Detecting Eating Using a Wrist Mounted Device During Normal Daily Activities

Yujie Dong[1], Adam Hoover[1], Jenna Scisco[2], Eric Muth[2]
[1]Department of Electrical and Computer Engineering [2]Department of Psychology
Clemson University, Clemson, USA
yujied@clemson.edu, ahoover@clemson.edu, jscisco@clemson.edu, muth@clemson,edu

***Abstract*—The prevalence of obesity is a growing, worldwide health concern. Self-monitoring of eating consumption is widely recognized as a necessity for weight loss. In this paper we describe a novel method for automated monitoring of eating. Our method uses a single sensor that is worn on the wrist, similar in form to a watch. Wrist orientation was captured at a rate of 60 Hz for an entire day while four subjects conducted their natural daily routine. In our first experiment, we manually segmented the wrist motion data according to task logs kept by the subjects, and developed an algorithm to classify the tasks, achieving an accuracy of 91%. In our second experiment, we automatically segmented the wrist motion data in order to detect eating sessions, achieving a detection accuracy of 82%. Our methods will enable new opportunities in the study of dietetics, weight loss and management, nutrition, and health monitoring.**

***Index Terms*—activity recognition, orientation sensor, body motion tracking, eating**

I. Introduction

This work is motivated by the growing prevalence of obesity in the world. In 2007-2008, the National Health and Nutrition Examination Survey showed that 68.3% of Americans were overweight and 33.9% of Americans were obese [1]. The World Health Organization reported that 1.5 billion adults (age 20+) were overweight and 500 million adults were obese worldwide [2]. Obesity is strongly associated with several major health risk factors, such as diabetes, heart disease, high blood pressure, stroke and higher rates of certain cancers [3]. In the United States, the annual medical expense of obesity has been estimated at $147 billion in 2008 compared to $78.5 billion in 1998 [4].

Weight control can be assisted by self-monitoring of intake consumption, which has been consistently related to successful weight loss [5]. The most well known tool for monitoring food intake is an eating diary; however, this tool places the burden on the user to manually record all foods eaten. In addition, people have a tendency to forget or underreport the calorie consumption [6] [7]. Some researchers have investigated using a scale embedded in a dining table [8] [9]. However, this method can only monitor consumption when people eat at the instrumented table. Another method is to use a PDA or a cell phone to take photos before and after the eating and use image processing to estimate the amount of food intake [10] [11]. However, because foods must be carefully separated and positioned for imaging, these methods have not yet been studied in natural daily living. Combinations of neck, ear, arm, and back worn sensors have been investigated for recognizing eating activities [12]. While these configurations may find applications in a laboratory or clinic, they are not suitable for day-to-day living. In summary, none of the existing methods automates the process of self-monitoring of eating consumption in an easy-to-use manner.

Our group has previously described methods using a micro-electro-mechanical system (MEMS) sensor to track wrist motion in order to measure the number of bites eaten during a meal [13]. We have discovered that while eating, the wrist motion of a person undergoes a characteristic rolling motion that is indicative of the person taking a bite of food [14]. However, our device requires the user to press a button to turn the device on before eating and turn the device off after eating. In this paper, we explore methods to overcome this limitation by differentiating eating sessions from other activities using the same MEMS sensor.

With their low power and small size, MEMS sensors can be comfortably worn on the human body and operated for hours at a time. Researchers have investigated their use for recognizing common daily activities such as walking, running, sitting and resting [15] [16] [17] [18], accidental falls [19], sports activities [20], assembly tasks [21], and tremors associated with Parkinson's disease [22]. Sensors can be placed on different parts of the body, such as the chest [15], shoulder [19], waist [18] [19], thigh [19], ankle [20], hip [17] and wrist [17]. The sensor type varies as well. The most common type is accelerometers [15] [18] [19] [20] [21] [23], while ECGs [16] [17], light sensors [19], microphones [19] [21] and temperature sensors [17] have also been used.

