define a positive roll as clockwise direction motion if viewed from the elbow looking towards the hand, and negative roll as a counterclockwise motion. This coordinate system is defined for a right hand; the same coordinate system could be applied to a left hand but with the roll directions reversed.

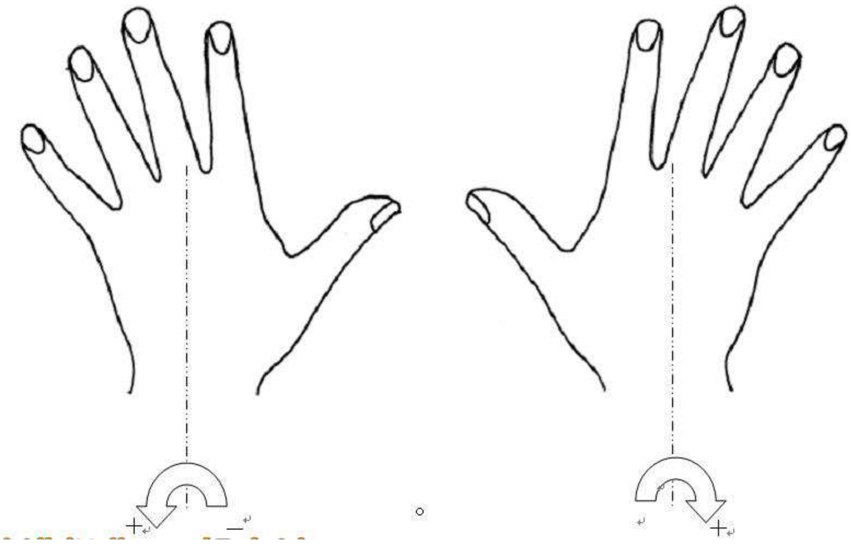

Figure 2.12 Coordinate system for defining wrist motion

The characteristic motion involves a cycle of the roll motion that contains an interval of positive roll followed by an interval of negative roll. Figure 2.13 shows the characteristics of the motion.

If the velocity of the roll is measured over time, then three events define the motion that corresponds to a bite. First, the velocity must surpass a positive threshold (10 degrees/second in our

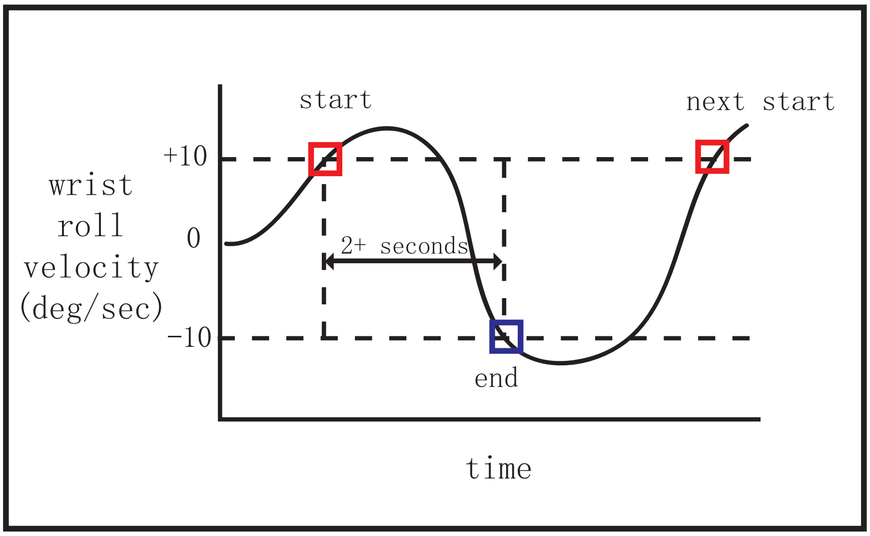

Figure 2.13 Roll motion corresponding to a bite

figure). Second, a specified period of time must elapse (2 seconds in our figure). Third, the velocity must surpass a negative threshold (-10 degrees/second in our figure). The detection of these three events provides a strong evidence that a person has taken a bite of food.

This characteristic roll is important because it differentiates wrist or arm motions caused by a variety of activities, such as moving food around a plate or engaging in non-eating-related activities, from a motion that can be directly associated with taking a bite of food. The detection of this characteristic roll is indifferent to the time taken between bites. Thus, we have discovered methods to build an actual bite detector.

An algorithm for implementing the detection of a bite via the characteristic wrist roll can be implemented as follows:

```
bite_start = 0
loop:
  Let v_t be the measured roll velocity at time t
  If v_t > T1 and bite_start = 0 then
     bite_start = 1
     Let s = t
  If v_t < T2 and t-s > T3 then
     Bite detected
     bite_start = 0
```

The variable *bite_start* notes the first event of the cycle of roll motion. The thresholds $T1$ and $T2$ define the roll velocities that must be exceeded to trigger detection of the first and second events of the roll motion. The threshold $T3$ defines the interval of time that must elapse between the first and second events of the roll motion. In our default setting, $T1$ is 10 (degrees/second), $T2$ is -10 (degrees/second) and $T3$ is 2 seconds.

For a typical person, the positive roll happens when a person is raising food from an eating surface (such as a table or plate) towards the mouth. The negative roll happens when the hand is being lowered, or when food is being picked up by fingers or placed on a utensil. The actual placing of food into the mouth usually occurs between the positive and negative rolls. However, even when a person does not follow this particular pattern, the cycle of motion (positive to negative roll) is almost always witnessed during the taking of a bite of food. We present data to support this conclusion later.

Figure 2.14 shows three images demonstrating the two events defining the roll motion corresponding to a bite. In the first image, the subject's wrist has exceeded the threshold for positive roll; in the third image, the subject's wrist has exceeded the threshold for negative roll; the second image shows the bite of food taken in between.

