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Title: **Toward objective monitoring of ingestive behavior in free living population**

Running head: **Objective monitoring of ingestive behavior**

Edward Sazonov[1], Stephanie Schuckers[1], Paulo Lopez-Meyer[1], Oleksandr Makeyev[1], Edward L. Melanson[2,4], Michael Neuman[3] and James Hill[4]

[1] Clarkson University, Department of Electrical and Computer Engineering, Potsdam, NY, USA

[2] University of Colorado Denver, Division of Endocrinology, Metabolism, and Diabetes, Aurora, CO, USA.

[3] Michigan Technological University, Department of Biomedical Engineering, Houghton, MI, USA.

[4] University of Colorado Denver, Center for Human Nutrition, Denver, CO, USA.

Correspondence: Edward Sazonov, Department of Electrical and Computer Engineering, Clarkson University, Potsdam, NY, 13699, USA. Phone: +1 315 268-3914 Fax: +1 315 268-7600 E-mail: esazonov@ieee.org

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Abstract

Understanding of eating behaviors associated with obesity requires objective and accurate monitoring of food intake patterns. Accurate methods are available for measuring total energy expenditure and its components in free living populations, but methods for measuring food intake in free-living people are far less accurate and involve self-reporting or subjective monitoring. We suggest that chews and swallows can be used for objective monitoring of ingestive behavior. This hypothesis was verified in a human study involving 20 subjects. Chews and swallows were captured during periods of quiet resting, talking and meals of varying size. The counts of chews and swallows along with other derived metrics were used to build prediction models for detection of food intake, differentiation between liquids and solids, and for estimation of the mass of ingested food. The proposed prediction models were able to detect periods of food intake with greater than 95% accuracy and a fine time resolution of 30s; differentiate solid foods from liquids with greater than 91% accuracy; predict mass of ingested food with greater than 91% accuracy for solids and 83% accuracy for liquids. In earlier publications we have shown that chews and swallows can be captured by non-invasive sensors that could be developed into a wearable device. Thus the proposed methodology could lead to the development of an innovative new way of assessing human eating behavior in free living conditions.

Keywords: obesity, ingestive behavior, energy intake, chewing (mastication), swallowing (deglutition), wearable sensors, free living individuals

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1. Introduction

Rates of overweight and obesity are increasing globally. The World Health Organization estimated that there were approximately 1.6 billion overweight and at least 400 million obese adults worldwide in 2005 and that there will be 2.3 billion overweight and 700 million obese adults worldwide by 2015 (*1*). Overweight and obese individuals have an increased risk of developing chronic diseases such as type 2 diabetes, cardiovascular disease and cancer (*2*-*4*).

Overweight and obesity result from an imbalance between energy intake and energy expenditure, but the etiology of that imbalance and the underlying mechanisms are still incompletely understood. Our physiology, our behavior and our environment must all be considered in understanding the etiology of obesity. There is a debate about the relative importance of genetic/physiological factors and environmental factors in the etiology of obesity. Clearly there are genetic/physiological contributions to obesity (*6*-*9*) but some weight gain can be attributed to an environment that provides an abundance of inexpensive, highly palatable and energy dense foods, while requiring only minimal levels of physical activity (*10*-*13*). Part of our lack of understanding of the etiology of obesity is the fact that most weight gain likely occurs due to very small differences between energy intake and energy expenditure, necessitating very accurate measurements of energy intake and energy expenditure.

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A variety of methods are available for accurate and objective measurement of energy expenditure and its components, including doubly labeled water (DLW), indirect calorimetry, and accelerometry (*15-17*). These techniques can be used in the laboratory and in free-living populations. Energy and food intake can be accurately monitored in the laboratory by directly measuring consumed food. It is currently not possible to accurately monitor food intake in free-living populations. Several methods have been proposed to measure free-living food intake including observation, weighed food records, estimated records, diet history, food-frequency questionnaires, food recall methods, etc (*18*). In a review of 43 studies comparing these methods to indirect measurement using DLW, the majority suffered from underestimation of energy intake on the order of 0.83 (ratio of intake estimate to energy expenditure) (*19*).

