Comment on 'Non-invasive monitoring of chewing and swallowing for objective quantification of ingestive behavior'

Oliver Amft

Signal Processing Systems, Einhoven University of Technology, 5300 MB Eindhoven, The Netherlands

E-mail: `amft@tue.nl`

Abstract. The paper of Sazonov et al. [1] addresses the topic of on-body sensor-based measurement and analysis of food intake and eating behaviour. The authors rightly pinpoint a lack of solutions to estimate eating behaviour and energy intake in contrast to the active development of energy expenditure prediction tools.

Unfortunately, Sazonov and colleagues have missed to review a considerable amount of published research in the field of ubiquitous and wearable computing. Moreover, it should be noted that objective measurement techniques exist for laboratory studies of chewing and swallowing that could have served for the validation of their work. This letter summarises relevant related works and identifies refinements of the study methodology suggested by Sazonov et al.

Food intake behaviour is very variable and hard to capture. Nevertheless the approaches towards Automatic Dietary Monitoring (ADM) cited in this letter confirm a broad potential for sensing and pattern recognition techniques. ADM could eventually supplement or replace intake diaries.

Keywords: Ubiquitous computing, automatic dietary monitoring, chewing, swallowing, pervasive healthcare

The paper of Sazonov et al. [1] addresses a relevant topic of on-body sensor-based measurement and analysis – monitoring of food intake and eating behaviour. The authors rightly pinpoint a lack of solutions to estimate eating behaviour and energy intake in contrast to the active development of energy expenditure prediction tools. To date, food intake diaries and food frequency questionnaires [2,3] are prevalent methods in clinical and ambulatory assessments of food intake and estimation of consumed calories. In particular, the doubly-labelled water method [4] measures integral CO^2 production over time from body water and hence, permits estimation of energy expenditure and not energy intake as claimed by Sazonov et al.

Unfortunately, Sazonov and colleagues have missed to review a considerable amount of published research in the field of ubiquitous and wearable computing. These investigations have not only focused on identifying sensors to monitor food intake, but also developed solutions for automatic pattern recognition and prediction of eating behaviour from sensor data. Sazonov et al. have emphasised that such a recognition would be their goal of future research. I am referring to the sensor-based recognition approach as *Automatic Dietary Monitoring* (ADM) [5–12], since it aims to release individuals from laborious manual diet reporting in day-to-day food reports.

While providing a full review of relevant literature on this topic is beyond the scope of this letter, the following exemplary references shall indicate concepts utilised in ADM. On-body inertial sensors have been used to automatically recognise and identify intake gestures (arm and torso motion related to eating, e.g. by using a spoon, fork and knife, etc.) [6,11]. Information on particular types of gestures can help to distinguish consumed foods. Chewing has been analysed using ear-worn microphones to automatically identify food type [5] and spot chews in continuous sensor data [10]. For swallowing, a number of sensor modalities have been investigated, sensor pattern recognition for ADM has been evaluated for swallowing sound and Electromyographic (EMG) modalities [7]. Moreover, combined approaches of on-body and ambient sensor networks have been utilised by Patterson et al. [13] and Chang et al. [14]. Both investigations used radio-frequency-identification (RFID) tags on household objects and food containers and RFID readers worn at the users' hands to identify objects and infer eating behaviour. Further ambient systems include the work of Chang et al. [14] on weight-sensitive tables, intake gesture monitoring using video by Gao et al. [15], and video-based food consumption systems, e.g. [16]. It should be noted that all of these projects evaluated their sensing approach to estimate eating behaviour using pattern recognition techniques. One can regret that the actual sensor data evaluation of Sazonov et al. builds on manual analysis by human raters only. The authors did not deploy an automatic technique, which could have proved applicability of their sensor approach and provided more insight into the pattern quality.

Supporting this line of argumentation it should be noted that objective measurement techniques for laboratory studies of chewing and swallowing exist. A extensive body of research on chewing has used surface EMG to monitor mandibular activity, e.g. [17], as well as movement trackers, e.g. [18]. Contradictory to the statements of Sazonov et al., EMG measurement using surface electrodes is used in deglutiton investigations as well (see Cooper & Perlman [19], page 260, Figure 9-3).