Figure 2.14 Images of a subject demonstrating the wrist roll events that correspond to eating a bite

Figure 2.15 shows the wrist roll data that was recorded simultaneously to the images shown in Figure 2.14. The square shows when the positive roll velocity threshold was first exceeded, and corresponds to the image on the left. The right-most line shows when the negative roll velocity threshold was first exceeded, and corresponds to the image on the right. The rectangle in between those marks corresponds to when the subject first placed food into his mouth, as shown in the middle image in Figure 2.14.

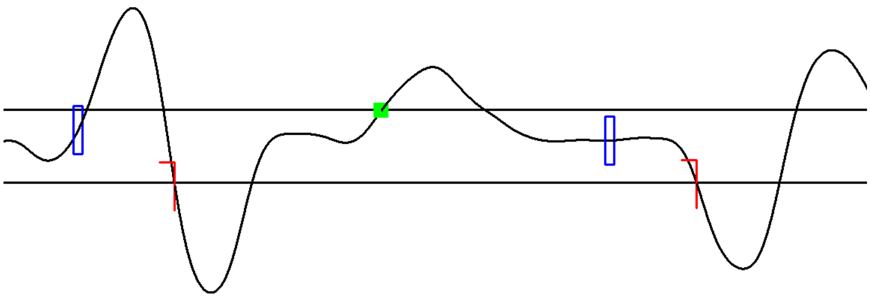

Figure 2.15 Wrist roll velocity over time, showing the events that correspond to eating a bite

2.4 Video capture

A Canon HG10 video camcorder is used to record the meal. This enables the experimenter to review the video with the synchronized sensor data after the meal. The camcorder is placed in front of a subject in order to capture the subject and the food he or she eats. The camcorder starts to record before the subject begins to eat. It keeps recording until the subject finishes eating. The video is saved in a MTS file format and it can be transferred to a personal computer through a USB port.

2.5 Graphical user interfaces

Two user interfaces have been developed for this project. Both use the WIN32 API in Microsoft Visual C++ 6.0.

2.5.1 User interface of bite detection in real time

The first user interface is used to display the raw sensor and the bite information in real time. It includes the bite counts and the bite speed, for instance bites per minute. It gives feedback about the amount of the food eaten to the subject. Figure 2.16 shows the interface we have developed. On the top is the time elapsed. When a bite is detected by the computer, the line in the axis increases by 1 and the total number of bites is shown on the line. In the middle part of the user interface, it gives the feedback of the bite speed (bites per minute) and the raw sensor data.

2.5.2 User interface of bite review

The second type of graphical user interface is used to review the stored information. This graphical user interface is shown in Figure 2.17.

As shown in Figure 2.17, the lower part is the sensor data. The top left part is the corresponding video. There are five buttons beside the video, which are used to play forward, rewind, pause and stop the video. The instruction is on the top right part. The green square is the current point, the blue rectangle is the manual bite detection and the red line is the automatic bite detection by the computer. The first line in the right center section is the index of the sample data; it corresponds to the point where the green square is. The second line is the corresponding time according to the green square and the third line is the value of the sensor data. The user interface has three main functions. We will discuss them in the following subsections.

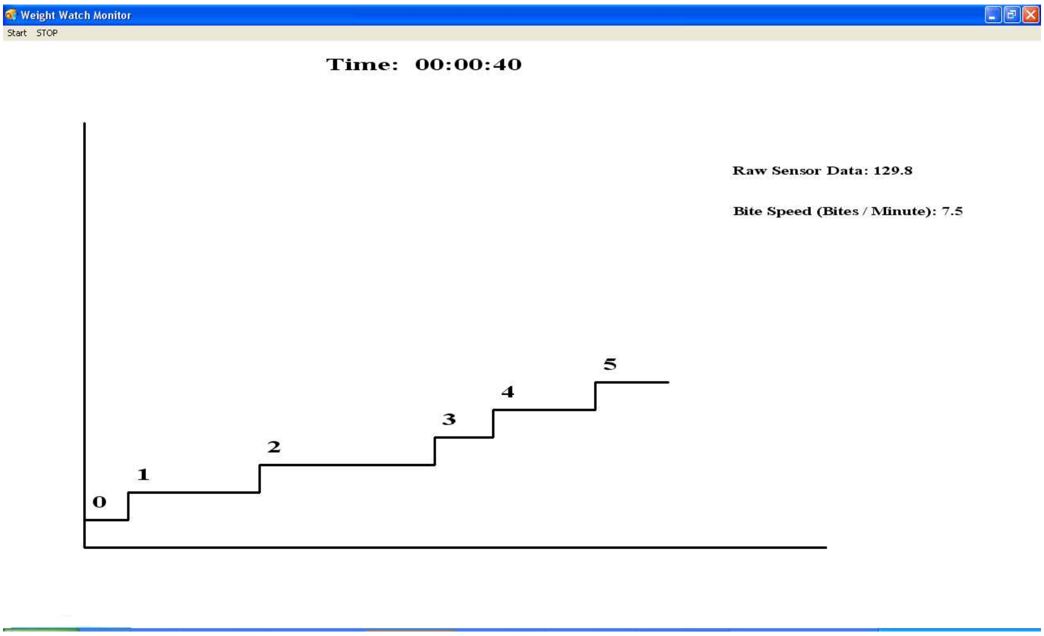

Figure 2.16 The graphic user interface to detect the bite information in real time

Figure 2.17 The graphic user interface to review the eating video and recorded data, detect the bite offline with regard to different parameter settings, and evaluate the bite detector