There is an urgent need for innovative strategies for the accurate assessment of free-living energy intake and Monitoring of Ingestive Behavior (MIB) in humans. The goal of this study is to explore whether accurate and objective information about ingestive behavior, such as detecting short episodes of food intake, differentiating between liquid and solid foods, and estimating the mass of food intake could be obtained by measuring chews and swallows. Since chewing and swallowing events can potentially be captured by non-invasive wearable sensors, this could lead to the first accurate method of assessing free-living food intake. This method may lead to a more objective direct measurement of total energy intake when combined with other methods (e.g. electronic food diaries, food photography, etc.).

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2. Methods and Results

The models reported in this paper were built using data from a human study described previously (20). Twenty volunteers (11 males and 9 females) with an average body mass index (BMI) of 29.0 $\pm$ 6.4 participated in four visits, each of which consisted of: (1) a 20 minute resting period; (2) a meal period of unlimited time; (3) a second 20 minute resting period. Two fixed sizes of the meal (standard and large) were used with the large size being 50% bigger than the standard. The food selection during experiments represented a wide range of food properties such as crispiness, moistness, softness/hardness and tackiness that could impact chewing and swallowing. The provided drink was bottled water. To evaluate the impact of a meal-time conversation on patterns of chews and swallows, the subjects were involved in a dialogue with a member of the research team during the second and fourth visits and ate in silence during the first and third visits. Overall, the human study resulted in 66 hours of monitored activity, and captured a total of 10,099 swallows and 46,238 chews. We certify that all applicable institutional and governmental regulations concerning the ethical use of human volunteers were followed during this research. The Institutional Review Board at Clarkson University approved the study, and all subjects signed informed consent forms.

The time series of chews and swallows were used to build prediction models centered on the following hypotheses:

(1) The frequencies of swallowing above a threshold T^{INGEST} or presence of chewing correspond to food ingestion;

(2) The frequencies of swallowing above a threshold $T^{LIQUID} > T^{INGEST}$ and absence of chewing correspond to liquid ingestion;

(3) The number of chews and swallows is proportional to the ingested mass.

2.1 Time scale selection

The predictive models assigned a class label to a time window of certain length (a decision epoch). Every epoch in a subject's visit was assigned a label from the set {'no intake','intake'} indicating the state of food intake. Epochs labeled as 'intake' were further labeled from the set {'solid','liquid'} thus differentiating between food types. The choice of epoch duration was an important factor defining the time resolution. Naturally, a shorter epoch should provide better time resolution and, in theory, detect shorter events. Such capability would be very important for monitoring of snacking habits. At the same time, the shortest epoch duration is limited by the minimal detectable changes in the predictor variables.

To estimate the duration of a decision epoch we define the Instantaneous Swallowing Frequency: $ISF_i = 60/(t_i - t_{i-1})$ (sw/min), where t is time of swallow occurrence in seconds, $i = 2,...,N$ and N is the total number of swallows. In other words, this measure provides instantaneous information on the number of swallows per minute. A graph of *ISF* for a subject's visit (Fig.1, A) provides an intuitive illustration of *ISF's* predictive abilities. The duration of a decision epoch should be long enough to detect an increase in the number of swallows associated with food consumption and short enough to provide adequate time resolution for detection of food intake. An average of *ISF* over duration of an Epoch is defined as $EISF_J$. To use $EISF_J$ as a predictor variable the duration of a decision epoch will need to be greater than lower bound on *ISF* for ingestion (established experimentally as the 1st percentile of *ISF* during food intake ISF_{FOOD}^{LB}), which equals ~2 sw/min. Experimental data (Fig.1, B) also show that for periods with no ingestion the median $ISF \approx 2$ sw/min, thus leading to a conclusion that decision epoch length of 30s is the most appropriate one, providing the best trade-off between recognition accuracy and time resolution.

2.2 Group model for detection of food intake

Food ingestion can be identified by swallowing alone or by a combination of chewing and swallowing. Chewing by itself cannot identify intake of liquids and thus is not considered. Recognition of food intake with swallowing frequency as a predictor can be performed on a model (Supplementary Table 1, Model 1) that uses Bayes optimal threshold (*21*) T^{INGEST} which defines an optimal decision boundary between the classes of 'intake' and 'no intake'. Food intake is detected if the swallowing frequency is greater or equal than the threshold. This prediction model is based on population-based probability density estimates (*22*) and therefore is termed a group model. The decision threshold $T^{INGEST} = 4$ sw/min was established at the intersection of probability density estimates for 'no intake' and 'solid food' (Fig.1, C). Accuracy of prediction was calculated based on the standard statistical definitions of sensitivity and specificity (*23*).