Sazonov et al. have focused their contribution on evaluating reliability of three raters who annotated intake events (bites, chews, swallows). These raters scored previously recorded sensor data of two in-lab food consumption sessions recorded with five subjects. The raters had video footage, as well as data from the included on-body sensors at their disposal. Unfortunately, this procedure prevents identifying what information had been used for the rating. It could be assumed that raters primarily reviewed the video instead of on-body sensor data. Consequently, the overall performance e.g. of a strain sensor that measures skin movement corresponding to mandible motion, cannot be determined. To this end, one might assume that this strain sensor is sensitive to head motion and may fail, depending on tissue thickness.

Aboofazeli & Moussavi [20] observed a broad inter- and intra-individual variability for normal swallowing. Based on my personal experience when working with students, annotation of chewing and swallowing sensor data (with and without visual cues) require considerable training. Nonetheless, a consistent annotation of event boundaries is vital to apply pattern recognition techniques. However, Sazonov and colleagues found a similar performance in the scoring result for both, amateurs and expert raters. While the authors developed a dedicated protocol for the scoring procedure, its neither presented nor discussed. Such details would have allowed to replicate their investigation and confirm the results. Additionally, since the authors did not provide details on the total number of rated bites, chews, and swallows, the generality of this investigation could not be determined.

Sazonov et al. found a remarkable inter-rater agreement for bites, chews, and swallows. However, their evaluation methodology does not permit to assess whether the scoring is sufficiently accurate in identifying event boundaries for deployment of recognition algorithms. The smallest epoch size was 10 seconds. In comparison, typical durations for chews and swallows are below 1 s and 1.5 s respectively [10, 20]. Consequently, raters may have matched the correct epoch, but could have entirely failed to identify the event bounds.

The authors postulated their ultimate goal to apply recognition techniques on this dataset to identify food type, amount, and energy content. However, their conceptual work did not discuss the intended approach. It would have been interesting for readers to understand, how the sensor capabilities contribute to this recognition. While some indication on food amount and bolus viscosity have been found in acoustic signals of pharyngeal swallowing [7], none of the other modalities used by Sazonov et al. is obviously related to food type, amount, or energy content.

The complexity of food intake in behaviour pattern as well as inter- and intra-individual pattern variability are primary challenges for the success of ADM techniques. While behaviour pattern complexity often requires several complementary sensor modalities, pattern variability requires robust recognition models as well. Obviously, using multiple sensors increases system complexity and user burden, which will eventually limit system acceptance. Nevertheless, for several ADM approaches that have been cited above applicability has been confirmed. To date, however, none of the ADM approaches has reached maturity to actually replace food intake diaries or to determine energy intake.

Hence, there is a broad potential for additional research to identify viable sensing solutions and recognition techniques to estimate intake schedule, food type, amount, and energy content. Interested readers may refer to a recent review of on-body sensing approaches for ADM [12].

Conflict of interest

None.

References

[1] Edward Sazonov, Stephanie Schuckers, Paulo Lopez-Meyer, Oleksandr Makeyev, Nadezhda Sazonova, Edward L Melanson, and Michael Neuman. Non-invasive monitoring of chewing and swallowing for objective quantification of ingestive behavior. *Physiological Measurement*, 29(5):525–541, May 2008.

[2] Jelia C. Witschi. Short-term dietary recall and recording methods. In W Willett, editor, *Nutritional Epidemiology*, volume 4, pages 52–68. Oxford University Press, 1990.

[3] W Willett. Food frequency methods. In W Willett, editor, *Nutritional Epidemiology*, chapter 5, pages 69–91. Oxford University Press, 1990.

[4] D. A. Schoeller. Measurement of energy expenditure in free-living humans by using doubly labeled water. *The Journal of Nutrition*, 118(11):1278–1289, Nov 1988.

[5] Oliver Amft, Mathias Stäger, Paul Lukowicz, and Gerhard Tröster. Analysis of chewing sounds for dietary monitoring. In Michael Beigl, Stephen Intille, Jun Rekimoto, and Hideyuki Tokuda, editors, *UbiComp 2005: Proceedings of the 7th International Conference on Ubiquitous Computing*, volume 3660 of *Lecture Notes in Computer Science*, pages 56–72. Springer Berlin, Heidelberg, September 2005.

[6] Oliver Amft, Holger Junker, and Gerhard Tröster. Detection of eating and drinking arm gestures using inertial body-worn sensors. In Bradley Rhodes and Kenji Mase, editors, *ISWC 2005: IEEE Proceedings of the Ninth International Symposium on Wearable Computers.*, pages 160–163. IEEE Press, October 2005.

