CARE: Chewing Activity Recognition Using Noninvasive Single Axis Accelerometer

Shuangquan Wang
Institute of Computing
Technology, CAS
Beijing, China 100190
wangshuangquan@ict.ac.cn

Gang Zhou
College of William and Mary
Williamsburg, VA 23187 USA
gzhou@cs.wm.edu

Lisha Hu
Institute of Computing
Technology, CAS
Beijing, China 100190
hulisha@ict.ac.cn

Zhenyu Chen
Institute of Computing
Technology, CAS
Beijing, China 100190
chenzhenyu@ict.ac.cn

Yiqiang Chen
Institute of Computing
Technology, CAS
Beijing, China 100190
yqchen@ict.ac.cn

UbiComp/ISWC '15 Adjunct, September 7-11, 2015, Osaka, Japan.
ACM 978-1-4503-3575-1/15/09.
http://dx.doi.org/10.1145/2800835.2800884

Abstract
In this paper, we focus on user's Chewing Activity REcognition and present a novel recognition system named CARE. Based on the observation that during chewing the mastication muscle contracts and accordingly bulges in some degree, CARE uses a single axis accelerometer attached on the temporalis to detect the muscle bulge and recognize user's chewing activity. CARE is also able to calculate the chewing frequency through recognizing the periodic pattern of acceleration data. Experiments are conducted and the results show that CARE obtains high accuracy on both chewing activity classification and chewing frequency detection.

Author Keywords
Chewing Activity; Chewing Frequency; Accelerometer

ACM Classification Keywords
H.5.m. Information Systems: Information Interfaces and Presentation—Miscellaneous

Introduction
As one of the major causes of chronic diseases, unhealthy diet and excessive energy intake leads to prevalence of obesity [1], especially in developed

countries. As one necessary step of dietary process, chewing is essential but often overlooked.

In recent years, some chewing activity monitoring methods have been proposed. Eating process recall or self-report diary [2] is simple and straightforward but tedious and not accurate enough. Audio based method needs to deploy sensors in outer ear [3] or at throat area [4], which is invasive. Video based method does not require a person to wear any sensor, but demands a camera to capture mouth movement [5] and hence brings privacy concern. Motion based method aims to recognize wearer's hand motion and indirectly deduce eating behaviors [6], but cannot recognize chewing activities. Sensor embedded method (e.g. in artificial teeth [7]) can capture chewing activity directly, but is invasive and hence difficult to be widely accepted. In addition, physiological sensors (e.g. EMG sensor) or physical sensors (e.g. piezoelectric strain gauge sensor in [8]) can also be utilized, but need to be tightly adhered to skin, which is invasive and discomforting.

In this paper, we propose a Chewing Activity REcognition system named CARE, which uses a single axis accelerometer attached on the temporalis to detect the muscle bulge. CARE can not only identify the chewing activity in a noninvasive way, but also detect the chewing frequency accurately. Plus, CARE does not record any private information (audio, video, etc.) and provides a low-cost, power-efficient solution for continuous dietary monitoring.

CARE System

As depicted in Figure 1, the CARE system mainly contains two parts: the accelerometer embedded wearable objects and smart mobile/wearable devices. The sensing module collects accelerometer data and transmits it to mobile/wearable devices through Bluetooth. In mobile/wearable devices, a chewing activity recognition application is installed which has three main components: chewing activity classification module, chewing frequency detection module and the graphical user interface module.

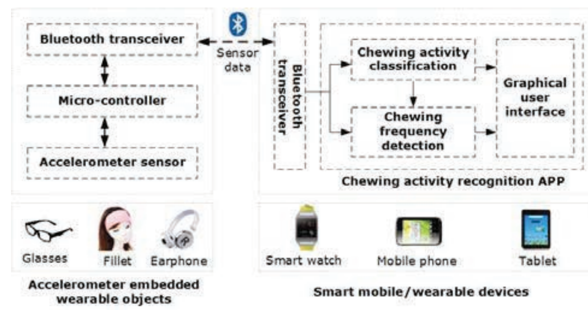

Figure 1: System architecture of CARE

Chewing activity classification has two processes, training process and testing process. In training process, raw acceleration data is calibrated using formula (1), where L is the window length and Z_i is the ith sample in the window. Eight time domain features and 12 frequency domain features are extracted and normalized to build the training dataset. The time domain features include the mean of absolute value, standard deviation, the maximum, the minimum, the first quartile, the second quartile, the third quartile and the number of mean crosses. The frequency domain features include the 10 biggest Fast Fourier Transform (FFT) coefficients, spectral energy and spectral entropy. Based on a specific classification algorithm, a classification model is trained. In testing