None of these works has considered the problem of detecting eating activities during normal daily life. To our knowledge, the methods we describe herein are the first to look at this difficult problem. In addition, many of the previous works on activity recognition require a large set of sensors [17] [19] [23], that together with the wiring, are difficult to wear outside the laboratory. Experiments are typically performed in a laboratory setting where subjects are asked to repeat activities of interest, interspersed with other motions [15] [16] [17] [20]. In contrast, we instrumented our subjects with a single sensor and instructed them to conduct normal activities for an entire day. While the results presented in this paper are preliminary and on a limited number of subjects, we believe our methods will ultimately enable new opportunities

Fig. 1. InertiaCube3 prototype

Fig. 2. Data collection using a single orientation sensor on the wrist

for weight management and weight loss paradigms.

The rest of the paper is organized as follows: In section II we describe our approach of classifying eating activity on pre-segmented motion data and detecting eating sessions in real time. In section III we present experimental results to validate our proposed algorithms. Finally, we conclude our paper and discuss future work in section IV.

II. Methods

A. Hardware and prototype

A wired InertiaCube3 sensor produced by InterSense Corporation (InterSense, Inc., 36 Crosby Drive, Suite 150, Bedford, MA 01730, www.isense.com) was used to record the wrist motion data. It is composed of an accelerometer, a gyroscope and a magnetometer on each of the three axes which provide an orientation heading in each of these three orientations: roll, pitch, and yaw. Figure 1 shows the wired Inertiacube3 sensor and its size compared to a US quarter. The sensor was connected to an external 9V battery as a power source and a laptop with a running program to store collected data through an RS232 interface. Both the external battery and the laptop were carried by the subject in a backpack. The adjustable wire connecting the two parts was long enough to make sure the subject's normal behaviors were not being affected.

B. Data collection

Subjects were asked to wear the sensor and carry the backpack to record their wrist motion data when they got up in the morning, and to stop recording the data when they went to bed at night. As shown in Figure 2, the subject placed the sensor on the dominant eating hand, and then wrapped the band tightly around the forearm to ensure it would not slide around the arm. The program running on the laptop in the backpack (Figure 3) was set up to collect the orientation data from the sensor in real time.

Using the recording program on the laptop was straightforward. Double clicking the program icon on the desktop would automatically start it to record the pitch, yaw and roll

Fig. 3. Data collection using a single orientation sensor on the wrist

orientation at a rate of 60Hz. Due to the fact that the battery in the laptop could only last for about four hours, the program generated continuous beeping for 3 minutes when the battery level of the laptop dropped to 10%. The subject was asked to close the program and replace the battery (an extra was provided in the backpack) when he or she heard the beeping reminder. He or she was asked to restart the program afterward to continue recording.

During recording, subjects were asked to conduct daily activities as naturally as possible. The subject was asked to remove the device when engaging in activities which would damage the device, such as taking a shower or playing contact sports. The subject was asked to record activity behaviors in a written log book. The subject was asked to record the start time and the name of the activity for each new task. For example,

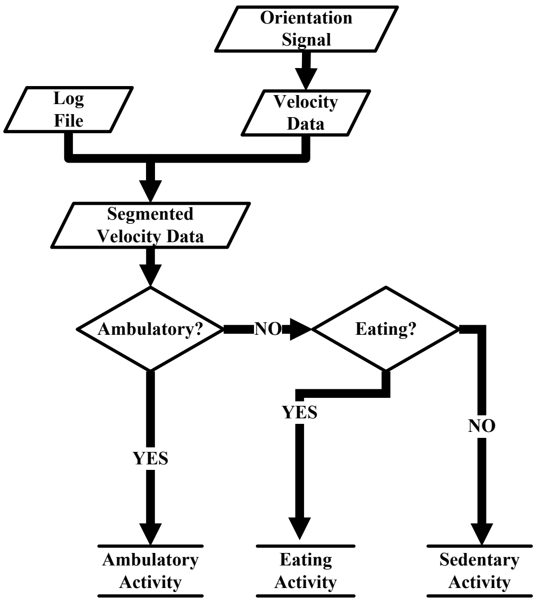

Fig. 4. Diagram of offline detection

08:02:04 eating; 13:24:58 walking. A task was defined as a piece of work or activity to be finished. The log information written by the subject was used for segmenting the ground truth tasks from the wrist motion data later.

