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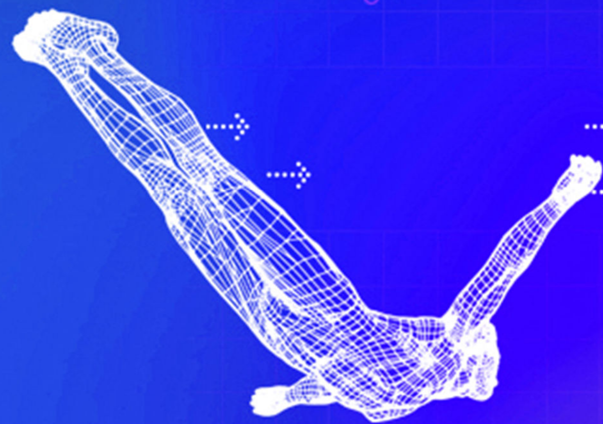


Wearable Sensors for Detection and Characterization of Food Intake

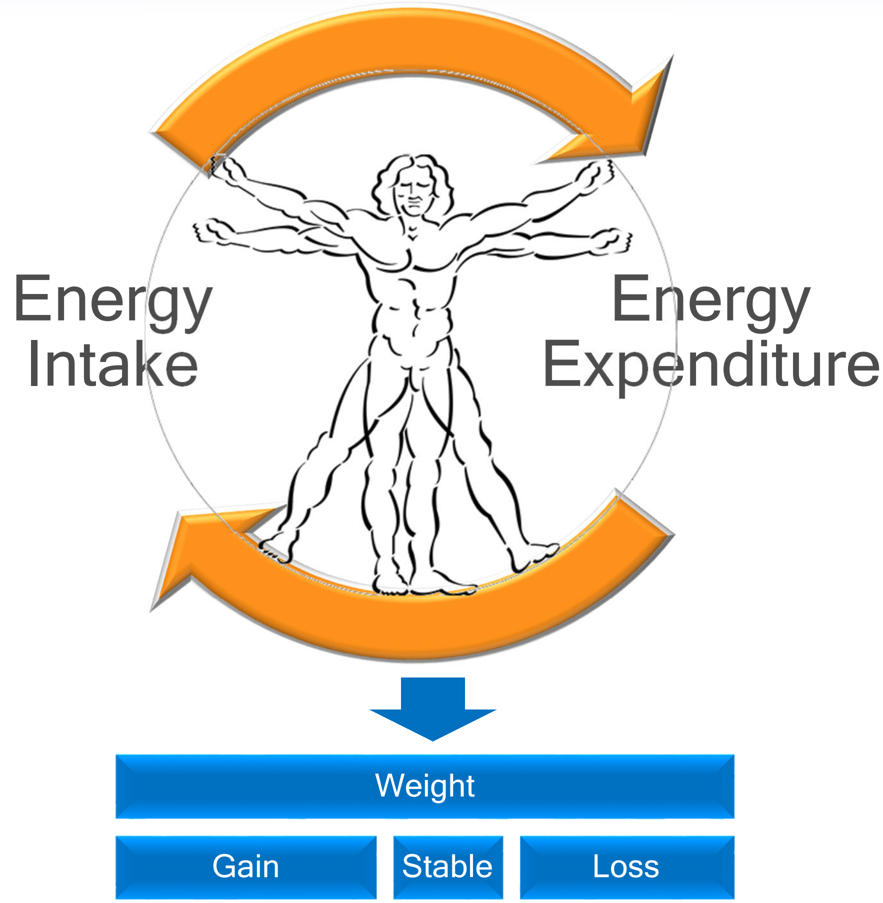
Outline

- Challenges in monitoring the energy balance
- Why sensors?
- Detection and characterization of food intake
  - Hand gesture sensors
  - Chewing sensors
  - Swallowing sensors
  - Characterization of ingestive behavior
- Conclusions and future directions

Energy balance

Calories ingested:

- Fat
- Protein
- Carbohydrates
- Alcohol



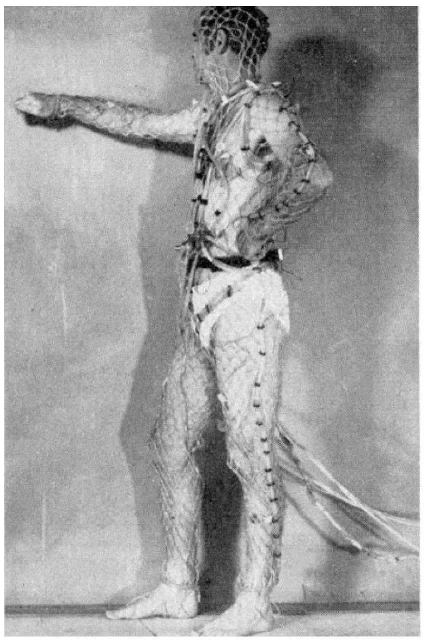
Calories spent:

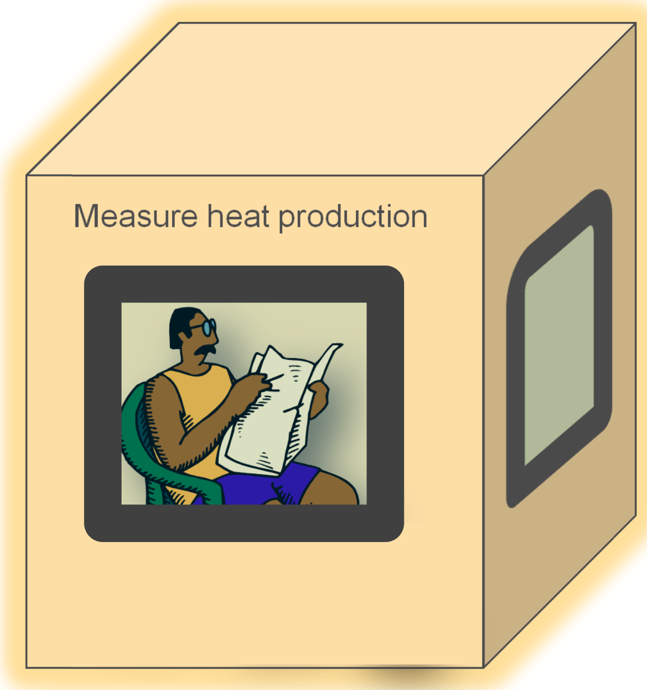
- Basal Metabolic rate
- Thermal effect of food
- Physical Activity

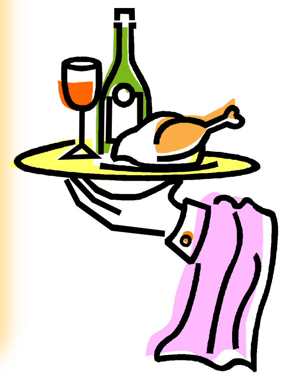
Both Energy Intake (EI) and Energy Expenditure (EE) are hard to measure, especially in free living individuals

Energy balance

- Measuring energy balance **directly**







Measure caloric content of all foods served

- Most true
- Not a natural environment, not suitable for free living
- Affects EI and EE behavior

Energy balance

- Most methods for measuring energy balance are **indirect**

Energy expenditure:

- self-report (diary)
- indirect calorimetry
- DLW
- accelerometers
- heart rate monitors
- others

Energy Intake:

- self-report (diary. multimedia diary, 24hr recall, food frequency questionnaires, etc.)

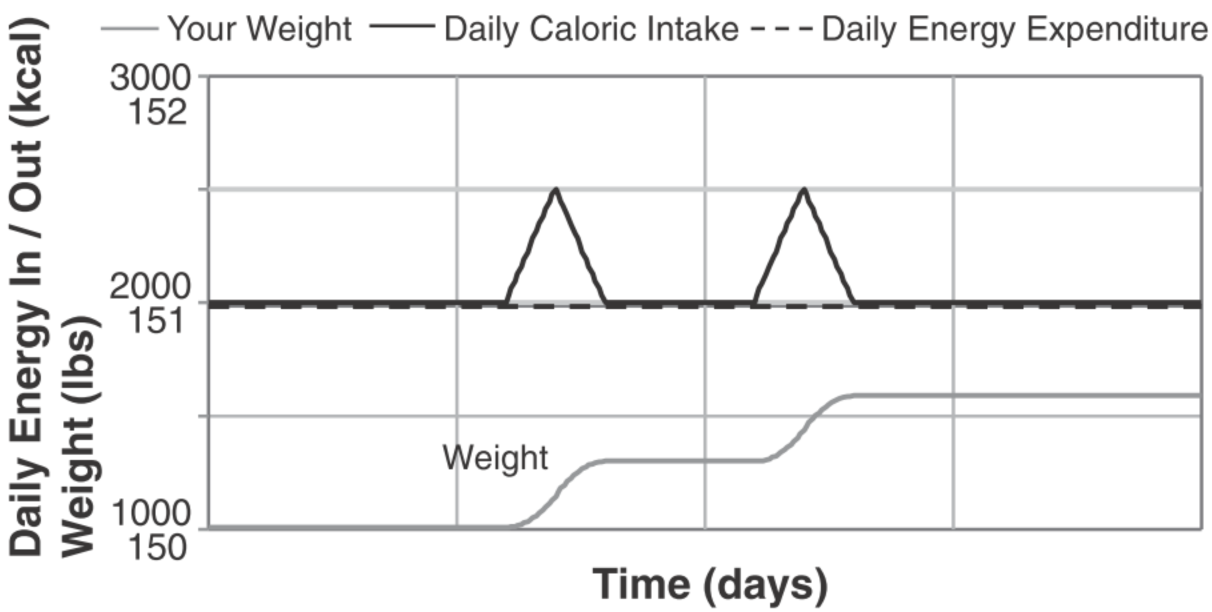
• reasonably accurate
• some approaches work well for free living

• mostly rely of self-report
• not very accurate
• high burden

There is room for improvement both in measuring EE and EI!

