A parametric Probabilistic Context-Free Grammar for food intake analysis based on continuous meal weight measurements

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***Abstract*— Monitoring and modification of eating behaviour through continuous meal weight measurements has been successfully applied in clinical practice to treat obesity and eating disorders. For this purpose, the Mandometer, a plate scale, along with video recordings of subjects during the course of single meals, has been used to assist clinicians in measuring relevant food intake parameters. In this work, we present a novel algorithm for automatically constructing a subject's food intake curve using only the Mandometer weight measurements. This eliminates the need for direct clinical observation or video recordings, thus significantly reducing the manual effort required for analysis. The proposed algorithm aims at identifying specific meal related events (e.g. bites, food additions, artifacts), by applying an adaptive pre-processing stage using Delta coefficients, followed by event detection based on a parametric Probabilistic Context-Free Grammar on the derivative of the recorded sequence. Experimental results on a dataset of 114 meals from individuals suffering from obesity or eating disorders, as well as from individuals with normal BMI, demonstrate the effectiveness of the proposed approach.**

I. INTRODUCTION

Obesity (OB) and Eating Disorders (EDs), including Anorexia Nervosa (AN) and Bulimia Nervosa, affect a great portion of today's modern population. According to the World Health Organisation, more than half a billion people were suffering from OB in 2008[1]. The situation is not predicted to improve in the next years [8]; in fact, the number of people suffering from OB, as well as other diseases which OB is an important contributor for [9], will dramatically increase [8].

The Mandometer treatment method was introduced in 1996 in [2]. The Mandometer is a small scale that records the weight of the plate (and food) resting on it at a constant sampling rate; thus producing continuous meal weight recordings. This recording is then processed by clinical experts, sometimes with the help of additional video recordings of the meal, to create the Food Intake (FI) curve of the meal. According to [6], the cumulative FI curve can be sufficiently modelled using a second order polynomial curve $w(t) = \alpha t^2 + \beta t + \gamma$, where α is the FI acceleration, β is the initial FI rate and $\gamma = 0$, since no food has been consumed at the beginning of a recording.

The reason for this modelling of the FI curve is based on the evidence presented in [10] and [4], where two main patterns were identified in [10]: linear and decelerated eating. Interestingly, both OB and EDs populations were found to be linear eaters ($\alpha \simeq 0$) in [4], in contrast to normal populations who are characterised by decelerating eating ($\alpha < 0$). This is evidence that the quadratic modelling of the eating pattern can be used to detect high risk OB and EDs individuals. Furthermore, the use of Mandometer can modify the eating pattern of linear eaters, as shown in [11], and thus reduce the risk for developing such diseases. Indeed, in [1], results from $1,428$ subjects taken over 18 years show remission rates of 74%, out of which only 10% has relapsed.

However, the processing of the Mandometer recording is not a trivial task. Usually, clinicians who process the recordings in order to create the FI curves rely heavily on empirical rules and some guessing, introducing errors in the interpretation. On the other hand, additional video recordings can be used to aid the clinicians, but this process is very laborious and requires additional work (such as synchronisation, etc). In this work we present a novel algorithm that automatically constructs the FI curve using only on the Mandometer recording, based on a parametric Probabilistic Context-Free Grammar (PCFG). This algorithm significantly improves over the algorithms presented in [7]. Experiments on a large dataset validate the algorithm's efficiency.

The rest of this paper is organised as follows: Section II presents the algorithm. Section III presents the experimental setup and the behavioural indicators, while results are presented in Section IV. Section V concludes the paper.