A total of 4 subjects participated in this experiment. Two were male and two were female. All the data was collected in a completely free living condition, with no supervision.

C. *Offline eating classification*

For our first experiment, we consider the problem of classifying the eating activity using both the collected motion data and time information in the log book. An outline of the process for the offline eating classification is shown in Figure 4.

Since different subjects might wear the sensor at different angles, it is difficult to define the task if we use the absolute value of the orientation data. Therefore, we calculate the derivative data, which is comparable. Since we have recorded the data at 60Hz, the simplest way to calculate the derivative data is in Equation 1 where d_t is the derivative data at time t and o_t is the orientation data at time t.

$$d_t = (o_t - o_{t-1}) \times 60 \qquad (1)$$

The second step is to segment the derivative data into tasks based on the log file. In the log file, subjects recorded the start time for each new task. We use the start time of current task as one boundary and the start time of the next task as the other boundary for the current task to segment the derivative data. For each segmented data, we categorize it based on the content in the log file into one of 23 categories, as shown in Table I.

Although we were able to map most user defined tasks into Table I, a few tasks were difficult to categorize. First, two categories may happen at the same time, such as eating apples and working on a computer. Second, different people can make notes on the same activity in different ways. For instance, some subjects may categorize "walk to car, stop to talk to a friend" as one log entry, but some other subjects put it into two categories. Because we are interested in eating activities, any note with eating is categorized as "eating". Any notes without eating mentioned were categorized to the best of our ability.

TABLE I
ACTIVITY CATEGORY

Eating activity	Sedentary activity	Ambulatory activity
Eating	Using computer	Cooking
	Using phone	Walking
	Reading	Driving
	Writing	Washing dishes
	Napping	Cleaning
	Talking	Doing laundry
	Watching TV	Packing
	Changing laptop battery	Brushing
	Filing nail	Shopping
	Playing card game	
	Going to restroom	
	Being passenger in car	
	Playing video game	

Since eating is the most important activity to us, we do not need to classify all these 23 tasks. We cluster these 23 categories into three clusters:

1) Eating activity: eating activity is a task which related to eating food or drinking liquid.
2) Sedentary activity: sedentary activity is a task (except eating) which involves sitting down, not moving or not exercising. All tasks in the middle column of Table I belong to this category.
3) Ambulatory activity: ambulatory activity is a task which is related to walking, moving or exercising. All tasks in the right column of Table I belong to this category.

These clusters were chosen because it is typically easier to distinguish sedentary and ambulatory activities. Once these have been separated, eating activities can be recognized as a subset of sedentary activities.

To classify the segmented tasks, we calculate five features for each task:

1) Variance of yaw velocity (Y_VAR)
2) Variance of pitch velocity (P_VAR)
3) Variance of roll velocity (R_VAR)
4) Bites per minute (BPM) using bite detection method. The method to detect bite counts using the derivative data is described in our previous work [13].
5) Occurrences when the bite detection method does not detect a bite over a span of at least one minute (NOT_EAT).

Using these features, each task is classified as follows:

1) A task is classified as an ambulatory activity if any of the following conditions are met:
    a) Y_VAR + P_VAR + R_VAR $>$ T1