Energy balance

- Most people do not understand the nature of body's energy balance



T. Abdel-Hamid, F. Ankel, M. Battle-Fisher, B. Gibson, G. Gonzalez-Parra, M. Jalali, K. Kaipainen, N. Kalupahana, O. Karanfil, A. Marathe, B. Martinson, K. McKelvey, S. N. Sarbadhikari, S. Pintauro, P. Poucheret, N. Pronk, Y. Qian, E. Sazonov, K. V. Oorschot, A. Venkitasubramanian, and P. Murphy, "Public and health professionals' misconceptions about the dynamics of body weight gain/loss," Syst. Dyn. Rev., vol. 30, no. 1–2, pp. 58–74, Jan. 2014.

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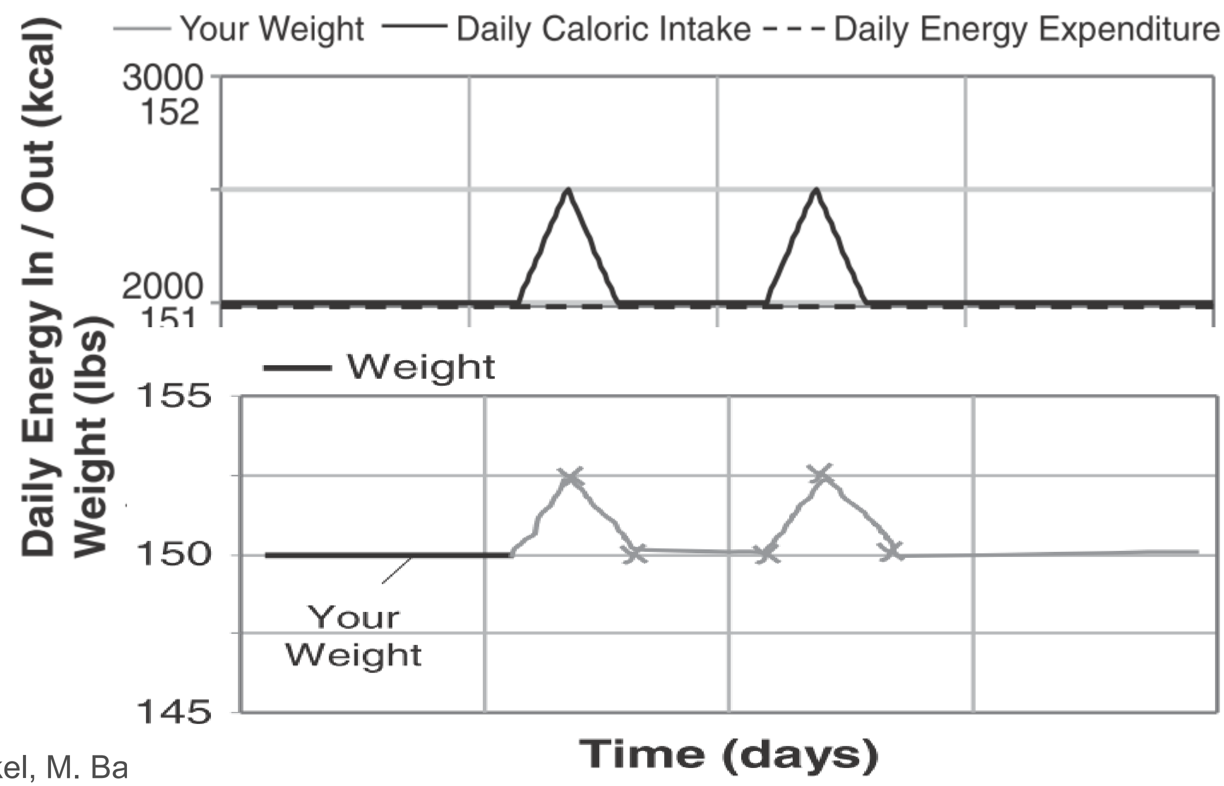

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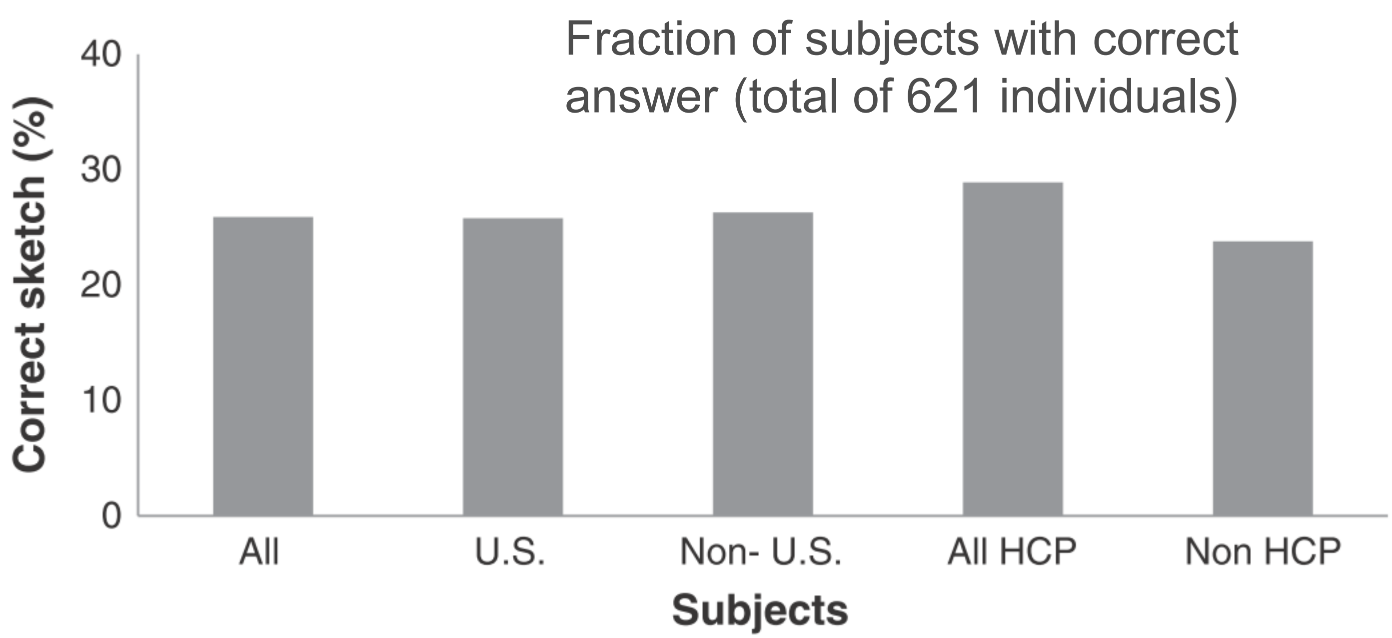

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Why sensors?

1. The commonly used self-report is notoriously inaccurate.

   Energy intake of respondents in US National Health and Nutrition Examination Survey from 1971-2012 was not physiologically plausible for 67.3% of women and 58.7% of men - **i.e. the number of calories is "incompatible with life."** [1]

2. Self-report is subject to reporting and observation biases, long-term compliance issues

3. The sensors enable real-time feedback capabilities

1. E. Archer, G. A. Hand, and S. N. Blair, "Validity of U.S. Nutritional Surveillance: National Health and Nutrition Examination Survey Caloric Energy Intake Data, 1971–2010," *PLoS ONE*, vol. 8, no. 10, p. e76632, Oct. 2013.

Why sensors?

1. The commonly used self ... accurate.
   Energy int ... Nutrition
   ... umber

2. S ... to reporting and ob ... on biases,
   lo ... compliance issu ...

3.

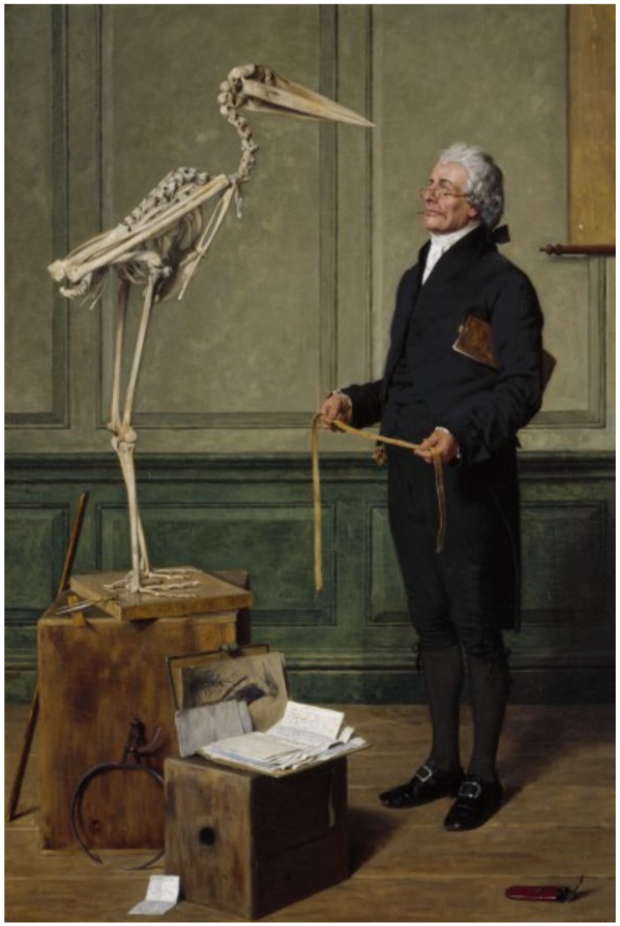
Sensors have the potential to enable objective and accurate measurement of EI

Feedback from the sensors may guide behavioral change

1. E. Archer, G. A. Hand, and S. N. Blair, "Validity of U.S. Nutritional Surveillance: National Health and Nutrition Examination Survey Caloric Energy Intake Data, 1971–2010," *PLoS ONE*, vol. 8, no. 10, p. e76632, Oct. 2013.

Why sensors?