2.5.2.1 Review the sensor data and the synchronized video

First, we must extract the frame from the video and show it on the user interface. Canon HG10 video camcorder was used to record the meal and the format of the video file is MTS, which is the AVCHD video file format. Because the publicly available library can only read MPEG-1 files, we use the following steps to convert the MTS file to a MPEG format:

1. Use the software "Avchd_Convert_V5" to convert the MTS file to five separate files (AC3, AVC, DGA, PCM and AviSynth Script)

2. Use the software "VirtualDub" to convert these files to JPEG image sequence.

3. Use command "djpeg" in Linux operating system to convert JPEG image sequence to PPM image sequence.

4. Use command "ppmtompeg" in Linux operating system to convert PPM image sequence to the MPEG-1 file.

5. Use the library "mpeg2raw" to display the frame of eating video (MPEG-1 format) on the user interface. Note that the frame rate of the MPEG file is 30Hz after conversion.

Second, we must synchronize the sensor data and the eating video. In our experiment, the video camcorder has always been opened before we run the bite detection program, and we will also ask the subject not to move his or her hand before the bite detection program starts running. To make the video and the data synchronous, we should first find out a time where a video frame is point to the corresponding sensor data. We watch the sensor data to find out the first time the sensor data has some waves instead of a horizontal line, for example if it is the S th sensor data then we watch the video and find out which frame is the first frame the subject move his or her hand, for example, it is the F th frame. The F th frame and the S th sensor data we find should be almost synchronous. Note that video frame rate is always 30 Hz. Suppose that our recording sensor data is T Hz (The default value is 60 Hz, but we can change the sample rate easily which will be discussed in the next chapter), thus the X th sensor data should correspond to the Y th video frame where Y can be computed by Equation 2.5:

$$Y = F - \frac{T}{30(S - X)} \tag{2.5}$$

Then we can review the video and the sensor data again. If we find they are not synchronizing exactly, we just need to change the value F in a small range to find the best consequence.

After synchronizing the video and the sensor data, we can play the eating video as mentioned before. We have five buttons on the right side of the video. From the left to the right, they are fast back, slow back, start/pause, forward, fast forward. By pressing the fast back button, the video goes back 10 frames; by pressing the slow back button, the video goes back 1 frame; by pressing the forward button, the video goes forward 1 frame; by pressing the fast forward button, the video goes forward 10 frames. After clicking the buttons, the video will play, and the corresponding data in the low part of the graphical user interface will also play. In addition, the sample index, the current time and the value of the data shown in the middle right section will also be updated.

2.5.2.2 Detect the bites offline

We can run our bite detection algorithm offline to review the bite counts or bite speed (bites per minute). We can also change the record frequency and setting parameters in the graphical user interface to improve our bite detector. The setting parameters including the Gaussian-weighted window size, the Gaussian-weighted window variance, the derivation window size, the interval of time that must elapse between the first and second events of the roll motion and the thresholds which define the roll velocities that must be exceeded to trigger detection of the first and second events of the roll motion. The results will be discussed in the next chapter.

2.5.2.3 Mark the ground truth bites and evaluate the bite detector device

We can also manually mark the ground truth time of a bite taken. As mentioned in the first chapter, we define a bite as when a person puts food in his or her mouth. Because every second has 30 video frames, it is hard to tell which frame is exactly the ground truth bite. In this thesis, we define a reasonable way to mark the ground truth bite. For example, Figure 2.18 and Figure 2.19 shows continuous 30 frames of a subject during his eating. The process includes the subject picking up the food, putting the food in his mouth, eating it and putting the utensil down. We can approximately tell that in frame 10, the food first reached the subject's mouth and in frame 23, the food first left the subject's mouth which means from frame 10 to frame 22, the food is in the subject's mouth. As a result, we mark the middle frame of 10 and 22 as the time whcih a ground truth bite happened. This frame is frame 16.

Using this method, we can mark all the ground truth throughout the whole eating process. For