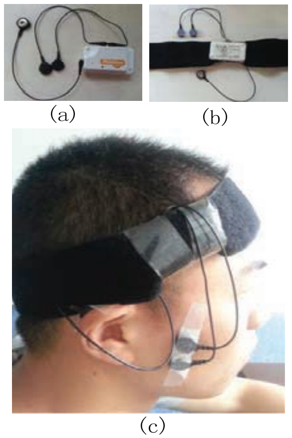

Figure 2: Data collection device and deployment

	DT	NN	MLP	SVM	WSVM
Accuracy	94.4	95.8	97.0	93.5	96.0
Precision	86.6	89.7	94.6	93.5	90.6
Recall	88.4	91.6	91.6	75.8	91.6
F_score	87.5	90.6	93.0	83.7	91.1

Table 1: CVT classification results of five classifiers

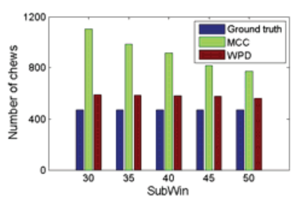

Figure 3: Chewing detection results for User 1

process, unlabeled feature vectors are sent to the model, and the classification results are obtained.

$$Z_i = Z_i - \frac{1}{L}\sum_{i=1}^{L} Z_i \qquad (1)$$

For chewing frequency detection, the acceleration data is firstly calibrated using formula (1). Then a low pass filter and a centered moving average filter are utilized in order to smooth the data. To compute the chewing frequency, two popular algorithms are compared: 1) mean crossing counts (MCC) [9], which slices each sliding window into sub-windows of width *SubWin* and counts each positive crossing of the sub-window mean as a chew; and 2) window peak detect (WPD) [9]. WPD slices each sliding window into sub-windows of width *SubWin*, then counts one peak as a chew only if its value equals the maximum of corresponding sub-window. WPD is imposed the restriction that each sub-window contains at most one chew.

Experiment and Evaluation

Shimmer 2r sensor platform is used for data collection. It has an integrated accelerometer and EMG sensor. We fix Shimmer 2r in a fillet to sample acceleration and EMG data (Figure 2). The Z axis of the accelerometer directs outward. The EMG data is used for ground truth labeling. The sampling rate is about 100Hz. The food is multiple small pieces of watermelon. Four volunteers perform eating and six other noise activities (reading/speaking, standing, sitting, walking, drinking and coughing). In total, 150 minutes data is collected.

Cross validation test (CVT) is used to evaluate the classification performance of CARE. CVT combines all subjects' samples to form the dataset, and uses cross-validation algorithm to evaluate the classification accuracy of CARE on multi-subjects. The fold of CVT is set to 10.

Five classification algorithms in Weka toolkit [10] are compared: decision tree (DT), nearest neighbor (NN), multi-layer perceptron (MLP), support vector machine (SVM) and weighted SVM (WSVM). For SVM and WSVM, the LibSVM wrapper for Weka [11] is used. We adopt the default parameters for all classifiers. The weights of WSVM are set to 3 for positive class and 1 for negative class. The sliding window length is set to 2048.

Table 1 shows the CVT classification results of five classifiers. From Table 1 we can see that almost all the results of five classifiers are greater than 83% (except *Recall* of SVM). This demonstrates that CARE accurately differentiates chewing from other noise activities. MLP outperforms the other four classifiers, and its *Accuracy* and *F_score* reach 97% and 93%, respectively. SVM obtains relatively high *Precision* but low *Recall*, which indicates that SVM is biased to the negative class. This is because that the negative class has more samples than the positive class. Comparatively, WSVM has better balanced performance because of the weight for each class.