Henry Stacy Marks, R.A. 1829 - 1898



http://www.racollection.org.uk

Science is Measurement, 1879

Oil on canvas, 915 X 610 X 22 mm

Diploma Work given by Henry Stacy Marks, R.A., accepted 1879

((Science → Measurement)

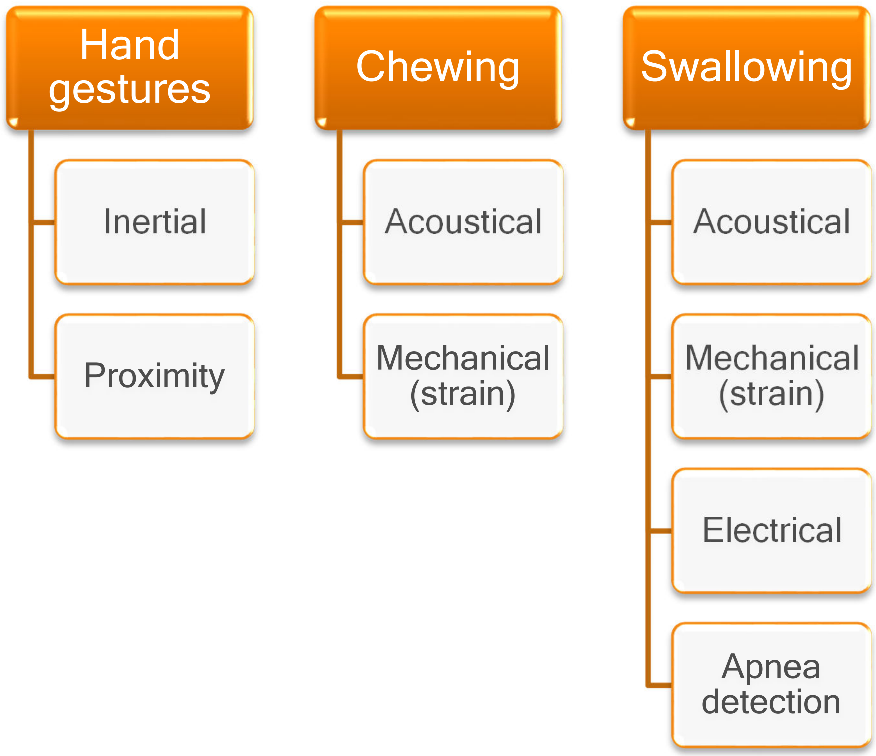
&

(Measurement → Sensor)) →

(Science → Sensor)

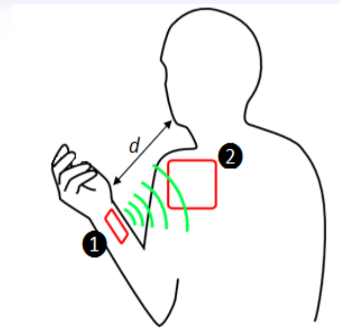
Detection and characterization of food intake

- Goals:
  - Detection of food intake
  - Characterization of ingestive behavior (number of episodes, ingestion rate, number of food items, mass, etc.)
  - Estimation of portion size and energy intake
- Indirect indicators of food intake are commonly used
- Challenges include accuracy, comfort and compliance

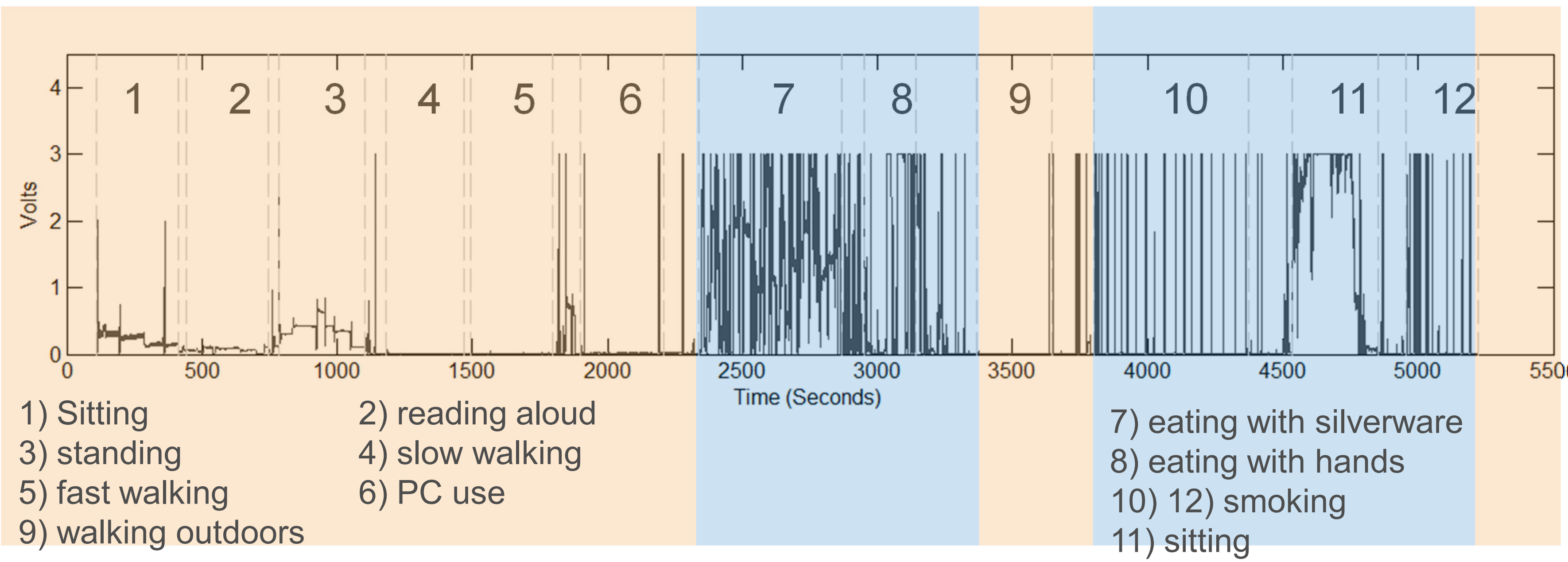


Hand gesture sensors

- Hand-to-mouth gestures are prevalent during food intake
- A **proximity sensor** can be used to track hand-to-mouth gestures



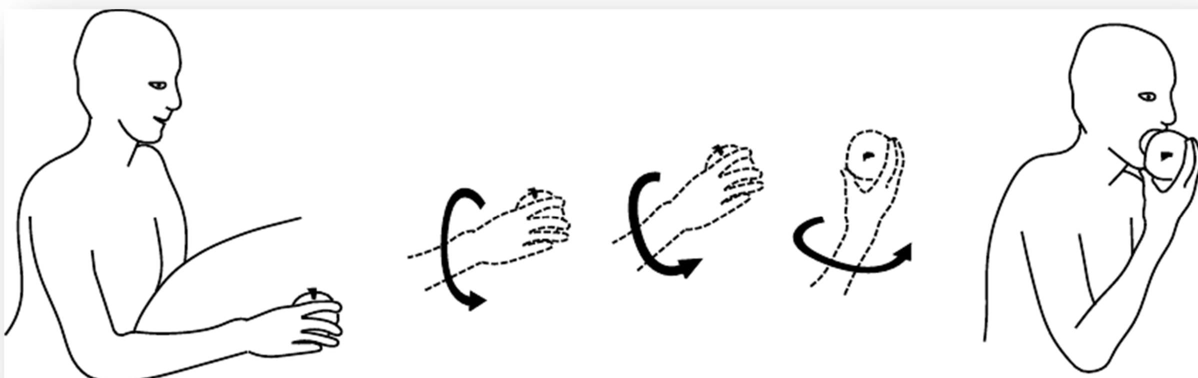
RF proximity sensor



P. Lopez-Meyer, Y. Patil, T. Tiffany, and E. Sazonov, "Detection of Hand-to-Mouth Gestures Using a RF Operated Proximity Sensor for Monitoring Cigarette Smoking," Open Biomed. Eng. J., vol. 9, pp. 41–49, Apr. 2013.

Hand gesture sensors

- Inertial sensors can be used to detect hand-to-mouth gestures
- The limitation is that the sensor has to be turned on/off manually



http://www.ces.clemson.edu/~ahoover/bite-counter/

Y. Dong, A. Hoover, J. Scisco, and E. Muth, “A New Method for Measuring Meal Intake in Humans via Automated Wrist Motion Tracking,” Appl. Psychophysiol. Biofeedback, vol. 37, no. 3, pp. 205–215, Sep. 2012.

