# MASTICATION COUNTING METHOD ROBUST TO FOOD TYPE AND INDIVIDUAL

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Abstract: In recent years, an increasing number of people have been suffering from over-weight, reminding the importance of a balanced dietetic lifestyle. Researches in nutrition and oral health have reported that not only the calorie intake amount, but also eating speed and the number of chews per bite were also important factors in obesity. Automatic mastication counting systems based on chewing sound processing have been proposed, though most of them have difficulties in detecting chewing strokes for various food types, and often require training logic or threshold that need to be customized for each user. To overcome these problems, we have developed a new model for automatic mastication counting based on new chew feature extraction and detection methods from natural chewing sound. Chewing sounds collected from 15 persons eating six different food types were recorded using a wearable bone-conduction microphone placed in ear. The chewing sound analysis model combining proposed chew feature extraction and detection methods was applied on the collected data set, showing a good overall accuracy while having better stability to different individuals and food types comparing to conventional models.

## 1 INTRODUCTION

In recent years, the importance of dietary habits monitoring for preventing lifestyle-related diseases has been increasing rapidly, drawing many researchers attention in modern society, since over-weight, which is increasing dramatically among all ages groups, has been proved to be related to many other diseases such as hypertension, diabetes, and heart diseases (Abraham et al., 1971; Hoffmans et al., 1989). Recent studies revealed that not only the calorie intake and consumption balance, but also eating speed and the number of chews per bite were also important factors for obesity (Nicklas et al., 2001).

Clinical studies have lead to develop a kind of weight scale for plates called Mandometer[1], which allows to know the eating amount per bite and eating speed. (Yasutomi and Masuda, 2008) have developed a device called ”kamikami sensor” to automatically count and display the number of mastication during eating. And the attention of researchers has started to focus on analyzing eating habits using internal body sounds such as (Amft et al., 2005; Nishimura and Kuroda, 2008; Shuzo et al., 2010).

In this paper, we describe and report about the efficiency of our proposed model for stable mastication counting based on sound signal using a new chewing features extraction method. This paper is organized as follows. In section 2, the characteristics of chewing sound during eating process and assumptions based on these characteristics are demonstrated. In section 3, all the steps of the data analysis method for the whole mastication counting process based on the physical properties are presented. In section 4, experiments and the data preparation for validation are described. In section 5, the model construction is illustrated by using data from experiments. Finally, a comparison study with conventional mastication counting models is shown in section 6. The conclusions are presented in section 7.

## 2 ASSUMPTIONS

### 2.1 Characteristics of the Chewing Process

The basic mechanics of mastication have been studied in detail by Amft et al. (Amft et al., 2005). They demonstrate that the structure of a single chewing segment into a chewing sequence is mainly composed of


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four phases: The closing of mandible for crushing the food(P1), a small pause(P2), the opening of the mandible(P3) in which food that stick to the teeth is uncompressed, and then another pause(P4).

### 2.2 Assumptions

According to the characteristics of chewing process, the following two assumptions are made to construct our model.

- The amplitude of P1 is larger than P3 in one chewing segment;
- The duration of P4 is longer than P2 in one chewing segment.

## 3 DATA ANALYSIS METHODS

### 3.1 Chew Pattern Extraction

The objective of chew pattern extraction is to find features that can differentiate a chew in the chewing process. For all the following pre-processing methods for chew pattern extraction, we use a common 20 ms signal frame with no overlap.

#### 3.1.1 Log Energy

Calculation of log energy based on a 20 ms frame is adopted in order to enlarge the differences among a chew and pauses in the chewing process.

#### 3.1.2 Zero Crossing Times

Zero crossing[2] times is a characteristic speech signal processing method to extract fundamental frequency, which consists in counting the number of sign-changes along the signal. As the frequency of a chew is different from the one of pauses, zero crossing times is a good descriptor since it is a rough approximation of the spectrum characteristics.

#### 3.1.3 Amplitude Differences Accumulation

According to the objective to extract the features that could demonstrate best the change of a chew, we proposed a new method called Amplitude Differences Accumulation (ADA), to amplify more clearly the difference between chews and pauses. The ADA of the $n_{th}$ frame can be illustrated by the following formula.

$$ADA_n = \sum_{m=(n-1)\times N+1}^{n\times N} |x(m) - x(m-1)|, \quad (1)$$

where $x$ represents the sound signal, $N$ is the number of sampling points in each frame.