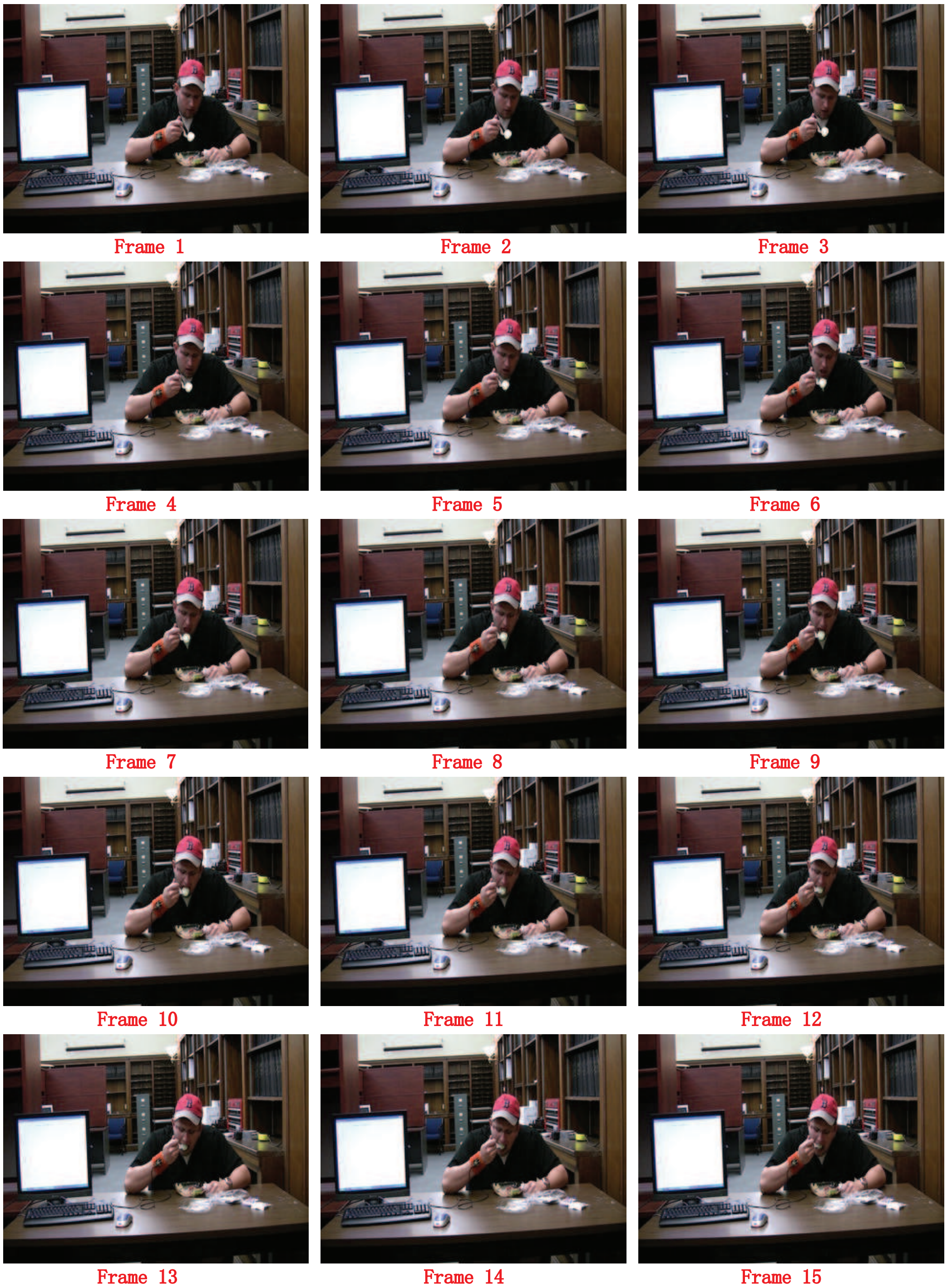

Figure 2.18 Continuous frames of a subject during eating (part 1)

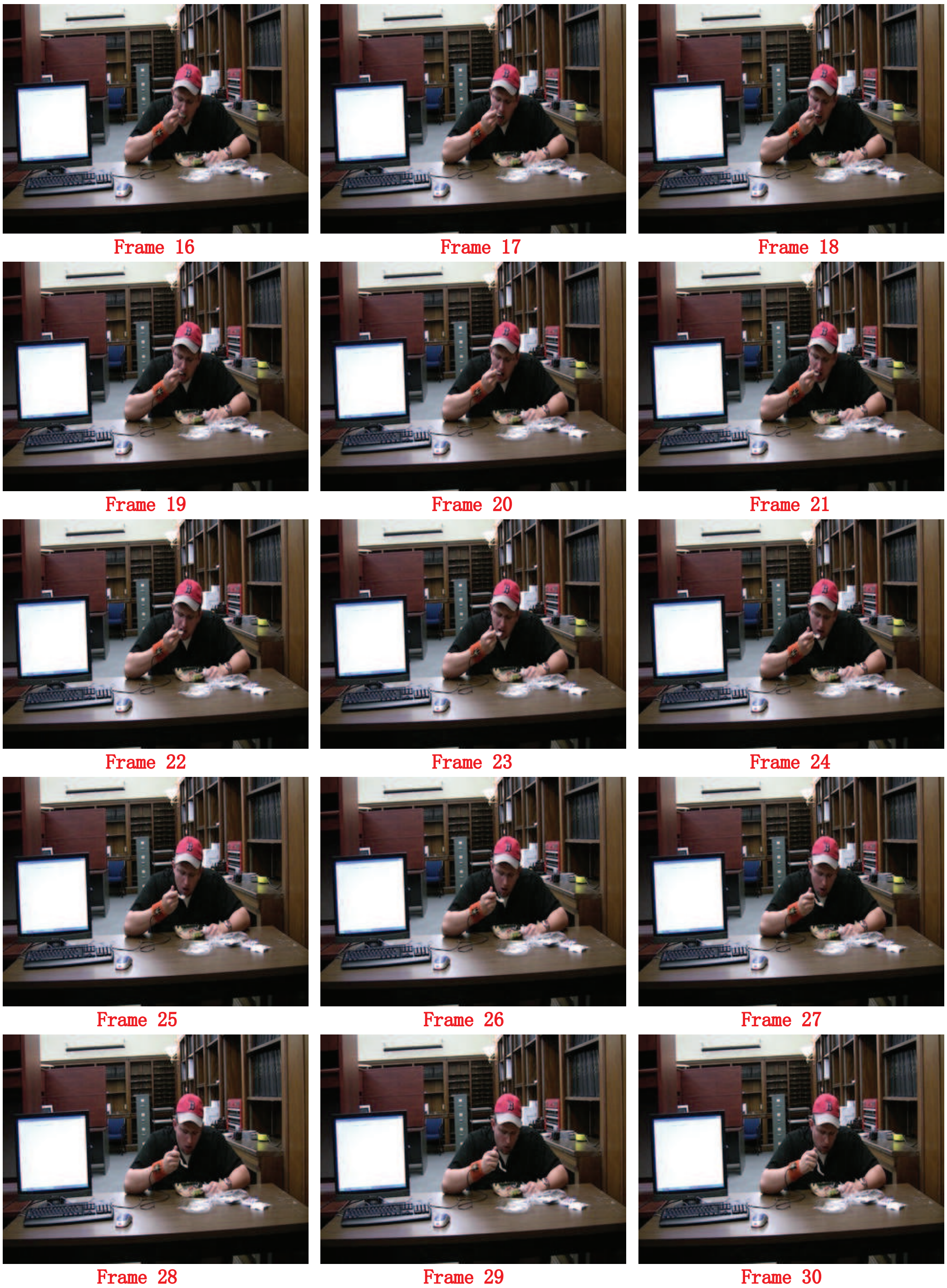

Figure 2.19 Continuous frames of a subject during eating (part 2)

each frame of the ground truth bite, we will input the corresponding sample index (in milliseconds) in sequence into a .txt file. If we finish this step, we can load the ground truth bite .txt file to see all the actual times of bites during a whole meal. We can also use our evaluation method in the next section to calculate the sensitivity of the bite detector.