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For food intake detection, the group model was capable to achieve an average accuracy of 82% (Table 1).

2.3 Floating average models for detection of food intake

Accuracy of detection of food ingestion was further improved by taking into account inter-individual variability in swallowing rates. The ratio of *EISF* during resting to *EISF* during solid food intake (Fig.1, D) has a well defined upper bound of ≈ 0.5, which means that regardless of the absolute value of resting *EISF*, the swallowing frequency during food consumption is approximately twice as high. A more accurate floating average model (Supplementary Table 1, Model 2) can be formulated with the decision threshold T_{FL}^{INGEST} being a product of a floating average of the swallowing frequency over several epochs and a scaling factor α which sets the threshold at a certain level above the floating average. This model self-adjusts to individual variations in swallowing rates and thus is expected to perform better than the group model which is based on population statistics. Training and validation of the floating average model demonstrated 87% accuracy of food intake detection and a reduced variation in prediction rates among subjects.

A floating model can also incorporate chewing as a binary indicator of food intake (Supplementary Table 1, Model 3). While in practical terms this requires an additional sensor that reports on the state of chewing (‘chewing’ or ‘no chewing’) the advantage is a higher accuracy of detecting intake of solids. Incorporating chewing increased the average accuracy to 95.5% (Table 1). Such high accuracy for 30s epochs should be sufficient for detection of most short-term events associated with snacking. An interesting observation is that, with the inclusion of chewing, the decision of food intake for solids relies heavily on the presence of chewing while a higher threshold ($\alpha \approx 1.7$) for swallowing frequency captures the consumption of liquids.

2.4 Models for differentiation of solids and liquids

The models for differentiation of liquid and solid foods were built using the same principles as models for detection of food intake. The group model (Supplementary Table 2, Model 1) based on the optimal Bayes threshold $T^{LIQUID} = 12 sw/\min$ (Fig.1, C) resulted in 82.2% average accuracy. The floating average model (Supplementary Table 2, Model 2) did not significantly improve the average recognition accuracy resulting in 82.5% average accuracy. However, a floating average model that included chewing (Supplementary Table 2, Model 3) made a dramatic improvement in accuracy. This could be expected since liquid consumption results in a high swallowing rate easily exceeding the ingestion threshold but it is quite uncommon to chew liquids. The model incorporating chewing produced 93.3% average accuracy. Similar to the model for detecting food ingestion, introducing chews into the decision rule increased the swallowing threshold ($\alpha \approx 2.3$) attributing solid food intake to the presence of chewing and intake of liquids to high swallowing rates.

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2.5 Mass prediction models

The third study hypothesis was tested by showing that chews and swallows can predict the total ingested food mass with reasonable accuracy. The mass prediction model for solid foods is based on a simple linear model using the total number of chews and swallows associated with a period of ingestion as predictors. Predicted mass of solid food was computed as $M_S = 0.5(\overline{M}_{SW}^{S} \cdot N_{SW} + \overline{M}_{CHEW} \cdot N_{CHEW})$ where $\overline{M}_{SW}^{S}$ is subject's average mass per swallow of solid food, N_{SW} is total number of swallows for a period of solid food intake, $\overline{M}_{CHEW}$ is average mass per chew and N_{CHEW} is total number of chews. The $\overline{M}_{SW}^{S}$ and $\overline{M}_{CHEW}$ are individual statistical estimates of the average mass consumed in a single swallow or a chew (Supplementary Appendix A).

The model for predicting ingested mass of liquids used only swallows since liquids do not involve chewing: $M_L = \overline{M}_{SW}^{L} \cdot N_{SW}$ where M_L is predicted mass of liquid and N_{SW} is the total number of swallows for liquid intake. However, absence of chewing was not the only reason to have a separate model for liquid intake. Our results show that the average size of a swallow (Fig. 2, A, B) is significantly larger (P<0.001) for liquids ($\overline{M}_{SW}^{L} \approx 17.8$gr) than for solids ($\overline{M}_{SW}^{S} \approx 6.08$gr). Therefore, a prediction model taking into account differentiation between solids and liquids is needed for higher accuracy. The population means of mass per swallow and mass per chew are not representative of subject's individual means due to observed high inter-subject variability (Fig. 2, A, B, C). This suggests a need for individual rather than population-calibrated models. Another interesting observation is that mass per swallow and mass per chew have no obvious correlation with subject's BMI.