### 3.2 Signal Smoothing

The signal from chew pattern extraction may contain some small vibrations caused by the noise covering the sound signal. A Butterworth low pass filter (LPF) was adopted for the purpose of noise reduction, the parameters were fixed to 4th order filter and 2.5 Hz cut off frequency, considering the reasonable maximum chewing cycles per second for human that is limited by the physical mechanics of the mandible.

### 3.3 Peak Detection

The peak detection algorithm is to find the local maxima in a certain interval. We adopt a Matlab function called *findpeaks*[3] to find peaks.

### 3.4 Rules for Mastication Counting

In the real eating process, the characteristics of eating signal change a lot due to different situations. However, according to the eating sound properties, the different signal characteristics can be summarized to the following two situations.

#### 3.4.1 Situation 1

In this situation, usually happened during eating very hard or crispy food, the characteristics of a chewing segment can be demonstrated as one of the following two possibilities.

- P1 and P3 merge so that P2 disappear;
- P1 and P3 are not merge, but P2 is very narrow.

In that case, after our proposed eating sound signal processing procedures, the main frequency component is only one low frequency.

#### 3.4.2 Situation 2

In the case of food types other than very hard or crispy, the eating sound signal has not so obvious characteristics like in situation 1. Indeed, P3 may be detected as a chew even if the situation obeys to the assumptions we made based on the physical properties of the eating process.

Our strategy is to adopt a rule that controls peak detection according to the characteristics of chewing sound and the assumptions. The rule consists in regulating the number of chews detected to no more than three chews in one second, and also not detecting chews that are too near from the previous one. To satisfy these rules, the next peak detected has to be separated by at least 15 frames of 20 ms after the frame in which the previous value have been calculated. The fixed threshold is in the same direction as time, and respects the chewing mechanics that there cannot be more than three chews in one second and the P2 stage is narrow.

# 4 EXPERIMENTS

## 4.1 Sensing Devices

A prototype of a wearable sensing system using bone-conduction sensor and IC recorder to analyse eating habits has been developed in previous work (Shuzo et al., 2010).

## 4.2 Experiments and Data Collection

Experiments were conducted to collect data for the validation of our proposed chew pattern extraction method and rule-based model. Hereafter is a list describing the experimental conditions.

- The quantity of food intake for one chewing process is not defined, participants can eat according to their will.
- Variety kinds of food with different textures are included in the experiments.
- Participants eat five times for each food type in the experiments.

This experiment has 15 participants, and eating sound of 6 food types was recorded. We chose the food types carefully in order to cover different food texture. Through this experiment, we can obtain 450 sound files for establishing the model for mastication count.

# 5 MODEL CONSTRUCTION

## 5.1 Introduction

In this section, the different chew pattern extraction methods demonstrated in section 3 are compared. The model was constructed based on the best performing chew pattern extraction method. The detailed performances are also reported in this section. The compared models are methods combination of log energy (LE), zero crossing times (ZCT), amplitude differences accumulation (ADA), and rule.

## 5.2 Comparison Study

The overall error rate was calculated based on the experimental. The performance was examined regarding four parameters, which detailed results are reported in Table 1.

## 5.3 Discussion

According to the results, the proposed rule can largely increase the overall accuracy of chews detection. Also, among the chew pattern extraction methods, the proposed method called ADA (amplitude differences accumulation) was proved to perform better.

# 6 COMPARISON STUDY WITH CURRENT MASTICATION COUNTING MODELS

In this section, our model has been compared with two other kinds of models referenced from Nishimura et al. and Shuzo et al. works (Nishimura and Kuroda, 2008; Shuzo et al., 2010). The utmost limit of performance that each model can achieve were compared. The details of these models are described in the following sub sections.

## 6.1 Models for Comparison

### 6.1.1 Low Passed Filter based Model (Shuzo et al., 2010)

The model was conducted for the extraction of the mastication number from the eating sound data. The number of mastication was counted by adopting a low pass filter and peak detection method. There are two settings in this model. The first is the cut-off frequency of the filter was set to a constant value of 1.5 Hz, the second setting is to change the cut-off frequency according to the power spectrum of sound data at that moment.