Hand gesture sensors

- Number of “bites” is correlated with mass of ingestion and energy intake

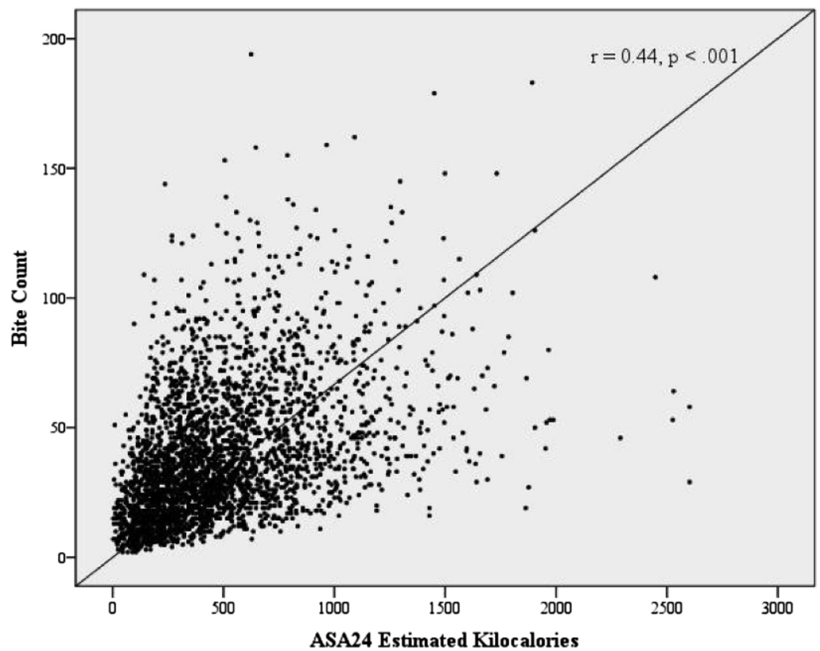
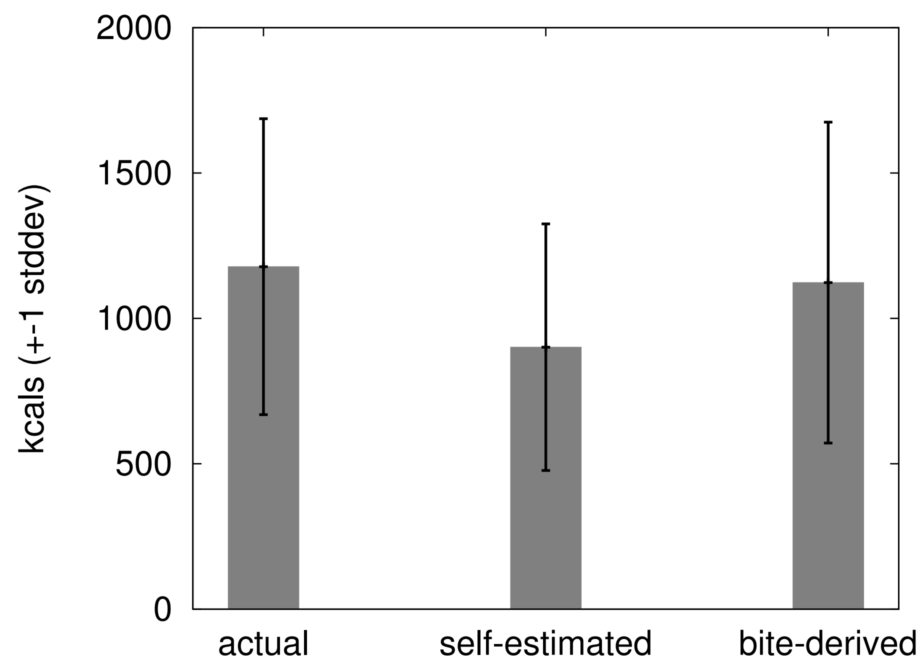


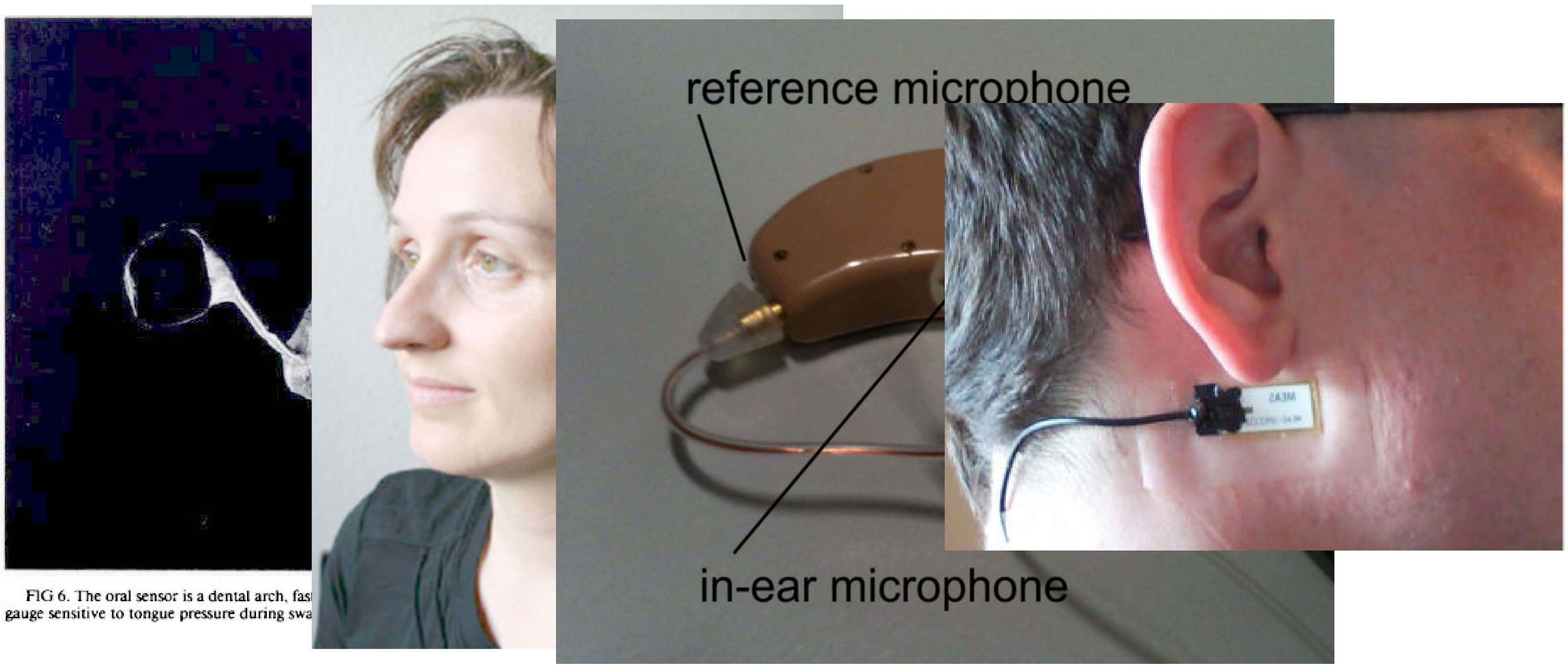
Figure 2. Scatterplot of the relationship between bite count and automated self-administered 24-hour dietary recall (ASA24) estimated kilocalories across all 2,975 eating activities (r=0.44; P<0.001).



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

Chewing sensors

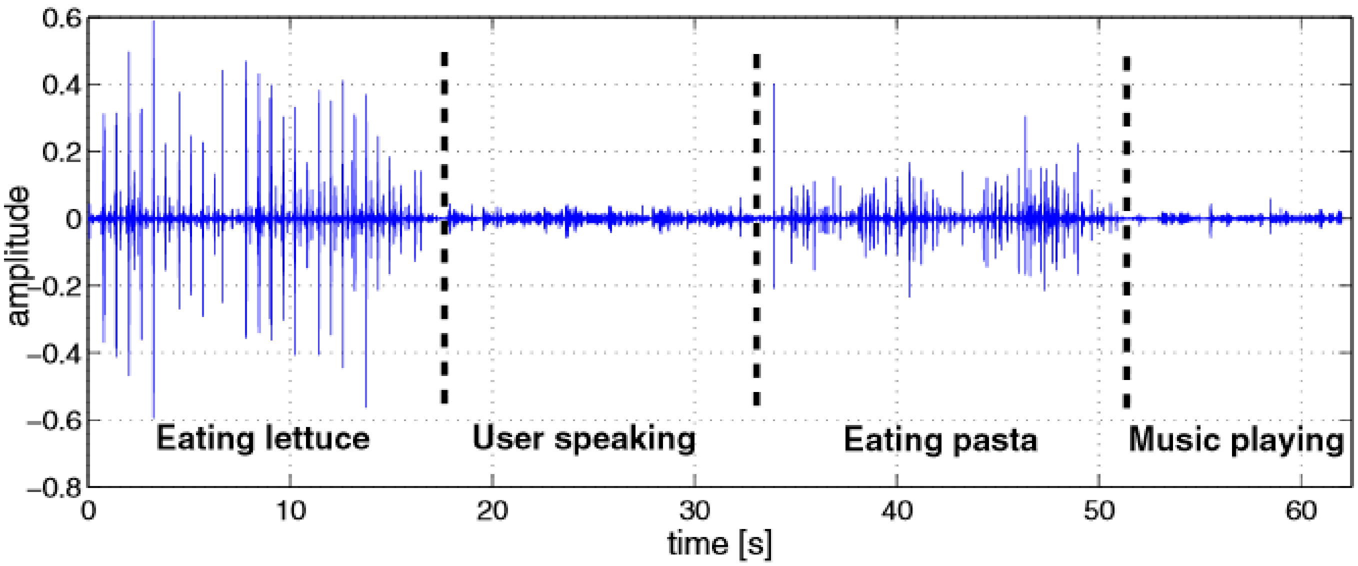
- Chewing is associated with intake of most solid foods and can be used as indicator of food intake



E. Stellar and E. E. Shrager, "Chews and swallows and the microstructure of eating," Am. J. Clin. Nutr., vol. 42, no. 5 Suppl, pp. 973–982, Nov. 1985.
O. Amft, "A wearable earpad sensor for chewing monitoring," in 2010 IEEE Sensors, 2010, pp. 222–227.
S. Päßler, M. Wolff, and W.-J. Fischer, "Food intake monitoring: an acoustical approach to automated food intake activity detection and classification of consumed food," Physiol. Meas., vol. 33, no. 6, pp. 1073–1093, 2012.
E. Sazonov and J. M. Fontana, "A Sensor System for Automatic Detection of Food Intake Through Non-Invasive Monitoring of Chewing," *IEEE Sens. J.*, vol. 12, no. 5, pp. 1340 –1348, 2012.

Chewing sensors

- The sound of mastication (food crushing) has relation to physical properties of the food, but little relevance to energy content



O. Amft, M. Stäger, and G. Tröster, "Analysis of chewing sounds for dietary monitoring," *UbiComp 2005*, pp. 56–72, 2005.
S. Päßler, M. Wolff, and W.-J. Fischer, "Food intake monitoring: an acoustical approach to automated food intake activity detection and classification of consumed food," Physiol. Meas., vol. 33, no. 6, pp. 1073–1093, 2012.