The accuracy of mass prediction for solid and liquid foods was estimated by six-fold cross validation (*23*) on the data from sixteen subjects with available four visits. The error was estimated as an absolute value of the percentage difference to the real weight of the food. The mass model of solid food intake achieved 91.79% (95% CI: 90.54%-93.05%) average accuracy (Fig. 3 A, B). The mass model for liquid intake achieved 83.76% (95% CI: 80.78%-86.73%) average accuracy. Lower accuracy of predicting mass of liquids could be attributed to the fact that the liquid ingestion model is based only on swallowing counts while the accuracy of the solid ingestion model is improved by taking chews into account. It should be noted that other parameters of ingestion such as duration of a swallow, total ingestion time, etc could potentially be factored in to improve accuracy.

3. Discussion

The results suggest that accurate capturing of chewing and swallowing events could lead to development of a novel method of accurately measuring human eating behavior and food intake. This in turn could substantially improve our ability to study the eating behaviors associated with obesity.

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Based on the reported results we estimate that measuring chews and swallows can achieve >95% accuracy in detection of food ingestion on short 30-second decision epochs, which should be sufficient to capture short events of snacking; differentiate between solid foods and liquid foods with >91% accuracy; and estimate mass of solid food intake with >91% accuracy and mass of liquids with >83% accuracy. These numbers are likely to improve with development of more sophisticated and self-adjusting individualized prediction models. However, the current accuracy of detecting ingestion is sufficient for reliable behavioral monitoring and providing information on patterns of food intake. Further research is needed to improve accuracy of mass prediction, potentially achieved through incorporation of more features such as time of chewing and duration of swallowing. The advantages of using chews and swallows for monitoring of ingestive behavior include: (1) a more objective means of monitoring of food intake than methods currently available (2) the ability to provide an accurate assessment of the daily pattern of eating and drinking with a high time resolution (e.g. 30 seconds in this study) (3) information about solid vs. liquid consumption (4) accurate estimates of amount of food eaten (5) potential for utilizing this method in a wearable non-invasive device.

We also show that detection of food intake and differentiation of liquid/solid food can be performed by monitoring of swallowing alone though the overall accuracy is reduced. This may be important from the perspective of developing a simple biofeedback device to monitor food ingestion and provide feedback in a manner similar to that of a pedometer. Utilizing just one sensor may significantly simplify application of the device and reduce costs. We believe that such a device may be valuable for continuous monitoring of ingestive habits and adaptation of the lifestyle.

The further improvements of this method will likely result in greater accuracy and utility. For example, the microstructure of a meal (i.e. the specific sequence of chews and swallows) may be indicative of the type of food being consumed (*24*). Alternatively, food type may be reported by a high-tech electronic nose, through a food diary or automatic food photography.

Additional increases in prediction accuracy in detecting chewing, swallowing, and ingested mass may potentially be achieved by involving more of the features characterizing ingestion: time of chewing and duration of swallowing, chewing frequency, etc to name a few. The algorithms presented here may be combined in a number of ways which still need to be studied.

In this study the scores of chews and swallows were obtained manually from the signals captured by video, sound and other sensors (*20*). To be practically applicable in free living conditions, the method of capturing chews and swallows would have to rely on a reduced set of measurements that can be automatically processed by a wearable computing platform (*25*). An important part in our research is dedicated to building non-invasive wearable sensors and related signal processing and pattern recognition methods for automatic detection of swallowing instances and periods of chewing, thus not requiring a person to manually score the data. In our publications (*20, 26*) we have shown that swallowing events can be identified by a miniature microphone detecting a specific sound of deglutition and chewing events can be detected by a strain sensor positioned behind the outer ear. These sensor modalities represent just a few of the choices that can be explored for design of an inconspicuous wearable device that would detect and characterize food ingestion by measuring chews and swallows. Such a wearable device can be used for objective monitoring of ingestive behavior of a free living population. Since such a technique would not require a conscious effort on the part of the user, we may expect a reduced observation effect, though this issue will require a separate study.