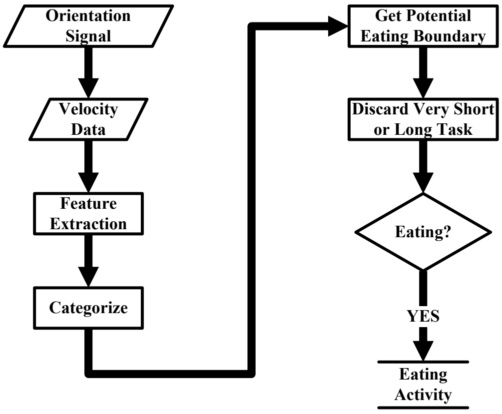

Fig. 5. Diagram of real time detection

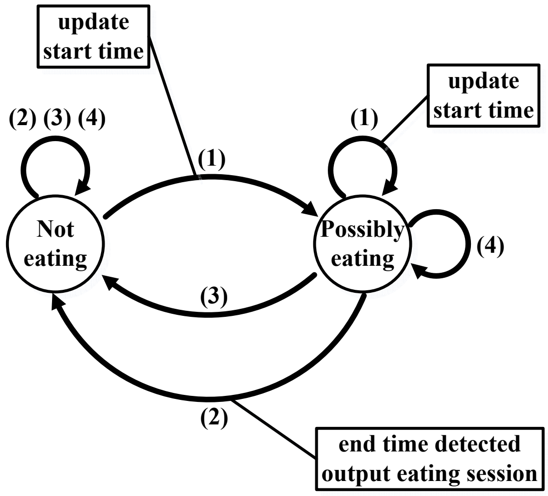

Fig. 6. State machine of potential eating session detection

   b) Y_VAR $>$ T2
   c) P_VAR $>$ T3
   d) R_VAR $>$ T4
2) A task is classified as an eating activity if all of the following conditions are met:
   a) Y_VAR $<$ T5 and Y_VAR $>$ T6
   b) P_VAR $<$ T7 and P_VAR $>$ T8
   c) R_VAR $<$ T9 and R_VAR $>$ T10
   d) BPM $>$ T11
   e) NOT_EAT $<$ T12
3) Otherwise a task is classified as a sedentary activity

Here, $\{$T1, T2, ... T12$\}$ is a set of thresholds. In our default setting, these values are $\{$8500, 5000, 1000, 5000, 3000, 200, 900, 150, 5000, 600, 2, 3$\}$. If the variance of the task's velocity data is large, it is considered as an ambulatory task. If this criterion is not met, the task is considered as either an eating task or a sedentary task. The eating activity has the following characteristics: the variance of pitch, yaw and roll should be within a certain range. In addition, the eating activity should have reached certain bite counts per minute and should not include a long period where no bite is detected. These characteristics are used to separate eating tasks from sedentary tasks.

D. *Real time eating detection*

Our second experiment considers the problem of detecting eating activity without knowing the start time of each task in the log file. This method has the potential to detect the eating activity in real time as we collect the data. The outline of our method is shown in Figure 5. In our algorithm, we only use the roll orientation data.

We calculate the roll velocity data from the orientation data, same as in section II-C. To identify eating activity in real time, we use a sliding window to extract the motion feature. The window size is set to 10 minutes and we update the motion feature every 1 minute. For each 10 minute window, the data is segmented into 2 parts, one from $t-10$ to $t-5$ and one from $t-5$ to t. Each of these two parts is classified using the methods outlined in section II-C. Based on these classifications, the point at time $t-5$ is categorized as one of 4 categories:

1) category 1: this point may be a start boundary for an eating task.
2) category 2: this point may be an end boundary for an eating task.
3) category 3: this point cannot be inside an eating task.
4) category 4: this point may be inside or outside an eating task.

Figure 6 illustrates a state machine that shows our method. Initially we are in the state "not eating". After that, we update the transition condition (category of the time stamp) every 1 minute. If the transition condition is category 1, the state transits to "possibly eating", at the same time, we update the potential start time of an eating session. While in the state "possibly-eating", if the transition condition is category 1, we update the start time; if the transition condition is category 3, we go back to state "not eating"; if the transition condition is category 2, we have detected a potential eating session. We output the start time and the end time of the potential eating session and go back to state "not eating".

For every potential eating session, we examine the duration. If the duration is too short or too long, it is not to be considered as an eating activity.

We also extract the features and run the same algorithm illustrated in section II-C to classify the potential eating session. If all criteria are met, an eating session is detected.

III. Results

As described in Section II-B, a total of 4 subjects were recorded, each for an entire day. We had no restriction on how subjects should do their activities and how long they should do each task. For any eating task, subjects could eat their own food and liquid, and use any utensils they preferred (hand, spoon, fork, or chopsticks). Each recording session was completely unsupervised.