2.6 Evaluation of bite detection algorithm

We have also developed a simple evaluation to assess our bite detector; First, we manually mark the ground truth bites. Then, we calculate the correspondences of computer-detected wrist motion cycles to manually marked bites taken. Figure 2.20 shows an illustration of how detections were classified. For each wrist motion cycle detected, a single bite taken within its cycle was classified as a true detection. Any additional bites taken within that cycle are classified as undetected bites. A wrist motion cycle detected in which no bites occurred is classified as a false detection. Sensitivity of the device was calculated for each subject as Equation 2.6:

$$sensitivity = \frac{total \quad true \quad detections}{total \quad true \quad detections + total \quad undetected \quad bites} * 100\% \tag{2.6}$$

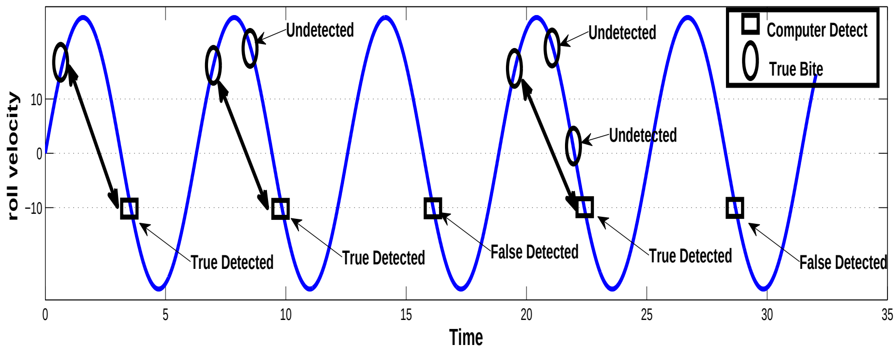

Figure 2.20 Methods for classification of computer detections versus actual bites

CHAPTER 3

RESULTS

We have conducted trials to determine the accuracy of our invention. In our experiments there were 10 subjects for the preliminary test. They used different hands and different utensils. Eight of them used their right hand to eat, and two of them used their left hand to eat. Five of them used forks to eat, three of them used spoons to eat, and two of them used their fingers to eat.

The first experiment tests the raw roll degree data recorded by both the InertiaCube3 sensor and the STMicroelectronics LIS3L02AL sensor and compares both the noise and the performance. The second experiment measures the number of bites taken during the meal. The third experiment calculates the average and variance of time between a bite period. It also measures the number of times bite is taken between +/- roll or between -/+ roll. The fourth experiment measures the performance of the bite detector based on 10 subjects. The fifth experiment will analyze the reason for false detections and undetected bites. The sixth section will bring in 10 different bite patterns to better evaluate a person's eating behavior. At last, we will try down-sampling and setting the new parameter due to the nature of the processor and the memory.

3.1 Comparison of InertiaCube3 sensor and STMicroelectronics LIS3L02AL sensor

In the first experiment, we test the raw roll sensor data recorded by both the InertiaCube3 sensor and the STMicroelectronics LIS3L02AL sensor. Both sensors were worn at the same time, recording the same motion. As can be seen in Figure 3.1, the data recorded by the STMicroelectronics LIS3L02AL sensor is much noiser than the data recorded by the InertiaCube3 sensor. However, after applying our methods for smoothing and calculating the roll velocity from the raw roll data, both signals are almost the same. This demonstrates that a small STMicroelectronics LIS3L02AL sensor is capable of detecting the motion events that corresponding to the motion of taking a bite.

To further verify our conclusion, we calculate the performance of our bite detector on these two different sensors. Table 3.1 shows the performance of our bite detector using InertiaCube3 sensor and STMicroelectronics LIS3L02AL sensor at the same time, recording the same motion. We find that the true bite detections and the undetected bites are the same. When the STMicroelectronics LIS3L02AL sensor is used, we detect three less false detections. That means even though the recorded

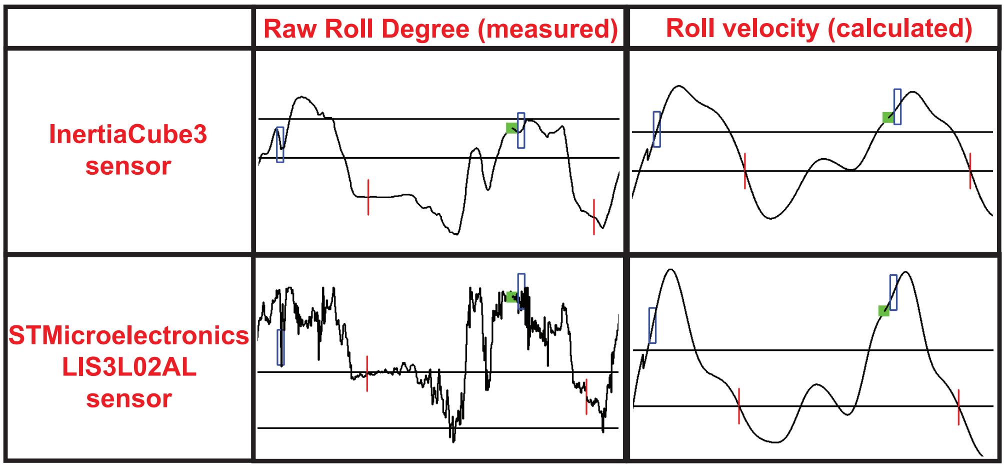

Figure 3.1 Noise comparison between the InertiaCube3 sensor and the LIS3L02AL sensor