II. THE PARAMETRIC PCFG ALGORITHM

The algorithm aims at constructing the (cumulative) FI curve of the meal. The FI curve describes the weight of food the subject has consumed throughout the duration of the meal. For this purpose, the raw meal recording is processed, yielding a version free of non eating-related weight fluctuations (Fig. 1a). These fluctuations can either be Food Additions (FAs) or artifacts. FA refers to adding additional quantity of food during the meal evolution (Fig. 1b). On the other hand, an artifact describes a temporary shifting of the weight (first a rise and then a drop); this can have various causes, such as pressure applied by a knife (which registers a spike-like artifact) or the resting of a fork/spoon on the plate (which registers a plateau-like shape, Fig. 1c). As a result, the PCFG assumes the following symbols: B for a bite event, F for a FA event, and A for an artifact event. Each event is assigned a probability based on parameters extracted from the meal recording. Finally, the interpretation of the meal with the highest likelihood is obtained.

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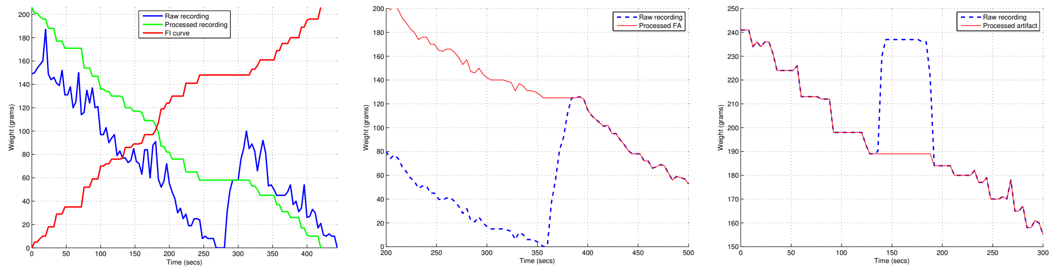
[1]`http://www.who.int/mediacentre/factsheets/fs311/en/`



(a) Entire meal (b) FA (c) Artifact

Fig. 1: Illustration of processing of the Mandometer recording. Fig. 1a shows the raw recording, the processed recording, and the FI curve, and Fig. 1b and 1c show the processing of a FA and an artifact.

TABLE I: Length of structuring element u used in pre-processing based on the value of parameter ξ

ξ	< 0.3	< 0.6	< 1	< 2	< 3	$< +\inf$
$length(u)$	2	3	5	7	11	15

A. Pre-Processing and Smoothing

Before applying the PCFG, some pre-processing is performed on the raw recorded data. Initially, the start and end of the meal are first detected. Given a sequence of recorded meal weights $w_0'(n)$, the start and end of the meal are considered as the first and last sample of the recording at which the recording is decreasing; all samples not in-between the first and last one are discarded. The resulting sequence is denoted as $w_0(n)$.

A smoothing step is then applied, that removes spikes caused during fork/knife use on the plate. The smoothing is performed by applying the *opening* morphological operator [3] on the raw data, using a structuring element u of ones. The length of the structuring element is determined automatically, based on the raw data with the help of the Delta coefficients (or Deltas).

The Deltas capture the trend (increasing or decreasing) of the curve. Given a sequence $x(n)$, they are defined as

$$\delta_D(n) = \frac{\sum_{k=-D}^{D} kx(n+k)}{\sum_{k=-D}^{D} k^2} \tag{1}$$

where the parameter D defines the range $[-D, D]$ where the trend of the curve is estimated.

Given a meal recording $w_0(n)$ of N samples, the length of the structuring element u is determined based on the following quantity

$$\xi = \frac{\sum_{k=1}^{N} \left|\delta_5\left(w_0\left(k\right)\right) - \delta_{15}\left(w_01\left(k\right)\right)\right|}{\sum_{k=1}^{N} \left|\delta_{15}\left(w_0\left(k\right)\right)\right|} \tag{2}$$

This is a rough estimation of the smoothness of the curve; the higher the value of ξ the less smooth the meal is, and thus harder smoothing is required. The length of u is determined using Table I. The result of the application of *opening* on $w_0(n)$ using u is denoted as $w(n)$.