We evaluate the accuracy of frequency detection in the following experiments. The cut off frequency of low pass filter is set to 3Hz. The window size of the centered moving average filter is set to 40. The ground truth of "number of chews" for user 1, user 2, user 3 and user 4 are 473, 587, 323 and 370, respectively. To describe the detection accuracy, the following detection error rate is used:

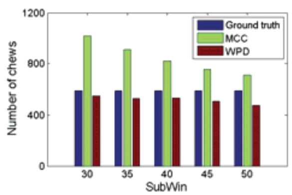

Figure 4: Chewing detection results for User 2

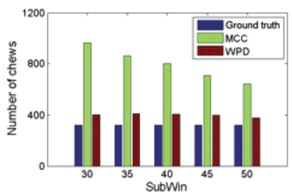

Figure 5: Chewing detection results for User 3

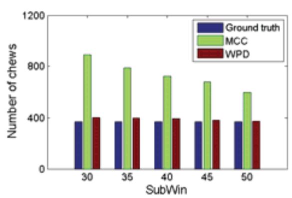

Figure 6: Chewing detection results for User 4

$$Error\ rate = \frac{Detected\ number - Ground\ truth}{Ground\ truth} \times 100\% \qquad (2)$$

Figures 3 - 6 depict the chewing detection results for each user. We can observe that: 1) compared with MCC, the detection results of WPD are closer to the ground truth. At the same time, the performance of WPD is relatively stable to the sub-window width; 2) when *SubWin* equals 50, WPD achieves the highest accuracy (except user 2). The error rates for the four users are 17.8%, -18.7%, 17.3% and 1.4%, respectively. Normally, the detection result of WPD is overcounted because of noise peaks contained in the acceleration data. The centered moving average filter is able to eliminate these noise peaks. However, how to choose appropriate window size for the moving average filter is a dilemma. On the one hand, a too-small window cannot filter the noise peaks; on the other hand, a too-big window may smooth away the real peaks.

Conclusion

We propose a noninvasive Chewing Activity REcognition system named CARE, which accurately identifies the chewing activity and counts the number of chews only using a single axis accelerometer attached on the temporalis. Experiments are conducted with multiple human subjects, and the results demonstrate that the proposed method is valid and promising.

Acknowledgement

This work was supported in part by U.S. National Science Foundation under grants CNS-1253506 (CAREER), Natural Science Foundation of China (NSFC) under Grant No.61472399 and No.61173066, and Beijing Natural Science Foundation under Grant No.4144085.

References

1. www.who.int/mediacentre/factsheets/fs310/en/
2. Vivienne A. Vance, et al. 2009. Self-reported dietary energy intake of normal weight, overweight and obese adolescents. *Public Health Nutr.* 12, 2: 222-227.
3. Oliver Amft, et al. 2005. Analysis of chewing sounds for dietary monitoring. In *Proc. UbiComp 2005*, 56-72.
4. Koji Yatani and Khai N. Truong. 2012. BodyScope: a wearable acoustic sensor for activity recognition. In *Proc. UbiComp 2012*, 341-350.
5. Steven Cadavid, et al. 2012. Exploiting visual quasi-periodicity for real-time chewing event detection using active appearance models and support vector machines. *Personal Ubiquitous Comput.* 16, 6, 729-739.
6. Yujie Dong, et al. 2012. A new method for measuring meal intake in humans via automated wrist motion tracking. *Appl Psychophysiol Biofeedback* 37, 3, 205-215.
7. Cheng-Yuan Li, et al. 2013. Sensor-embedded teeth for oral activity recognition. In *Proc. ISWC 2013*, 41-44.
8. Edward S. Sazonov, et al. 2012. A Sensor System for Automatic Detection of Food Intake through Non-Invasive Monitoring of Chewing. *IEEE Sensors Journal* 12, 5, 1340-1348.
9. Agata Brajdic and Robert Harle. 2013. Walk detection and step counting on unconstrained smartphones. In *Proc. UbiComp 2013*, 225-234.
10. Weka toolkit, http://www.cs.waikato.ac.nz/ml/weka/
11. EL-Manzalawy, Y. 2005. WLSVM. http://www.cs.iastate.edu/~yasser/wlsvm/