raw roll data of the STMicroelectronics LIS3L02AL sensor is much noiser than the InertiaCube3 sensor, after applying our bite detection algorithm, the result is very close. This conclusion will enable us to develop an embedded device in the future.

Sensor	**True detections**	**False detections**	**Undetected**
InertiaCube3 sensor	**62**	**12**	**11**
STMicroelectronics LIS3L02AL sensor	**62**	**8**	**11**

Table 3.1 Performance comparison between the InertiaCube3 sensor and the STMicroelectronics LIS3L02AL sensor

3.2 Number of bites taken during the meal

For the 10 people tested, we measure the number of bites taken during the meal. This number varies from 19 to 65. In order to evaluate our methods, we first present data supporting the conclusion that the taking of a bite of food can be characterized by the detection of the three motion events as outlined in our methods. Table 3.2 shows the number of bites taken by each person, and the relationships between bites taken and wrist roll cycles.

We can see from Table 3.2 that there are a total of 283 bites occurring 1:1 with wrist roll cycle, 28 occurrences of >1 bite in a wrist roll cycle, and 121 occurrences of 0 bite in a wrist roll cycle. Thus, for 66% of the total roll cycles, exactly one bite occurs between a positive roll and the subsequent positive roll (a wrist roll cycle). For 6.5% of the total roll cycles, more than one bite occurs during the cycle, and for 28% of the total roll cycles detected, no bites occur.

We can also see from Table 3.2 that there are a total of 347 bites for all the ten people. Thus, for 82% of the total bites, exactly one bite occurred between a positive roll and the subsequent positive roll (a wrist roll cycle). For 8.1% of the total bites, more than one bite occurred during the cycle, and for 35% of the total cycles detected, no bites occurred.

3.3 Average value and variance of time between a bite period

Breaking it down further, Table 3.3 shows the statistics for the bites taken that corresponds directly to the wrist roll cycles (the bites in column 3 of Table 3.2). As can be seen, there is a great deal of variance on the time elapsed between the detected positive and negative roll motion events. This is why it is important to detect both events in order to verify a bite has been taken. However, the

Person	Total bites taken	Bites occurring 1:1 with wrist roll cycle	Occurrences of >1 bite in a wrist roll cycle	Occurrences of 0 bites in a wrist roll cycle
1	65	44	10	12
2	21	20	0	8
3	60	43	6	13
4	35	35	0	12
5	37	37	0	15
6	26	14	6	6
7	23	23	0	22
8	30	25	2	20
9	19	19	0	1
10	31	23	4	12
total	347	283	28	121
Average	34.7	28.3	2.8	12.1

Table 3.2 Correspondence of wrist roll cycles to bites taken

last two columns of Table 3.3 show that in most cases the actual bite of food is taken between the positive and negative roll motion events.

Person	Average and variance of time between +/- roll	Average and variance of time between -/+ roll	Number of times bite is taken between +/- roll	Number of times bite is taken between -/+ roll
1	8.0 (57.32)	3.1 (4.8)	40	14
2	8.7 (63.22)	5.8 (31.75)	14	6
3	7.9 (85.01)	4.9 (17.95)	44	5
4	4.3 (19.06)	8.5 (28.65)	31	4
5	6.3 (15.96)	4.3 (8.49)	35	2
6	9.6 (58.36)	3.7 (13.18)	17	3
7	7.0 (64.54)	8.8 (61.67)	19	4
8	4.0 (25.94)	9.0 (96.47)	21	6
9	6.2 (10.56)	3.9 (2.72)	19	0
10	6.7 (161.35)	8.0 (237.16)	18	9

Table 3.3 Statistics for single bites corresponding to wrist roll cycles

3.4 Performance of the bite detector

In order to evaluate the performance of our bite detector, we calculated the correspondences of computer-detected wrist motion cycles to manually marked bites taken. Figure 2.20 shows an illustration of how detections were classified. For each wrist motion cycle detected, a single bite taken within its cycle is classified as a true detection. Any additional bites taken within that cycle are classified as undetected bites. A wrist motion cycle detected in which no bites occurred is classified as a false detection. Table 3.4 summarizes the performance of our bite detector using these classifications on the 10 subjects. The sensitivity of the device was 91% and only 9% of the actual bites were undetected. In its current state, the device is sensitive, erring on the side of over-detection.

Person	True detections	False detections	Undetected	Sensitivity
1	54	12	11	83%
2	20	8	1	95%
3	49	13	11	82%
4	35	12	0	100%
5	37	15	0	100%
6	20	6	6	77%
7	23	22	0	100%
8	27	20	3	90%
9	19	1	0	100%
10	27	12	4	87%

Table 3.4 Performance of our bite detector on 10 subjects

3.5 Reasons for false detections and undetected bites

Although the bite detector works quite well, we still want to find out the reasons for the false detections and the undetected bites. As a result, we reviewed the video and analyzed each bite of these 10 subjects. Table 3.5 and Table 3.6 summarize the reasons for our false detections and the undetected bites.