B. The Parametric PCFG

The generative model for the PCFG, as described in the first paragraphs of Section II, is expressed by the following substitution rules

$$S \rightarrow BS \,|\, FS \,|\, AS \,|\, e \tag{3}$$
$$B \rightarrow D \,|\, RD \tag{4}$$
$$F \rightarrow R \tag{5}$$
$$A \rightarrow RSD \tag{6}$$

where S is the starting symbol, e is the empty string symbol, and "|" denotes the *or* operator. Symbols R and D describe weight increasing (rise) and decreasing (drop) segments, and substitute the following strings

$$R \rightarrow rr^* \tag{7}$$
$$D \rightarrow dd^* \tag{8}$$

where * is the Kleene star operator, and symbols r and d are the PCFG terminal symbols. They are obtained directly from the derivative of the meal recording, forming the string representation x of the meal using the following equation

$$x(n) = \begin{cases} d, & \text{if } d_w(n) < 0 \\ r, & \text{if } d_w(n) > 0 \\ e, & \text{if } d_w(n) = 0 \end{cases} \tag{9}$$

The derivative of $w(n)$ is computed as $d_w(n) = w(n) - w(n-1)$. Thus, each sample of the recording produces one terminal symbol, with the exception of the first sample.

The probabilities assigned to substitution rules of Eq. 7 and Eq. 8 are $p(R) = 1$ and $P(D) = 1$. This choice is based on the fact that symbols have no physical interpretation; they are merely means to aggregate subsequent rises or drops, in order to remove the dependence on the sampling rate of the Mandometer.

On the other hand, a bite event registers a drop on the recording. Usually however, the applied force by the fork/knife causes a temporary weight rise; this pattern is captured by the rule of Eq. 4. Total weight drop during a bite event, denoted B_{dw}, is usually 5 to 15 grams, and total duration B_{dt} is approximately 1 to 3 samples. These two parameters are independent, and thus the probability of a segment of the recording being a bite event B is

$p(B) = p_{B1}(B_{dw})p_{B2}(B_{dt})$. The PDFs p_{B1} and p_{B2} are shown in Fig. 2a.

Similarly, a FA event registers a weight rise (see Fig. 1b), which is captured by Eq. 5. Therefore, the probability of a segment being a FA event F is $p(F) = p_F(F_{dw})$, where the PDF p_F is shown in Fig. 2b, and F_{dw} is the weight increase during the FA.

The artifact event describes the phenomenon during which (a) extra weight is added on the plate (e.g. a spoon or a knife, not food however), (b) optionally something else might occur (e.g. a bite), and (c) the weight is removed from the plate. This is essentially captured by Eq. 6. The probability of such an event is based on four parameters: (a-b) the durations of R and D, denoted R_{dt} and D_{dt} respectively, which must be short, (c) the difference between the weight increase during R and the weight decrease during D, A_{dw}, which must be close to zero, and (d) the duration of intermediate event S, S_{dt}, which should also not be too long. As a result, the probability of an event A is $p(A) = p_{A1}(R_{dt})p_{A2}(D_{dt})p_{A3}(A_{dw})p_{A4}(S_{dt})$, where p_{Ai}, $i = 1, 2, 3, 4$ are show in in Fig. 2c.

The probability of substituting S using any of the four rules of Eq. 3 depends on the particular substitution only. No other assumptions are made about the events, such as the total number of FAs, etc. Thus, $p(S \to XS) = p(X)p(S)$ for $X = B, F, A$, and $p(S \to e) = 1$.

The PCFG is ambiguous: more than one parse trees exist for each input string. Thus, dynamic programming is employed in order to determine all possible interpretations. For each tree, a likelihood is computed that the tree correctly interprets the meal. As a result, the parse tree with the highest likelihood is selected as the final interpretation of events during the recorded meal.

C. Post-Processing

Once the final interpretation of a meal has been obtained, the FI intake curve is reconstructed based on the smoothed recording $w(n)$ and the PCFG events. FAs are removed, by adjusting the recording as if the entire food quantity had been added on the plate before the beginning of the meal (see Fig. 1b). Furthermore, artifacts are also removed, by cancelling out the weight rise and drop of the R and D parts of the event, and by subtracting the weight offset caused by the R and D from all samples of the embedded S part, if it exists (see Fig. 1c).