In summary, we have presented a rationale and preliminary results for a novel method of accurately assessing ingestive behavior in free living humans based on chewing and swallowing information. This method has the potential to improve our understanding of human eating behaviors associated with obesity.

4. Disclosure

The authors declare no conflict of interest.

5. Acknowledgements

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Tables

Table 1. Sensitivity, specificity and confidence intervals of predictor models.

Model	Sensitivity (95% confidence interval)	Specificity (95% confidence interval)
Group model of intake detection	73.4% (72.8%-74.0%)	90.6% (90.2%-91.0%)
Floating average model of intake detection	83.0% (82.7%-83.3%)	91.0% (90.8%-91.2%)
Floating average model of intake detection incorporating chewing	95.0% (94.8%-95.1%)	96.0% (95.9%-96.1%)
Group model, solids vs. liquids	74.8% (73.6%-75.9%)	89.61% (88.2%- 89.9%)
Floating average model, solids vs. liquids	71.3% (70.2%-72.4%)	93.8% (93.6%- 93.9%)
Floating average model incorporating chewing, solids vs. liquids	95.5% (95.1%-95.8%)	91.1% (90.8%-91.3%)

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Figure Captions

Fig.1 Instantaneous Swallowing Frequency (*ISF*) is a key predictor for differentiation between intake/no intake of food and solid/liquid food. (A) *ISF* graph clearly indicates ingestion during the course of a meal. Resting periods (no intake) are labeled 1; intake of pizza - 2; yogurt - 3; apple - 4; peanut butter - 5; water - 6. (B) Population-based box plot of *ISF* for no intake/solid food/liquid. (C) Probability Density Estimations for 30-second *EISF* define optimal Bayesian thresholds T^{INGEST} for food intake and T^{LIQUID} for liquid intake detection in the group model (D) Ratio of mean *EISF* for periods of no food intake to mean *EISF* of solid food intake and mixed solid/liquid intake. Data shown for 69 complete meals from 18 subjects.

Fig.2 Average mass per swallow for solids and liquids and average mass per chew for solids are the key predictors in estimating the mass of ingested food. (A) Average mass per solid food swallow per subject arranged by subject’s BMI (B) Average mass per chew per subject arranged by subject’s BMI (C) Average mass per liquid swallow per subject arranged by subject’s BMI.

Fig. 3 The error of mass prediction (A) Average accuracy of absolute prediction for mass of solid food per subject. Each data point represents an average across six folds of training/validation. (B) Average accuracy of absolute prediction for mass of ingested liquid.