Table II shows some statistics of all the tasks for these subjects. The total time recorded for these four subjects ranged from 9.4 hours to 13.4 hours. The total number of tasks for each subject was between 23 and 39. Table II also shows the shortest task duration, longest task duration, average task duration, and standard deviation of task duration for each subject. In addition, the most frequent task for different subjects varied.

We also include the statistics of eating tasks for these 4 subjects in Table III. The total eating time of each subject was from 0.7 hour to 1 hour. This was consistent with the "American Time Use Survey" from the United States Bureau of Labor Statistics [24] which reported an average of 1.18 hours on eating and drinking per weekday. The total number of eating tasks was within a range from 4 to 6 times. Table III also shows the shortest eating session, longest eating session, average eating session, and standard deviation of eating session for each subject.

Table IV shows the results of task classification using the information on the log file. There were 125 total tasks across all 4 subjects; 16% of the tasks were eating activity, 43% of the tasks were sedentary activity, and the rest were ambulatory activity. The classification accuracy is calculated using Equation 2. In our experiment, the classifcation accuracy was 91%.

$$sensitivity = \frac{sum\ of\ correct\ classifications}{total\ number\ of\ classifications} \quad (2)$$

Table V shows the results of real time eating activity recognition without knowing any information in the log file. In the table, the second and the third column show the ground truth time of each eating task. The second column shows the start time of the eating task and the third column shows the end time of the corresponding eating task. The fourth column and the fifth column show the computer detected boundary for each eating task. The fourth column shows the detected start time of each eating task and the fifth column shows the detected end time of the corresponding eating task. All of these numbers are in minutes. A row without any number in the fourth and fifth column indicates that there is an undetected eating task. A row without any number in the second column and third column indicates that there is a false detection of an eating task. A row with numbers in all columns indicates that this is a detected eating task. The sensitivity is calculated using Equation 3 and the positive predictive value (PPV) is calculated using Equation 4

$$sensitivity = \frac{true\ detected}{true\ detected + undetected} \quad (3)$$

$$PPV = \frac{true\ detected}{true\ detected + false\ detected} \quad (4)$$

TABLE V
REAL TIME CLASSIFICATION RESULT (MINUTES)

	Ground Truth		PC Detect	
Subject	Start time	End time	Start time	End time
S1	11	17	9	17
S1	195	205	194	205
S1	393	400	393	399
S1	537	547	537	549
S1	654	673	653	674
S1			685	700
S2	78	91	78	96
S2	523	538		
S2	565	573		
S2			100	112
S2			192	201
S2			538	548
S3	85	94	85	94
S3	166	178	166	179
S3	257	269	258	272
S3	412	424	412	426
S3	603	615	601	615
S3			362	370
S4	14	27		
S4	270	277	270	276
S4	462	484	466	475
S4	518	527	515	528

Although there were a total of 20 eating sessions recorded by the subjects, 3 of them lasted for less than 3 minutes so they were not included in Table V. We excluded these tasks because they were so short that our feature set did not adequately describe them. For the remaining 17 eating tasks, 3 of them were not detected. There were 6 false detections. Thus the sensitivity was 82% and the positive predictive value was 70%. In addition, for the 14 eating sessions detected, 10 of them were detected with start and end boundaries which match the log file within 2 minutes. For the other 4 sessions, the boundary errors are (0, 5), (1, 3), (4, 9), (3, 1) minutes respectively. We hypothesize that these boundary errors are likely due to timing misalignments between the user logs and wrist motion data, as well as judgment calls by the subjects as to when they actually started and stopped eating.

IV. Conclusions

The prevalence of obesity is a growing, worldwide health concern. Self-monitoring of eating consumption is widely recognized as a necessity for weight loss. However, there are currently no automated methods for monitoring eating consumption in natural daily living. In this paper we have described preliminary experiments that use a single wrist-worn sensor to track wrist motion throughout the day, in order to detect eating sessions. Four subjects were recorded for an average period of 11 hours, performing an average of 31 self-classified tasks, of which an average of 5 were eating. In our first experiment, we segmented the wrist motion data according to the subjects' logs, and demonstrated a 91% accuracy in classifying the tasks. In our second experiment, we automatically segmented the wrist motion data and demonstrated an 82% accuracy in detecting eating sessions. While