[7] Oliver Amft and Gerhard Tröster. Methods for detection and classification of normal swallowing from muscle activation and sound. In Emile Aarts, Ryuji Kohno, Paul Lukowicz, and Jorge Carlos Trainini, editors, *PHC 2006: Proceedings of the First International Conference on Pervasive Computing Technologies for Healthcare*, pages 1–10. ICST, IEEE digital library, November 2006.

[8] Oliver Amft, Martin Kusserow, and Gerhard Tröster. Probabilistic parsing of dietary activity events. In Steffen Leonhardt, Thomas Falck, and Petri Mähönen, editors, *BSN 2007: Proceedings of the International Workshop on Wearable and Implantable Body Sensor Networks*, volume 13, pages 242–247. IFMBE Proceedings, Springer, March 2007.

[9] Oliver Amft, Martin Kusserow, and Gerhard Tröster. Automatic identification of temporal sequences in chewing sounds. In Tony Hu, Ion Mandoiu, and Zoran Obradovic, editors, *BIBM 2007: Proceedings of the IEEE International Conference on Bioinformatics and Biomedicine*, pages 194–201, San Jose, CA, USA, November 2007. IEEE Press.

[10] Oliver Amft and Gerhard Tröster. Recognition of dietary activity events using on-body sensors. *Artificial Intelligence in Medicine*, 42(2):121–136, February 2008.

[11] Holger Junker, Oliver Amft, Paul Lukowicz, and Gerhard Tröster. Gesture spotting with body-worn inertial sensors to detect user activities. *Pattern Recognition*, 41(6):2010–2024, June 2008.

[12] Oliver Amft and Gerhard Tröster. Automatic dietary monitoring: on-body sensing solutions for eating behavior monitoring. *IEEE Pervasive Computing*, 8(2):in press, April-June 2009.

[13] D.J. Patterson, D. Fox, H. Kautz, and M. Philipose. Fine-grained activity recognition by aggregating abstract object usage. In Bradley Rhodes and Kenji Mase, editors, *ISWC 2005: Proceedings of the Ninth IEEE International Symposium on Wearable Computers*, pages 44–51. IEEE Press, October 2005.

[14] K.-H. Chang, S.-Y. Liu, H.-H. Chu, J. Y. Hsu, C. Chen, T.-Y. Lin, C.-Y. Chen, and P. Huang. The diet-aware dining table: Observing dietary behaviors over a tabletop surface. In K.P. Fishkin, B. Schiele, P. Nixon, and A. Quigley, editors, *PERVASIVE 2006: Proceedings of the 4th International Conference on Pervasive Computing*, volume 3968 of *Lecture Notes in Computer Science*, pages 366–382. Springer Berlin, Heidelberg, May 2006.

[15] Jiang Gao, A.G. Hauptmann, A. Bharucha, and H.D. Wactlar. Dining activity analysis using a hidden markov model. In *ICPR 2004: Proceedings of the 17th International Conference on Pattern Recognition*, volume 2, pages 915–918, Aug. 2004.

[16] Yoshihiro Saeki and Fumiaki Takeda. Proposal of food intake measuring system in medical use and its discussion of practical capability. In *KES 2005: Proceedings of the 9th International Conference on Knowledge-Based Intelligent Information and Engineering Systems*, volume 3683 of *Lecture Notes in Computer Science*, pages 1266–1273. Springer, 2005. Category: Knowledge Based Intelligent Systems for Health Care.

[17] L. Mioche, P. Bourdiol, J. F. Martin, and Y. Nol. Variations in human masseter and temporalis muscle activity related to food texture during free and side-imposed mastication. *Archives of Oral Biology*, 44(12):1005–1012, Dec 1999.

[18] K. R. Agrawal, P. W. Lucas, and I. C. Bruce. The effects of food fragmentation index on mandibular closing angle in human mastication. *Archives of Oral Biology*, 45(7):577–584, July 2000.

[19] Donald Cooper and Adrienne Perlman. Electromyography in the functional and diagnostic testing of deglutition. In Adrienne Perlman and Konrad Schulze-Delrieu, editors, *Deglutition and Its Disorders: Anatomy, Physiology, Clinical Diagnosis, and Management*, chapter 9, pages 255–284. Singular Publishing Group, 1996. ISBN 1565936213, 9781565936218.

[20] Mohammad Aboofazeli and Zahra Moussavi. Analysis of swallowing sounds using hidden markov models. *Medical and Biological Engineering and Computing*, 46(4):307–314, April 2007.