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Figures

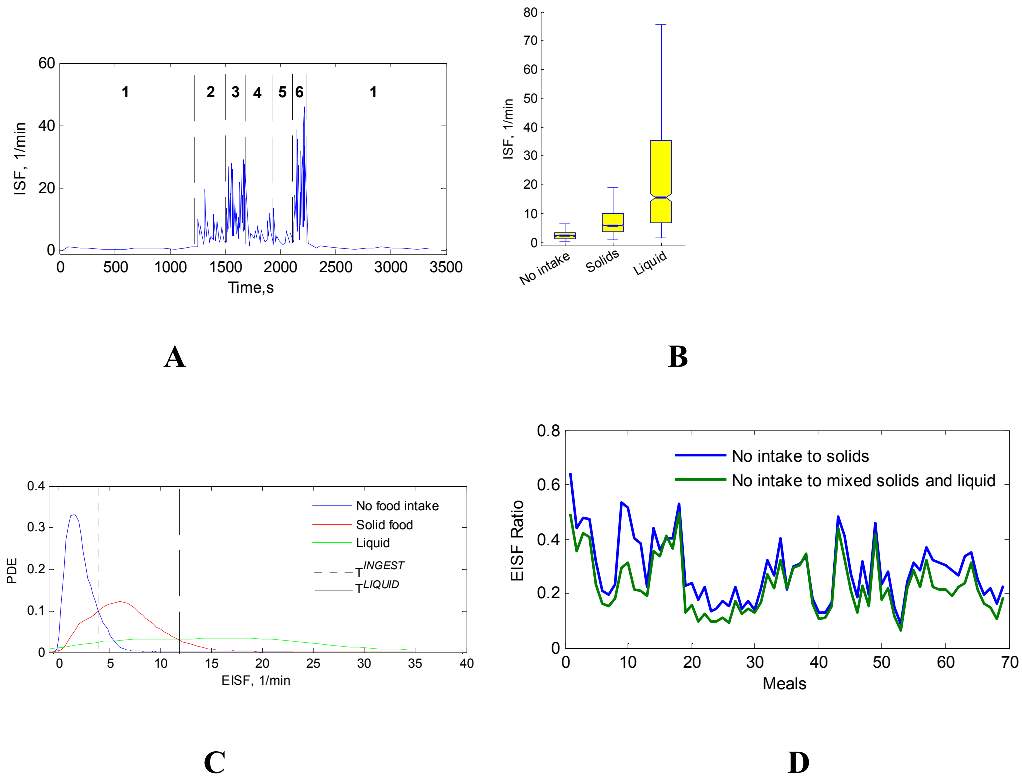
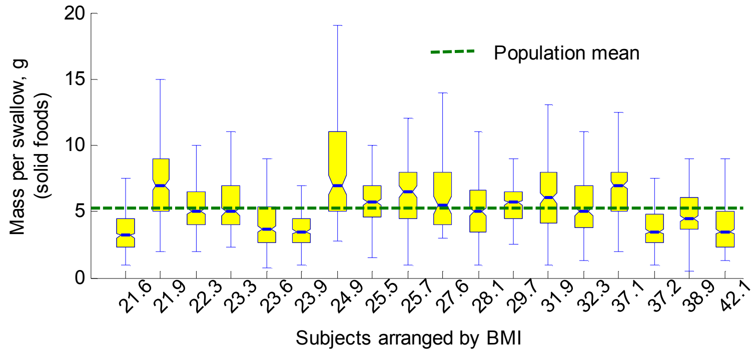
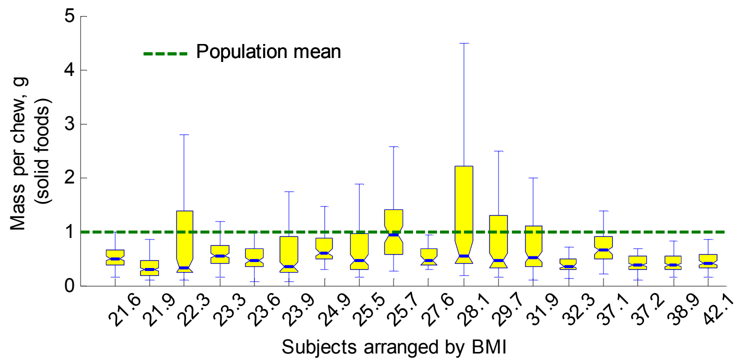


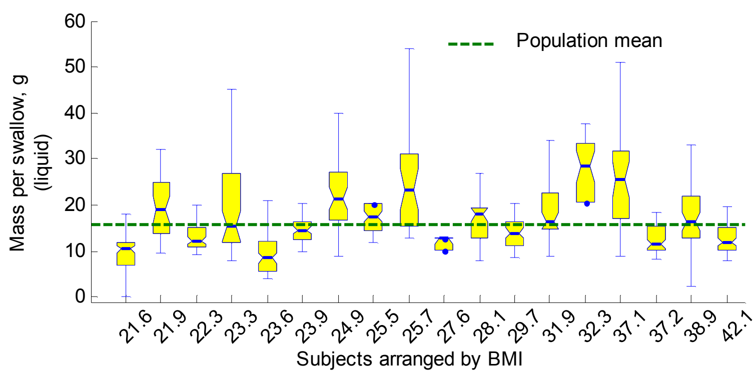
Fig.1


Population mean
Mass per swallow, g
(solid foods)
Subjects arranged by BMI
21.6 21.9 22.3 23.3 23.6 23.9 24.9 25.5 25.7 27.6 28.1 29.7 31.9 32.3 37.1 37.2 38.9 42.1
0 5 10 15 20

A


Population mean
Mass per chew, g
(solid foods)
Subjects arranged by BMI
21.6 21.9 22.3 23.3 23.6 23.9 24.9 25.5 25.7 27.6 28.1 29.7 31.9 32.3 37.1 37.2 38.9 42.1
0 1 2 3 4 5