TABLE II
STATISTICS OF ALL THE TASKS FOR THESE SUBJECTS

	Subject 1	Subject 2	Subject 3	Subject 4
total time of all tasks (h)	13.4	9.8	10.1	9.4
total number of tasks	39	36	23	27
shortest task (min)	3	1.2	3.3	3.5
longest task (min)	93.3	90.7	97.5	78.7
average task (min)	20.6	16.3	26.3	20.9
standard deviation of task (min)	20.6	19.1	27.4	21.7
most frequent task	Using computer	Driving	Eating	Using computer

TABLE III
STATISTICS OF EATING TASKS FOR THESE SUBJECTS

	Subject 1	Subject 2	Subject 3	Subject 4
total time of eating (h)	0.8	0.7	1	0.8
total number of eating sessions	5	5	6	4
shortest session (min)	5.8	1.2	3.3	7
longest session (min)	18.6	15.3	12.3	21.7
average session (min)	10.2	7.9	10	12.6
standard deviation of session (min)	5.2	6	3.6	6.5

TABLE IV
OFFLINE CLASSIFICATION RESULT

	Classify: Eating	Classify: Sedentary	Classify: Ambulatory
GT: Eating	17	2	1
GT: Sedentary	4	49	1
GT: Ambulatory	2	1	48

the number of subjects tested was small, this is the first work to examine the problem of automatically monitoring eating during daily living. In the future we plan to continue this experiment on a much larger number of subjects. We also intend to simplify the apparatus to something that can be worn completely on the wrist. For these first experiments, we used a laptop in a backpack in order to record the large amount of data generated during an entire day. For our next experiments we intend to use a "smart phone".

REFERENCES

[1] K. Flegal, M. Carroll, C. Ogden and L. Curtin, "Prevalence and trends in obesity among US adults, 1999-2008", in *Journal of the American Medical Association*, vol. 303, 2010, pp. 235-241.

[2] World Health Organization Media Center, "Obesity and overweight", http://www.who.int/mediacentre/factsheets/fs311/en/index.html, retrieved March 5, 2011.

[3] N. Wellman and B. Friedberg, "Causes and consequences of adult obesity: health, social and economic impacts in the United States", in *Asia Pacific Journal of Clinical Nutrition*, vol. 11, no. 667-751, 2002, pp. 705-709.

[4] E. Finkelstein, J. Trogdon, J. Cohen and W. Dietz, "Annual medical spending attributable to obesity: Payer- and service-specific estimates", in *Health Affairs*, vol. 28, 2009, pp. w822-w831.

[5] L. Burke, J. Wang and M. Sevick, "Self-monitoring in weight loss: A systematic review of the literature", in *Journal of the American Dietetic Association* vol. 111, no. 1, 2011, pp. 92-102.

[6] C. Champagne, G. Bray, A. Kurtz, J. Monteiro, E. Tucker, J. Volaufova and J. Delany, "Energy intake and energy expenditure: A controlled study comparing dieticians and non-dieticians", in *Journal of the American Dietetic Association*, vol. 102(10), 2002, pp. 1428-1432.

[7] K. Glanz, J. Brug and P. van Assema, "Are awareness of dietary food intake and actual fat consumption associated? A Dutch-American Comparison", in *Euro. J. of Clinical Nutrition*, vol. 51, 1997, pp. 542-547.

[8] H. Kissileff, G. Klingsberg and T. Van Itallie, "Universal eating monitor for continuous recording of solid or liquid consumption in man", in *Amer. J. of Physiology*, vol. 238 no. 1, 1980, pp. R14-R22.

[9] K. Chang, S. Liu, H. Chu, J. Hsu, C. Chen, T. Lin, C. Chen and P. Huang, "The diet-aware dining table: Observing dietary behaviors over a tabletop surface," in the proc. of *4th Int'l Conf. on Pervasive Computing*, LNCS vol. 3968, 2006, pp. 366-382.