Person	1	2	3	4	5	6	7	8	9	10	total
total false detections	12	8	13	12	15	6	22	20	1	12	121
grab the food, but don't eat	7	4	8	5	14	2	16	3	1	2	62
do stuff before the first bite of the meal		1		1				3		5	10
use the napkin			2	6				11		4	23
rotate when resting	5	3	1		1	1	2	3		1	17
sensor error			1								1
put down the utensil			1								1
for drink reason						3					3
rotate when eating							4				4

Table 3.5 Reasons for false detections

In Table 3.5 and Table 3.6, the first column lists the reason for false detections and undetected bites, the following ten columns list the number of occurrence. From these two tables, we can see that there are three main reasons for false detections. First, the subject grabs the food, but does not eat it and puts the food back on the plate or container. Second, the subject uses a napkin while eating. Third, after taking a bite, the subject tends to rest for a while before the next bite, however,

Person	1	2	3	4	5	6	7	8	9	10	total
total undetected bites	11	1	11	0	0	6	0	3	0	4	36
roll orientation doesn't rotate enough degrees	3		1			3		2		4	13
bite more than once with one utensil's food	8		10								18
for drink reason		1				2		1			4
the first bite of the whole meal						1					1

Table 3.6 Reasons for undetected bites

he or she keeps rotating his or her wrist during this period. All these three behaviors will seem like taking a bite to the bite detector so they will result in false detections. On the other hand, there are two main reasons for undetected bites. First, a subject does not roll enough degrees during a bite. In other words, a subject does not roll fast enough during a bite. Second, after the subject puts the food on the utensil, he or she does not eat all the food in one bite. Instead, he or she bites the food on the utensil several times until he or she finishes it. As a result, the bite detector thinks the subject only has taken one bite during the whole period.

3.6 Bite patterns

We have examined a set of "bite patterns" for our bite detector. Figure 3.2 shows the results. In the figure, "/" means when the subject raises his or her hand, "\" means when the subject puts down his or her hand, "_____" means when the subject rests during the meal, and "*" means when the subject takes a bite. We define a total of 10 patterns of the bites taken. They are:

1. The subject raises his or her hand, eats the food immediately, puts down his or her hand and rests for a while before the next bite.

2. The subject raises his or her hand, eats the food immediately, rests for a while, puts down his or her hand and rests for a while again before the next bite.

3. The subject raises his or her hand, rests for a while, and then eats the food, after the bite, he or she rests for a while again, puts down his or her hand and rests for a while before the next bite.

4. The subject raises his or her hand, rests for a while, and then eats the food, after the bite, he or she puts down his or her hand and rests for a while again before the next bite.

5. The subject raises his or her hand, rests for a while, eats some of the food in the utensil, rests again, eats some more food in the utensil, after that, he or she rests for a while again, puts down his or her hand and rests for a while before the next bite.

6. The subject raises his or her hand, eats the food immediately and puts down his or her hand while still eating.

7. The subject raises his or her hand, eats the food immediately, rests for a while and puts down his or her hand after rest.

8. The subject raises his or her hand, rests for a while, and then eats the food, after the bite, he or she rests for a while again and puts down his or her hand.

9. The subject raises his or her hand, rests for a while, and then eats the food, after the bite, he or she puts down his or her hand.

10. The subject raises his or her hand, rests for a while, eats some of the food on the utensil, rests again, eats some more food on the utensil, he or she rests for a while again and then puts down his or her hand.

From the figure, we can see that some patterns happen much more frequently than the others. For example, pattern 1, pattern 4 and pattern 6 occur almost $\frac{2}{3}$ of the total bites among these ten subjects.

On the other hand, different people have different patterns. For example, as for the first person, 58% of her patterns are pattern 1, pattern 6 and pattern 7. While for the second person, 89% of her patterns are pattern 1 and pattern 2. Table 3.7 shows the two or three most used patterns for each person and the percentage of these patterns. Analyzing these bite patterns will help the bite detector development in the future. As a result, we can consider to develop individual-oriented bite patterns to increase the percentage of true detections greatly.

Person	1	2	3	4	5	6	7	8	9	10	total
(1) /*____	9	9	9	27	19	2	2	15	7	13	112
(2) /*‾‾‾‾____	3	8	6		5	1	1			1	25
(3) /‾‾*‾‾____					3	5			1		9
(4) /‾‾‾‾*____		1	8	4	5	1	9	2	2	7	39
(5) /‾‾*‾‾*‾‾__			3					1			4
(6) /*\	10	1	9	2		4	4	6	1	4	41
(7) /*‾‾‾‾\	11		3		1				2		17
(8) /‾‾*‾‾\	7		4		4	6	2		3		26
(9) /‾‾‾‾*\	4			1		3	5	3	3	5	24
(10) /‾‾*‾‾*‾‾\	8		2								10

Figure 3.2 Ten bite patterns for ten subjects taken the experiment

Person	Most used pattern	Percentage
1	1, 5, 6	58%
2	1, 2	89%
3	1, 4, 6	62%
4	1	79%
5	1, 2, 4	78%
6	3, 6, 8	68%
7	4, 6, 9	78%
8	1, 6	78%
9	1, 8, 9	68%
10	1, 4	67%

Table 3.7 Most used patterns for different subjects

3.7 Down sampling and changing the default parameters of bite detection algorithm

Although our default parameter setting and sample rate works quite well in our bite detection, these default settings are based on our hypotheses. There may exist other good parameters. More importantly, the final envisioned embodiment of our bite detector device is a sensor of small size which is wearable. This means we want to embody a device that can easily and comfortably be worn on the wrist, similar to a wristwatch. If we down-sample and change some default parameters, we can use fewer buffers in the memory, which will both increase the speed of our algorithm and decrease the size of the memory on the device. Our default values are the following:

1. Sample rate is 60Hz.
2. Gaussian-weighted window size N = 120.
3. Gaussian standard deviation R = 20.
4. Derivative window size Q = 120.
5. Roll velocities that must be exceeded to trigger detection of the first events of the roll motion is $T1$ = 10.
6. Roll velocities that must be exceeded to trigger detection of the second events of the roll motion is $T2$ = -10.
7. Interval of time that must elapse between the first and second events of the roll motion is $T3$ = 2 seconds.