B


Population mean
Mass per swallow, g
(liquid)
Subjects arranged by BMI
21.6 21.9 22.3 23.3 23.6 23.9 24.9 25.5 25.7 27.6 28.1 29.7 31.9 32.3 37.1 37.2 38.9 42.1
0 10 20 30 40 50 60

C

Fig. 2

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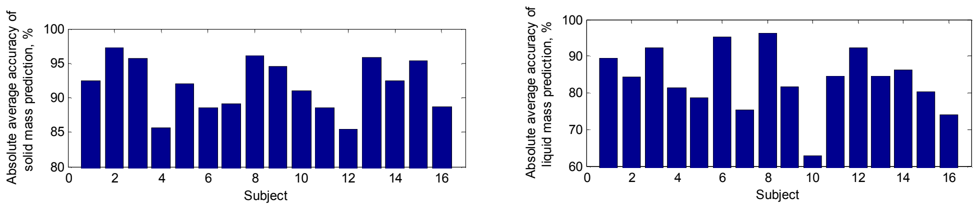

A **B**

Fig.**3**

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Supplementary Table 1. Models for detection of food intake

Model number	Model name	Model description*	Training/Validation methodology
1	**Group model**	$L_J = \begin{cases} \text{'intake'} & \text{if } EISF_J \geq T^{INGEST} \\ \text{'no intake'} & \text{if } EISF_J < T^{INGEST} \end{cases}$, where T^{INGEST} is the Bayes optimal decision threshold.	**Repeated random sub-sampling validation.** The training set for each class (‘intake’/’no intake’) was chosen randomly from the subject database and the rest of the database was used for validation. Accuracy was reported as an average of 100 runs of the algorithm.
2	**Floating average model**	$L_J = \begin{cases} \text{'intake'} & \text{if } EISF_J \geq T_{FL}^{INGEST} \\ \text{'no intake'} & \text{if } EISF_J < T_{FL}^{INGEST} \end{cases}$ $T_{FL}^{INGEST} = \alpha \cdot \frac{1}{N} \sum_{j=1}^{N} EISF_j$ where N is the number of epochs in the floating average window and $\alpha \approx 1.05$ is a scaling factor obtained by training.	**Repeated random sub-sampling validation.** The training set for each class (‘intake’/’no intake’) was chosen randomly from the subject database and the rest of the database was used for validation. The scaling factor was estimated using a training set of all the visits from a randomly selected half of the available subjects in a grid search procedure that found a value of α maximizing the prediction accuracy (the average between sensitivity and specificity) for the training set. The selected α was used to predict food intake for the validation set. Accuracy was reported as an average of 100 runs of the algorithm.
3	**Floating average model with chewing**	$L_J = \begin{cases} \text{'intake'} & \text{if } (EISF_J \geq T_{FL}^{INGEST}) \vee C_J \\ \text{'no intake'} & \text{if } (EISF_J < T_{FL}^{INGEST}) \vee C_J \end{cases}$ $C_J \in \{\text{'no chewing'}, \text{'chewing'}\}$ $T_{FL}^{INGEST} = \alpha \cdot \frac{1}{N} \sum_{j=1}^{N} EISF_j$ where N is the number of epochs in the floating average window and $\alpha \approx 1.7$ is a scaling factor obtained by training.	**Same as for floating average model**

* $L_J \in \{\text{'intake'}, \text{'no intake'}\}$ is a binary label defining the state of food ingestion in epoch *J;*

$EISF_J$ is Epoch Instantaneous Swallowing Frequency for epoch *J*: $EISF_J = \begin{cases} \frac{1}{K} \sum_{i \in E_j} ISF_i^J & \text{if } E_J \neq \varnothing \\ 0 & \text{if } E_J = \varnothing \end{cases}$, where $E_J = \{ISF_1^J, \ldots, ISF_K^J\}$ is a set of *ISF* of *K* swallows inside the boundaries of epoch

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Supplementary Table 2. Models for differentiation of solid and liquid foods