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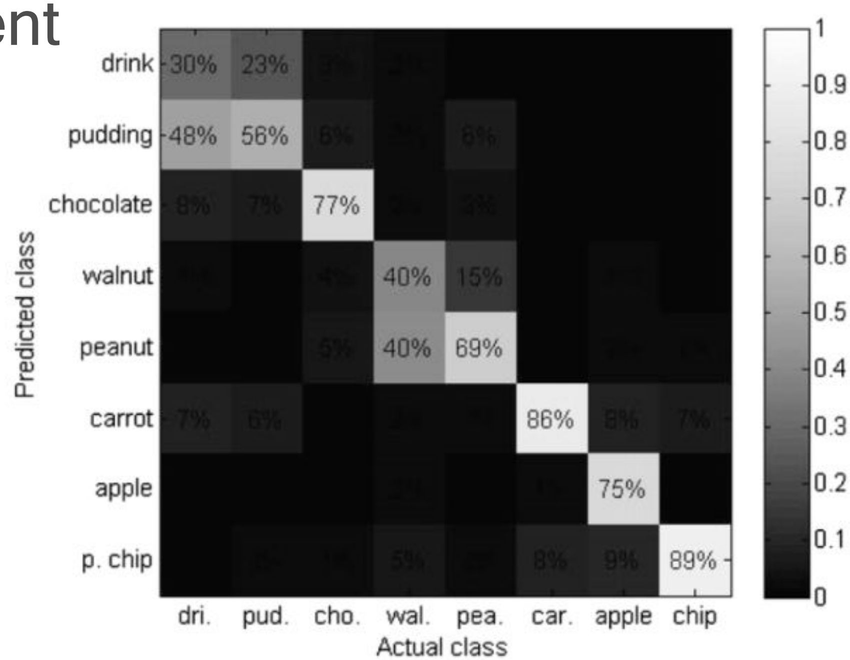


(b)

Figure 5. (a) Accuracies for evaluation with records of familiar participants. An overall accuracy of 79% was achieved. (b) Overall accuracies for evaluation with records of new participants. An overall accuracy of 66% was achieved.

O. Amft, M. Stäger, and G. Tröster, "Analysis of chewing sounds for dietary monitoring," *UbiComp 2005*, pp. 56–72, 2005.
S. Päßler, M. Wolff, and W.-J. Fischer, "Food intake monitoring: an acoustical approach to automated food intake activity detection and classification of consumed food," Physiol. Meas., vol. 33, no. 6, pp. 1073–1093, 2012.

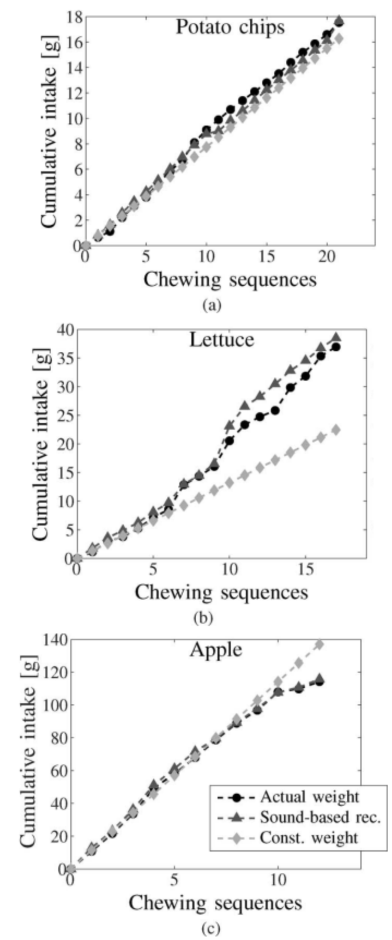
Chewing sensors

- The chewing sound could potentially be used to estimate the ingested mass

PERFORMANCE OF DIFFERENT BITE WEIGHT PREDICTION APPROACHES

Metric Mean (SD)	Foods Potato chips	 Lettuce	 Apple
Bite weight W [g]	0.8 (0.2)	2.3 (0.8)	7.8 (1.5)
Chews/Seq. (M_i)	26.9 (4.4)	20.0 (3.3)	14.9 (2.9)
	Sound-based recognition		
Absolute error [g]	0.2 (0.1)	0.6 (0.2)	1.4 (0.4)
Relative error [%]	**27.7 (9.5)**	**31.0 (5.5)**	**19.4 (4.3)**
	EMG detection		
Absolute error [g]	0.2 (0.1)	0.6 (0.2)	1.9 (1.1)
Relative error [%]	**26.5 (9.0)**	**28.9 (4.0)**	**27.8 (14.6)**
	Sound-based rec. (inter-individual)		
Absolute error [g]	0.2 (0.2)	0.8 (0.6)	2.3 (1.8)
Relative error [%]	**31.7 (30.6)**	**40.2 (38.2)**	**37.2 (37.1)**
	Constant weight[a]		
Absolute error [g]	0.3 (0.1)	0.9 (0.3)	3.3 (1.8)
Relative error [%]	**41.1 (25.8)**	**50.5 (29.8)**	**62.2 (33.8)**

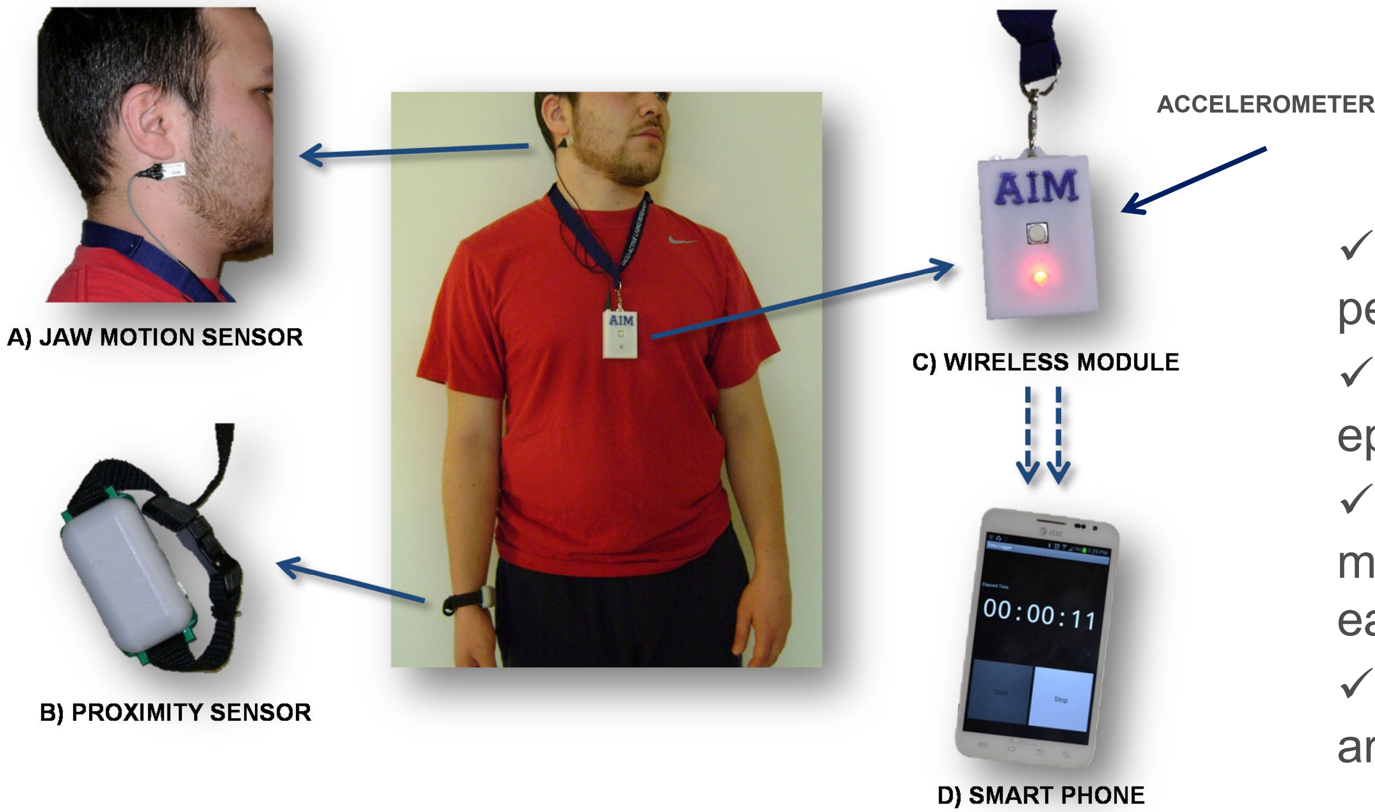
[a]Average weight of 2nd and 3rd chewing sequence.



O. Amft, M. Kusserow, and G. Troster, "Bite Weight Prediction From Acoustic Recognition of Chewing," *Biomed. Eng. IEEE Trans. On*, vol. 56, no. 6, pp. 1663–1672, 2009.