[10] F. Zhu, A. Mariappan, C. Boushey, D. Kerr, K. Lutes, D. Ebert and E. Delp, "Technology-Assisted Dietary Assessment", in *SPIE: Computational Imaging VI*, vol. 6814, 2008, pp. 1-10.

[11] R. Weiss, P. Stumbo and A. Divakaran, "Automatic Food Documentation and Volume Computation using Digital Imaging and Electronic Transmission", in *J. of American Dietetics Assoc.*, vol. 110 no. 1, 2010, pp. 42-44.

[12] O. Amft and G. Troster, "On-Body Sensing Solutions for Automatic Dietary Monitoring", in *Pervasive Computing*, vol. 8(2), 2009, pp. 62-70.

[13] Y. Dong, A. Hoover, and E. Muth, "A Device for Detecting and Counting Bites of Food Taken by a Person During Eating", in the proc. of *IEEE Conf. on Bioinformatics and Biomedicine*, 2009, pp. 265-268.

[14] Y. Dong, "A Device for Detecting and Counting Bites of Food Taken by a Person During Eating", master's thesis, Electrical & Computer Engineering Dept., Clemson University, 2009.

[15] A. Khan, Y. Lee, S. Lee and T. Kim, "A Triaxial Accelerometer-Based Physical-Activity Recognition via Augmented-Signal Features and a Hierarchical Recognizer", in *IEEE Trans. on Information Technology in Biomedicine*, vol. 14, no. 5, Sept 2010, pp. 1166-1172.

[16] T. Pawar, S. Chaudhuri and S. Duttagupta, "Body Movement Activity Recognition for Ambulatory Cardiac Monitoring", in *IEEE Trans. on Biomedical Engineering*, vol. 54, no. 5, May 2007, pp. 874-882.

[17] M. Ermes, J. Parkka, J. Mantyjarvi and I. Korhonen, "Detection of Daily Activities and Sports With Wearable Sensors in Controlled and Uncontrolled Conditions", in *IEEE Trans. on Information Technology in Biomedicine*, vol. 12, no. 1, Jan 2008, pp. 20-26.

[18] D. Karantonis, M. Narayanan, M. Mathie, N. Lowell and B. Celler,

"Implementation of a Real-Time Human Movement Classifier Using a Triaxial Accelerometer for Ambulatory Monitoring", in *IEEE Trans. on Information Technology in Biomedicine*, vol. 10, no. 1, Jan 2006, pp. 156-167.

[19] J. Yin, Q. Yang and J. Pan, "Sensor-Based Abnormal Human-Activity Detection", in *IEEE Trans. on Knowledge and Data Engineering*, vol. 20, no. 8, Aug 2008, pp. 1082-1090.

[20] J. Parkka, L. Cluitmans and M. Ermes, "Personalization Algorithm for Real-Time Activity Recognition Using PDA, Wireless Motion Bands, and Binary Decision Tree", in *IEEE Trans. on Information Technology in Biomedicine*, vol. 14, no. 5, Sept 2010, pp. 1211-1215.

[21] J. Ward, P. Lukowicz, G. Troster and T. Starner, "Activity Recognition of Assembly Tasks Using Body-Worn Microphones and Accelerometers", in *IEEE Trans. on Pattern Analysis & Machine Intelligence*, vol. 28, no. 10, Oct 2006, pp. 1553-1567.

[22] A. Salarian, H. russmann, C. Wider, P. Burkhard, F. Vingerhoets and K. Aminian, "Quantification of Tremor and Bradykinesia in Parkinson's Disease Using a Novel Ambulatory Monitoring System", in *IEEE Trans. on Biomedical Engineering*, vol. 54, no. 2, Feb 2007, pp. 313-322.

[23] L. Atallah, B. Lo, R. Ali, R. King and G. Yang, "Real-Time Activity Classification Using Ambient and Wearable Sensors", in *IEEE Trans. on Information Technology in Biomedicine*, vol. 13, no. 6, Nov 2009, pp. 1031-1039.

[24] United States Bureau of Labor Statistics, American Time Use Survey, "Eating and Drinking", http://www.bls.gov/tus/current/eating.htm retrieved March 5, 2011.