Model number	Model name	Model description*	Training/Validation methodology
1	**Group model**	$L_J = \begin{cases} \text{'liquid'} & \text{if } EISF_J \geq T^{LIQUID} \\ \text{'solid'} & \text{if } EISF_J < T^{LIQUID} \end{cases}$, where T^{LIQUID} is the Bayes optimal decision threshold.	**Repeated random sub-sampling validation.** The training set for each class ('solid'/'liquid') was chosen randomly from the database and the rest of the database was used for validation. Accuracy was reported as an average of 100 runs of the algorithm.
2	**Floating average model**	$L_J = \begin{cases} \text{'liquid'} & \text{if } EISF_J \geq T_{FL}^{LIQUID} \\ \text{'solid'} & \text{if } EISF_J < T_{FL}^{LIQUID} \end{cases}$ $T_{FL}^{LIQUID} = \alpha \cdot \frac{1}{N}\sum_{j=1}^{N} EISF_j$ where N is the number of epochs in the floating average window and $\alpha \approx 1.7$ is a scaling factor obtained by training.	**Repeated random sub-sampling validation.** The training set for each class ('solid'/'liquid') was chosen randomly from the database and the rest of the database was used for validation. The scaling factor was estimated using a training set from a randomly selected half of the available subjects in a grid search procedure that found a value of α maximizing the prediction accuracy (the average between sensitivity and specificity) for the training set. The selected α was used to predict the type of ingested food on the validation set. Accuracy was reported as an average of 100 runs of the algorithm.
3	**Floating average model with chewing**	$L_J = \begin{cases} \text{'liquid'} & \text{if } (EISF_J \geq T_{FL}^{LIQUID}) \vee \overline{C}_J \\ \text{'solid'} & \text{if } (EISF_J < T_{FL}^{LIQUID}) \vee \overline{C}_J \end{cases}$ $C_J \in \{\text{'no chewing'}, \text{'chewing'}\}$ $T_{FL}^{LIQUID} = \alpha \cdot \frac{1}{N}\sum_{j=1}^{N} EISF_j$ where N is the number of epochs in the floating average window and $\alpha \approx 2.3$ is a scaling factor obtained by training.	**Same as for floating average model**

* $L_J \in \{\text{'solid'}, \text{'liquid'}\}$ is a label defining the type of ingested food in epoch *J;*

$EISF_J$ is Epoch Instantaneous Swallowing Frequency for epoch J : $EISF_J$ is Epoch Instantaneous Swallowing Frequency for epoch J:

$$EISF_J = \begin{cases} \frac{1}{K}\sum_{i \in E_j} ISF_i^J & \text{if } E_J \neq \varnothing \\ 0 & \text{if } E_J = \varnothing \end{cases}$$, where $E_J = \{ISF_1^J, ..., ISF_K^J\}$ is a set of ISF of K swallows inside the boundaries of epoch

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Supplementary Appendix A.

Methods of estimating average mass per swallow and per chew

The estimates for $\overline{M}_{SW}^{S}$ and $\overline{M}_{SW}^{L}$, where S is solid and L is liquid, were computed on a bite level. During the data collection one atomic intake of solid food or liquid was considered a bite. The mass of the bite was measured by weighing the food before and after the bite on an accurate electronic scale. Average mass per solid food swallow for *i*-th bite was computed as $M_{SW_i}^{S} = \frac{M_{BITE\,i}}{N_{SW\,i}}$ where $M_{BITE\,i}$ is the mass of the *i*-th bite and $N_{SW\,i}$ is number of swallows associated with *i*-th bite. The average mass per swallow was estimated as $\overline{M}_{SW}^{S} = \frac{\sum_i N_{SW\,i} \cdot M_{SW_i}^{S}}{\sum_i N_{SW\,i}}$. The estimate of liquid mass per swallow $\overline{M}_{SW}^{L}$ was obtained identically, but the liquid consumed in one attempt was considered a bite. Similarly, average solid mass per chews associated with *i*-th bite was computed as $M_{CHEW\,i} = \frac{M_{BITE\,i}}{N_{CHEW\,i}}$ where $N_{CHEW\,i}$ is the number of chews associated with *i*-th bite. The statistical estimate of the average mass per chew was computed as $\overline{M}_{CHEW} = \frac{\sum_i N_{CHEW\,i} \cdot M_{CHEW\,i}}{\sum_i N_{CHEW\,i}}$.