Chewing sensors

Multi-sensor data fusion: Automatic Ingestion Monitor



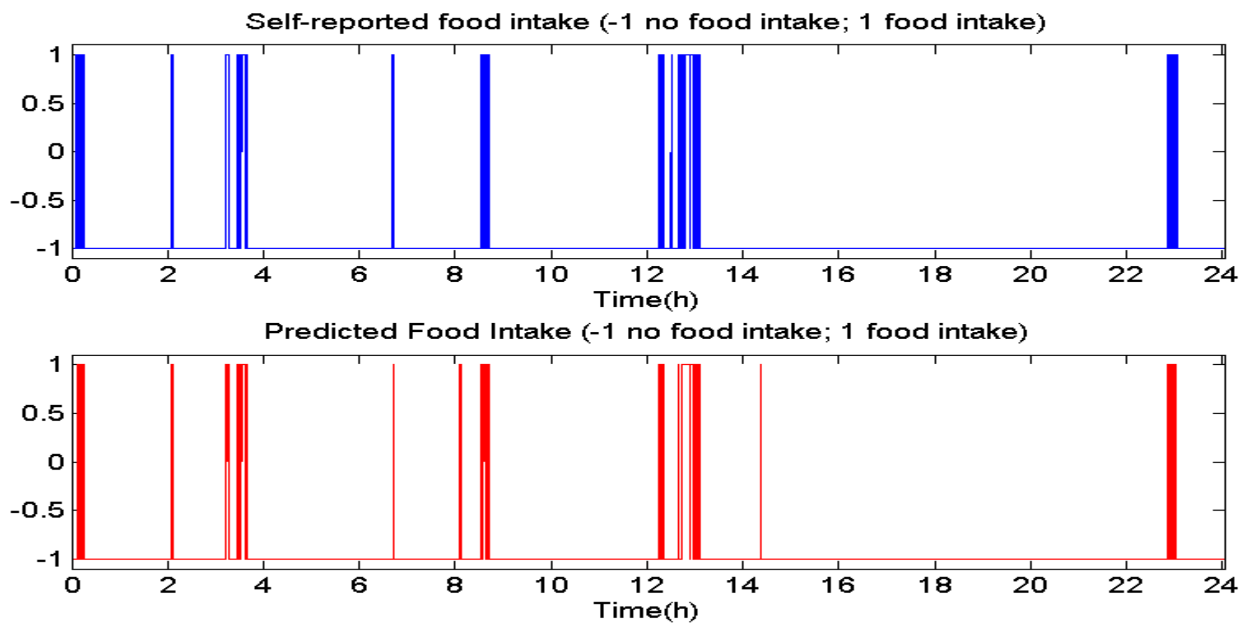
- ✓detect when people eat
- ✓how many episodes
- ✓how long, how much is ingested in each episode
- ✓how many foods are consumed

J. M. Fontana, M. Farooq, and E. Sazonov, "Automatic Ingestion Monitor: A Novel Wearable Device for Monitoring of Ingestive Behavior," IEEE Trans. Biomed. Eng., vol. Early Access Online, 2014.

Chewing sensors

<u>24-hrs monitoring of ingestive behavior by AIM</u>

- 12 subjects (6 male, 6 female)
- average age was 26.7 y (SD ± 3.7)
- average BMI 24.39 kg/m2 (SD ± 3.81)
- origins in 5 countries

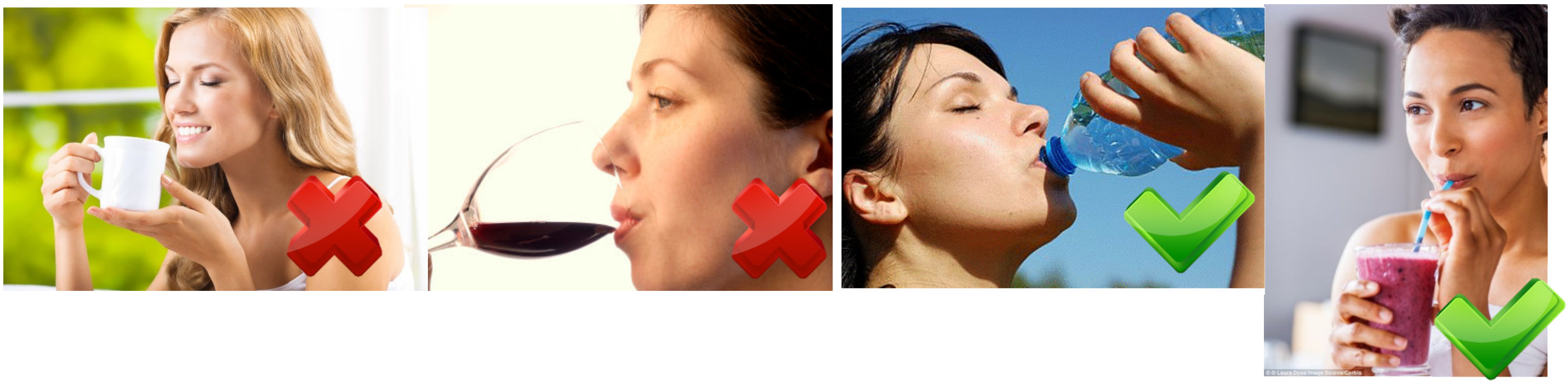


Food intake prediction results for an average performance (89% in terms labeling every 30s interval as a <u>binary prediction of "food intake" or "no food intake")</u>

J. M. Fontana, M. Farooq, and E. Sazonov, "Automatic Ingestion Monitor: A Novel Wearable Device for Monitoring of Ingestive Behavior," IEEE Trans. Biomed. Eng., vol. 61, no. 6, pp. 1772–1779, Jun. 2014.

Chewing sensors

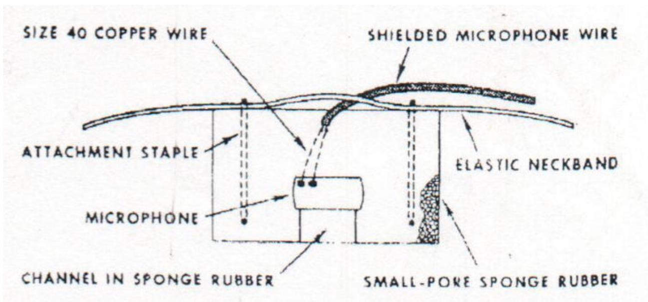
- Detection of jaw motion cannot pick up most liquids



- Jaw motion and chewing sound detection may fail at detection of certain foods!

Swallowing monitors

- One of the most reliable ways to detect ingestion



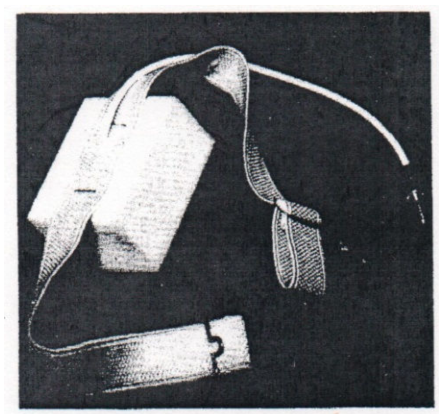


TABLE 4. HOURLY SWALLOWING RATES IN TWENTY SUBJECTS STUDIED OVER A 24-hr PERIOD

	Mean Rates	Standard Deviation
Eating and drinking	180·0	55·0
Sleeping	5·3	1·7
Other activity	23·5	11·4
Over-all rate	24·4	8·7

TABLE 5. SWALLOWING INCIDENCE AND RATES DURING VARIOUS PERIODS OF EATING AND DRINKING IN TWENTY SUBJECTS STUDIED OVER A 24-hr PERIOD

Activity	Swallows	Time (min)	Hourly rate
Breakfast	37·6	10·9	207·0
Lunch	37·3	14·2	157·6
Dinner	64·2	22·6	170·4
Between-meal snacks	65·2	22·5	173·9

C. S. Lear and C. F. Moorrees, “Swallowing frequency; a detection system employing FM telemetry,” *J. Dent. Res.*, vol. 45, no. 4, p. 1222, **Aug. 1966.**
C. S. C. Lear, J. B. Flanagan Jr., and C. F. A. Moorrees, “The frequency of deglutition in man,” *Arch. Oral Biol.*, vol. 10, no. 1, pp. 83–99, IN13–IN15, **January-February 1965**.

Swallowing monitors

- A variety of approaches exists to detect swallowing

Acoustical

Magnetic

Electrical

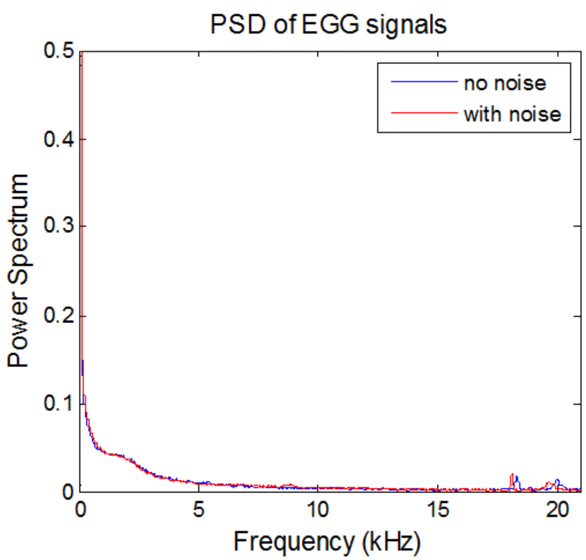
Piezoelectric

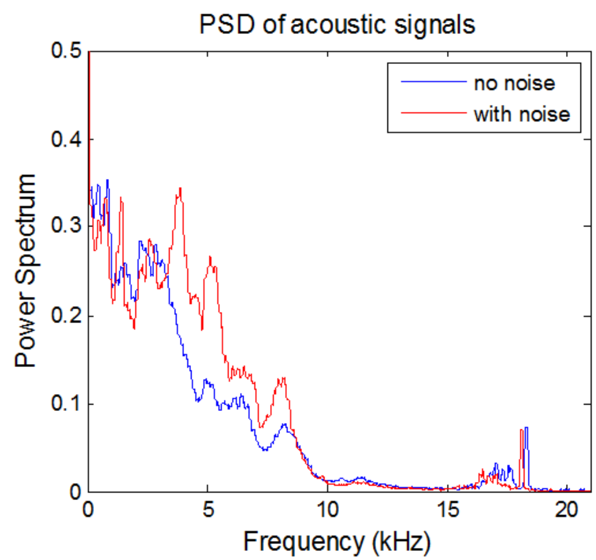
O. Makeyev, P. Lopez-Meyer, S. Schuckers, W. Besio, and E. Sazonov, “Automatic food intake detection based on swallowing sounds,” Biomed. Signal Process. Control, vol. 7, no. 6, pp. 649–656, Nov. 2012.
A. Kandori, T. Yamamoto, Y. Sano, M. Oonuma, T. Miyashita, M. Murata, and S. Sakoda, “Simple Magnetic Swallowing Detection System,” IEEE Sens. J., vol. 12, no. 4, pp. 805–811, Apr. 2012.
M. Farooq, J. M. Fontana, and E. Sazonov, “A novel approach for food intake detection using electroglottography,” Physiol. Meas., vol. 35, no. 5, p. 739, May 2014.
H. Kalantarian, N. Alshurafa, T. Le, and M. Sarrafzadeh, “Monitoring eating habits using a piezoelectric sensor-based necklace,” Comput. Biol. Med., vol. 58, pp. 46–55, Mar. 2015.