Table 3.8 shows the comparison between down-sampling and our default 60Hz data recording rate. We also have to change some parameters settings. When we down-sample at 10Hz, we choose N = 20, R = 3, Q = 20, $T1$ = 10, $T2$ = -10, and $T3$ = 2 seconds. The data in the parentheses is the result sampled at 60Hz. There are a total 304 of true detections when sampled at 10Hz, and 311 true detections when sampled at 60Hz; there are a total 128 of false detections when sampled at 10Hz, and 121 false detections when sampled at 60Hz; there are a total 43 of undetected bites when sampled at 10Hz, and 36 undetected bites when sampled at 60Hz. The result is quite similar. When sampled at 10Hz, there are only seven less true detections, seven more false detections and seven more undetected bites. Thus, if we are bounded by limited memory and limited processing in the device, considering down-sampling and use of fewer buffers is an alternative way that could still perform relatively well. As shown above, it will not affect the results much.

Person	True detections	False detections	Undetected
1	54(54)	10(12)	11(11)
2	20(20)	9(8)	1(1)
3	50(49)	13(13)	10(11)
4	35(35)	13(12)	0(0)
5	36(37)	15(15)	1(0)
6	21(20)	7(6)	5(6)
7	22(23)	22(22)	1(0)
8	23(27)	24(20)	7(3)
9	19(19)	0(1)	0(0)
10	24(27)	15(12)	7(4)
TOTAL	304(311)	128(121)	43(36)

Table 3.8 Bite detection result comparison between down sample rate and the default 60 Hz sample rate (in parentheses)

CHAPTER 4

CONCLUSIONS

4.1 Results discussion

In this thesis, we introduce a device for detecting and counting bites of food taken by a person during eating. This device can help people who are overweight or obese to manage their body weight. It can also control people's eating rate and help people with eating disorder.

We have introduced three sensor prototypes we used in our experiment. They are based on the wired InertiaCube3 sensor, the wireless InertiaCube3 sensor and the STMicroelectronics LIS3L02AL sensor respectively. We have developed our bite detection algorithm and discussed an evaluation method for our bite detector device. To give the feedback of bite counts in real time to the subject and to review the eating procedure, we have also developed two graphical user interfaces.

We have conducted several experiments based on the bite detector device we invented. We compare both the noise and the performance recorded by the InertiaCube3 sensor and the STMicroelectronics LIS3L02AL sensor. We also measure the number of bites taken during the meal and compute statistic results including the average and variance of time between a bite period. With the evaluation method, we measure the performance of the bite detector, analyze the reason for false detections and undetected bites and bring in 10 different bite patterns to better evaluate people's eating behavior.

The result is quite promising. All three prototypes can be used for motion measurement; our bite algorithm can decrease the effect of the noise and detect the bites very well. The sensitivity of the device is very high, it can reach as high as 91%. Down-sampling also results in good outcome so that we can save both the resources of the processor and the memory. The reason for false detections and undetected bites and the bite patterns applied on different people will also help the research in the future.

4.2 Future

In the near future, we will improve some defects in the proposed bite detector device. For example, the video conversion method is not only complicated but also time consuming; we want to find an easy way to convert the video. Another aspect of the device that needs improvement is the bite detection algorithm. We notice that there is still some high percentage of false detection that exists. To reduce the number of false detections and undetected bites, there are several things worth considering. For instance, we can use other methods to smooth the raw data, such as Kalman filter. We can also apply more factors on bite detection. For now, we only depend on the roll velocities that must be exceeded to trigger detection of the first events, roll velocities that must be exceeded to trigger detection of the second events, and the interval of time that must elapse between the first and second events of the roll motion. In the future, we can add more critical factors such as average value, variance, pitch data, yaw data and so on. We can also develop different patterns for different people. We already notice that different people have specific patterns while eating, so this may be also a very efficient way to improve the performance of the bite detector.

In long term, we would like to develop the second generation of the bite detector device. This device will be similar to the first generation device in a way that it will be fully self-contained, including an orientation sensor, onboard computing, memory storage, and battery. However, this device will also contain a feedback mechanism (actuator) that the device can use to notify the user of salient events. For example, during a period of eating, while the device is counting bites, the feedback mechanism could be used to alert the user that a specific count of bites has been reached. The purpose of the second generation device is to enable testing automated feedback (based upon bite count) to users during eating. Similar to the first generation device, this version will look much like a watch. It will be wearable on the wrist, taken on and off in a manner similar to a watch. It will have a simple on/off switch that the user is intended to toggle before and after eating a meal. Although this device will likely be somewhat larger than the first generation device, due to the inclusion of a feedback mechanism, we will try to keep the size as small as possible.

We will also develop desktop software that is intended for the user of a bite detector device. This software will allow the user to periodically download data from the device to a desktop computer, and store the data in a bite log. The user will be able to view his or her history of bites taken over a period of days, weeks, or months. Statistics will be calculated and graphed, such as the total time spent eating, the times of day when eating was monitored, and the relationship between the total bites taken and days of the week. The goal for this software is to provide the user with long-term information for motivational purposes, and to identify problem bite behaviors.

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