### 6.1.2 Log Energy based Model (Nishimura and Kuroda, 2008)

For this model, log energy was calculated based on 20 ms frame, and then a 4 order Butterworth filter with cut-off frequency of 2 Hz was applied to the signal. There is a threshold for sensitivity control for each person. The number of mastication can be obtained by counting the number of times regression coefficients calculated using low pass filter output values

Table 1: Results of comparisons using 5 parameters evaluation.

| Comparison situations No. | Overall error rate(%) | Lowest error rate for individual(%) | Highest error rate for individual(%) | Lowest error rate for food type(%) | Highest error rate for food type(%) |
|---|---|---|---|---|---|
| LE + LPF | 35 | 7 | 57 | 16 (Salad) | 61 (Fruit jelly) |
| ZCT + LPF | 41 | 8 | 61 | 31 (Salad) | 62 (Fruit jelly) |
| ADA + LPF | 30 | 7 | 55 | 13 (Salad) | 60 (Fruit jelly) |
| LE + LPF + rule | 8 | 2 | 17 | 4 (Salad) | 12 (Banana) |
| ZCT + LPF + rule | 11 | 3 | 20 | 8 (Fruit jelly) | 43 (Banana) |
| ADA + LPF + rule | 7 | 3 | 14 | 2 (Salad) | 11 (Marshmallow) |

of 9 frames crosses zero with a negative value slope and the local peak of low pass filter output is larger than the sensitivity threshold.

### 6.2 Comparison Results

The overall accuracy of the mastication counting models were compared (Table 2). The low pass filter based model with fixed cut-off frequency of 1.5 Hz was named as $M1$, the low pass filter based model with adaptive cut-off frequency was named as $M2$, the log energy based model was named as $M3$, and the model proposed in section 5 was named as $M$.

Table 2: Comparison of overall accuracy for 4 models.

| Methods | M | M1 | M2 | M3 |
|---|---|---|---|---|
| Accuracy(%) | 93 | 55 | 85 | 77 |

## 7 CONCLUSIONS

In this paper, we proposed a data analysis model for realizing automatic mastication counting for any individual and food type with high accuracy (93%). The proposed model reduces the influence of individual chewing ways differences (speed, strength, etc.) to a large extent, and is little influenced by chewing sound of different food types (soft, hard, crispy, etc.).

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## REFERENCES

Abraham, S., Collins, G., and Nordsieck, M. (1971). Relationship of childhood weight status to morbidity in adults. In *HSMHA Health Reports*. United States. Health Services and Mental Health Administration.

Amft, O., Stger, M., and Trster, G. (2005). Analysis of chewing sounds for dietary monitoring. In *Proceedings of 7th International Conference on Ubiquitous Computing*. Springer.

Hoffmans, A. F., Kromhout, D., and de Lezenne Coulande, C. (1989). Body mass index at the age of 18 and its effects on 32-year-mortality from coronary heart disease and cancer. a nnested case-control study among the entire 1932 dutch male birth cohort. *Journal of Clinical Epidemiology Vol. 42, Issue 6*, pages 513–520.

Nicklas, T., Baranowski, T., Cullen, K., and Berenson, G. (2001). Eating patterns, dietary quality and obesity. *Journal of the American College of Nutrition Vol. 20, Issue 6*, pages 599–608.

Nishimura, J. and Kuroda, T. (2008). Eating habits monitoring using wireless wearable in-ear microphone. In *Proceedings of International Symposium on Wireless Pervasive Communications (ISWPC08)*. IEEE.

Shuzo, M., Komori, S., Takashima, T., Lopez, G., Tatsuta, S., Yanagimoto, S., Warisawa, S., Delaunay, J.-J., and Yamada, I. (2010). Wearable eating habit sensing system using internal body sound. *Journal of Advanced Mechanical Design, Systems, and Manufacturing Vol. 4, Issue 1*, pages 158–166.

Yasutomi, K. and Masuda, Y. (2008). Example of food education for young japanese obese by wearing the 'kamikami sensor' while eating. *Journal of Japanese Society for Masticatory Science and Health Promotion Vol. 18, Issue 2*, pages 149–150.

## Notes

[1]http://www.mando.se/en/start-page/start-page-/1.aspx
[2]http://en.wikipedia.org/wiki/Zero_crossing
[3]http://www.mathworks.com/help/toolbox/signal/findpeaks.html