Swallowing monitors

- Acoustical vs. Impedance-based detection

The sensors





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Swallowing monitors

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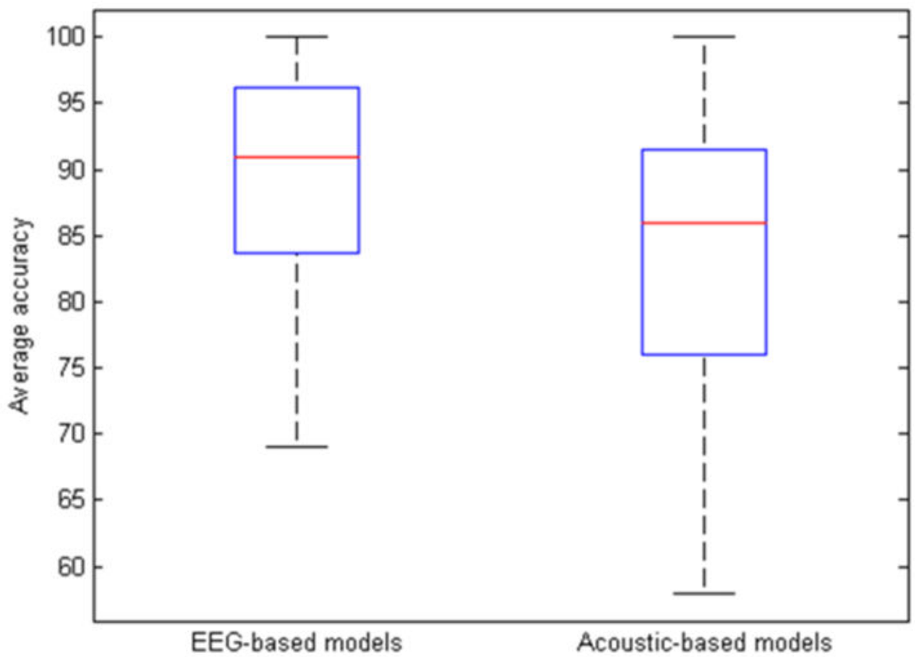


Distribution of the food intake detection accuracies obtained from both EEG-based and acoustic-based models.

M. Farooq, J. M. Fontana, and E. Sazonov, "A novel approach for food intake detection using electroglottography," Physiol. Meas., vol. 35, no. 5, p. 739, May 2014.

Swallowing monitors

- Common problem: people do not like “collars”
- Monitoring of breathing may detect swallowing apnea

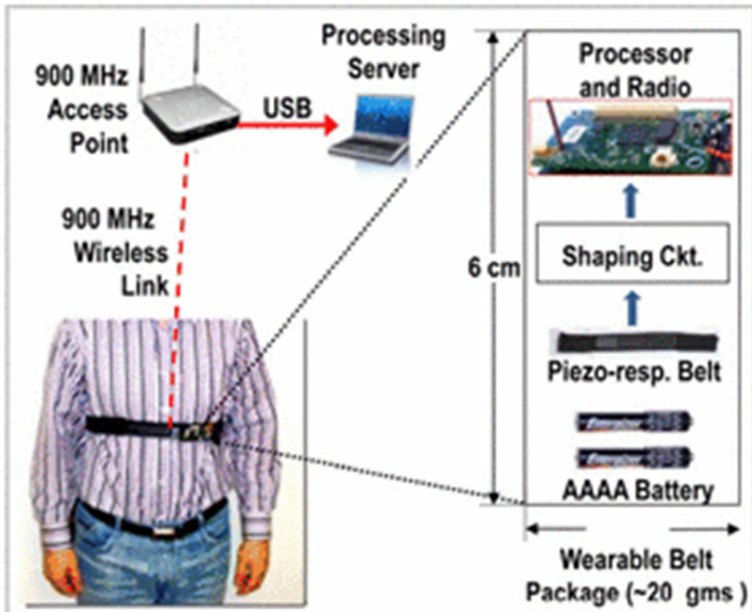


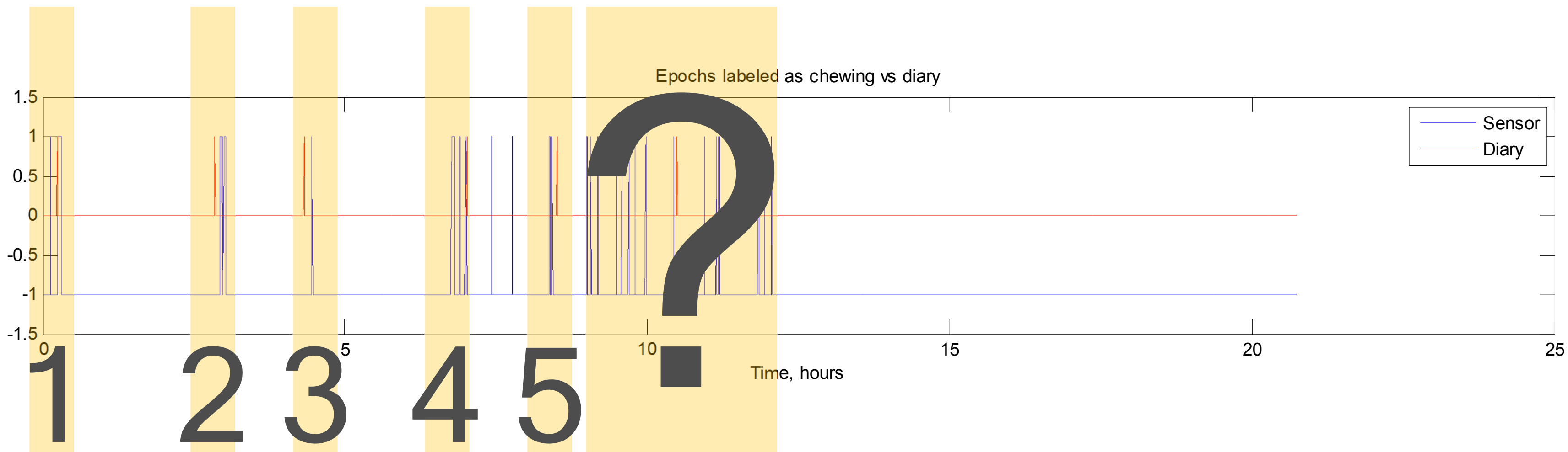
Fig. 1. Wearable wireless food intake monitoring system with a piezo-respiratory chest belt, signal shaping hardware, wireless transceiver, processor, 900MHz wireless link, and a wireless access point connected to a PC for out-of-body processing.

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

Characterization of ingestive behavior

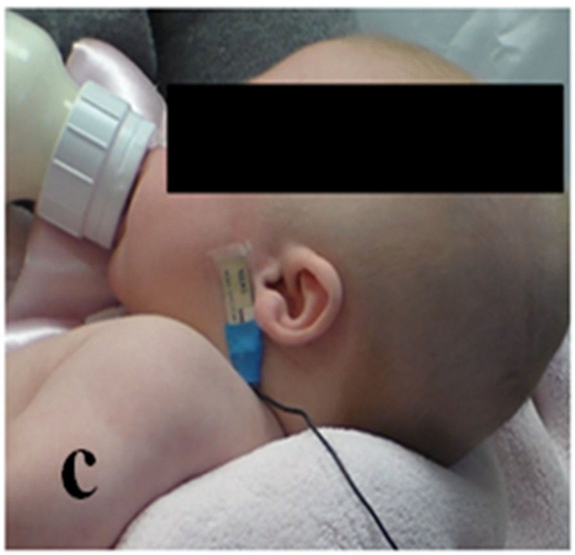
	9:58 AM	attached device	
1	10:12 AM	banana, muffin	
2	12:49 PM	salad, lasagna	
3	2:18 PM	3 cookies	
4	5:00 PM	small chocolate bar	
5	6:30 PM	dinner: 1 hour, grazing, cuban beef stew, plantains, rice, beans, avocaqdo, lo mein	
6	8:30 PM	popcorn	

Grazing!



Characterization of ingestive behavior

- Measuring the rate of ingestion

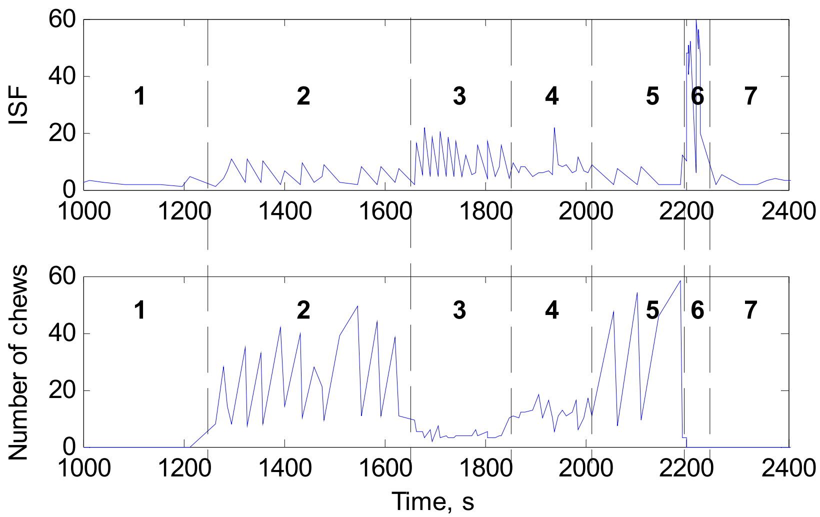


Infant (*k*)	Feeding mode	Human counted sucks	Algorithm estimated sucks	Per-segment Mean Count Error	Per-meal Mean Count Error
1	Breast-fed	573	494	4.53%	13.79%
2	Bottle-fed	416	411	-4.52%	1.20%
3	Bottle-fed	662	699	-15.49%	-5.67%
4	Bottle-fed	1023	886	6.13%	13.39%
5	Bottle-fed	596	624	-4.88%	-4.79%
6	Breast-fed	641	614	-7.10%	1.25%
			Mean:	**-3.55%**	**3.20%**
			STD:	**7.96%**	**8.56%**
		Absolute Mean:		**7.11%**	**6.68%**
		Absolute STD:		**4.23%**	**5.65%**

M. Farooq, P. Chandler-Laney, M. Hernandez-Reif, and E. Sazonov, “Monitoring of Infant Feeding Behavior Using a Jaw Motion Sensor,” J. Healthc. Eng., vol. 6, no. 1, pp. 23–40, Feb. 2015.
M. Farooq, P. Chandler-Laney, M. Hernandez-Reif, and E. Sazonov, “A Wireless Sensor System for Quantification of Infant Feeding Behavior,” to appear 2015.

Characterization of ingestive behavior

- Estimating the number of foods in a meal



Swallowing Frequency and Number of Chews per swallow during a visit.

1 – no food intake 2 – pizza
3 – yogurt 4– apple
5 – PB sandwich 6 – water

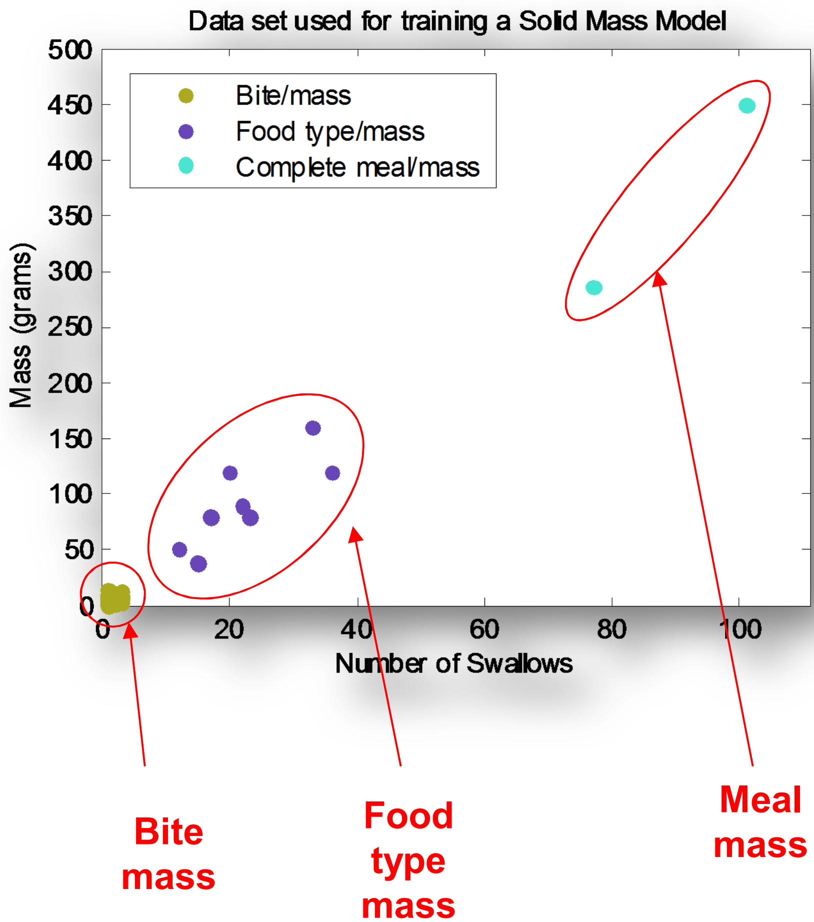
Accuracy of the models implemented on finding the correct number of 5 food items for different combinations of features.

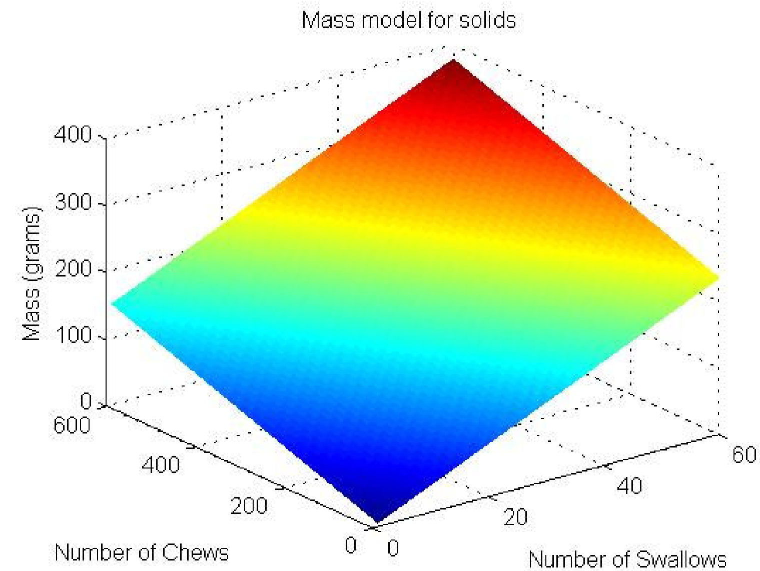
	$x_i \in \Re^3$	$x_i \in \Re^7$
Affinity propagation	88.8% (SD 14.1)	90.3% (SD 12.7)
Agglomerative Hierarchical Clustering	92.9% (SD 9.6)	95.3% (SD 8.5)

P. Lopez-Meyer, S. Schuckers, O. Makeyev, J. M. Fontana, and E. Sazonov, “Automatic identification of the number of food items in a meal using clustering techniques based on the monitoring of swallowing and chewing,” Biomed. Signal Process. Control, vol. 7, no. 5, pp. 474–480, Sep. 2012.

Characterization of ingestive behavior

- Measuring the mass of ingested foods





Mass prediction accuracy on one meal experiment

Solids: 92.0±3.8%
Liquids: 82.7±7%

Toward objective monitoring of ingestive behavior in free living population, E.Sazonov et. al, Obesity (2009) 17 10, 1971–1975.

Characterization of ingestive behavior

- Estimating the caloric content
- N=28, self-selected meals

Energy estimation methods	ENERGY			
	Training meals		Validation meal	
	Mean	SD	Mean	SD
CCS Models				
Chews only	19.42	10.14	30.42	23.08
Swallows only	18.76[a]	10.35	34.27	31.86
Chews and Swallows	15.83[a]	9.41	32.23	24.84
Diet diary	27.86	29.67	25.69	21.90
Photographic food records	19.95	11.45	21.11	15.55

Reporting errors (in %) for energy intake estimation for training and validation meals relative to energy intake assessed from the weighed records

J. M. Fontana, J. A. Higgins, S. C. Schuckers, F. Bellisle, Z. Pan, E. L. Melanson, M. R. Neuman, and E. Sazonov, "Energy intake estimation from counts of chews and swallows," Appetite, vol. 85, pp. 14–21, Feb. 2015..

Characterization of ingestive behavior

- Estimating the caloric density from imagery

Left: a subject wearing the food-intake sensor during lunch. Right: the profile of the sensor.

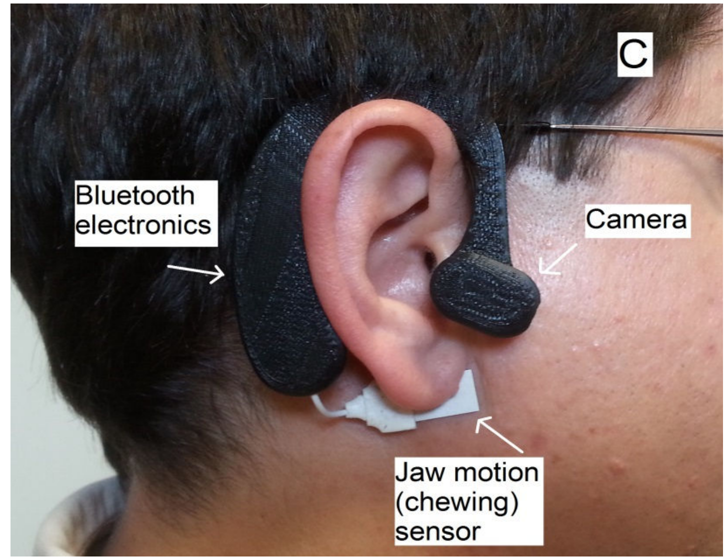
Snapshot	Time	Consumption (%)
	18.33	0
	18.35	20
	18.37	40
	18.39	60
	18.41	80
	18.45	100

An example of food intake log

J. Liu, E. Johns, L. Atallah, C. Pettitt, B. Lo, G. Frost, and G.-Z. Yang, "An Intelligent Food-Intake Monitoring System Using Wearable Sensors," in 2012 Ninth International Conference on Wearable and Implantable Body Sensor Networks (BSN), 2012, pp. 154–160..

Characterization of ingestive behavior

- Conclusions
  - No perfect solution exists at this time, but there is progress
  - The studies tend to report from limited, highly controlled lab conditions. Statistically significant experimentation in community is needed
- Future directions
  - Improving accuracy and comfort of sensors
  - Deriving better caloric estimates from fusion of imagery and sensor information
  - Developing efficient feedback mechanisms for behavior change



Concept of the next generation of Automatic Ingestion Monitor (2016)

Toward objective monitoring of ingestive behavior in free living population, E.Sazonov et. al, Obesity (2009) 17 10, 1971–1975.

Thank you!