Finally, each bite is adjusted so that the entire weight drop occurs at the last sample of the bite. Finally, the PCFG FI curve $y(n)$ is obtained by subtracting the value of the last sample from all samples, so that zero left-overs occur, and then flipping the curve upside-down, or simply $y(n) = w_c(1) - w_c(n)$.

III. Experimental Setup And Behavioural Indicators

In order to evaluate the effectiveness of the proposed algorithm, a dataset consisting of 114 meal recordings is used. These have been recorded from 105 females and 9 males, out of which 49 have been characterised as normal-weight, with mean age of 22.8 years and mean Body-Mass Index (BMI) of $22.2kg/m^2$, 23 have been characterised as obese, with mean age of 35.22 years and mean BMI of $37.21kg/m^2$, and the rest 46 as AN cases, with mean age of 21.7 years and mean BMI of $17.4kg/m^2$.

For each meal, both the raw Mandometer recordings, as well as the ground truth FI curves are provided. The ground truth FI curves of the clinical recordings have been produced by clinical experts at Mando clinics[2] and researchers at Karolinska Institutet, based on both the raw Mandometer data and video recordings of subjects eating. The standard procedure for this process is described in [5].

To evaluate the effectiveness of the PCFG algorithm, we apply it on each raw meal recording and obtain the PCFG FI curve. For each meal, we extract behavioural indicators both from the ground truth FI curve and the PCFG FI curve for evaluation. These indicators include: coefficients α and β of the quadratic approximation of the FI curve, total FI weight (in grams), total meal duration (in seconds), and average bite size (also in grams). For coefficients α and β, four and five classes are identified respectively by clinical experts, and are presented in Tables II and III.

TABLE II: The four classes for the α coefficient of the quadratic model of a FI curve

Class	Range ($\cdot 10^{-3}$)
C_1^α (decelerated)	$(-\infty, -4]$
C_2^α (semi-decelerated)	$(-4, -1.5]$
C_3^α (linear)	$(-1.5, 1.5]$
C_4^α (accelerated)	$(1.5, +\infty)$

TABLE III: The five classes for the β coefficient of the quadratic model of a FI curve

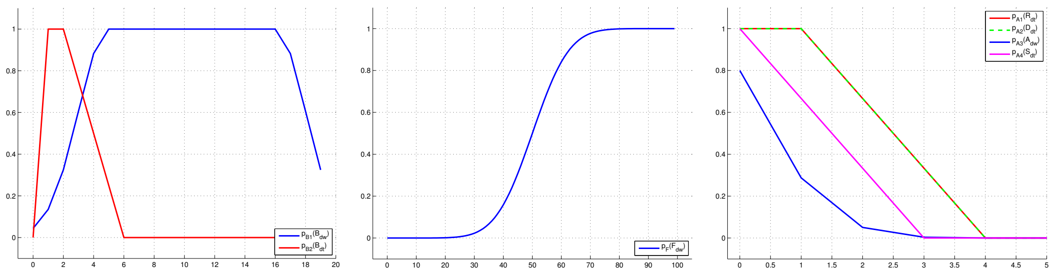
C_1^β	C_2^β	C_3^β	C_4^β	C_5^β
$(-\infty, -2]$	$(-2, -1.5]$	$(-1.5, -1]$	$(-1, -0.5]$	$(0.5, +\infty)$

Results for the α and β coefficients are presented in confusion matrices, where the ground truth class is assigned based on the value of the coefficient extracted from the ground truth FI curve, and the predicted class based on the value of the coefficient extracted from the PCFG FI curve. For the remaining indicators, the Mean Absolute Difference (MAD) and the Standard Deviation of Absolute Difference (StdAD) are computed across all meals.

IV. Results

The experimental results are presented in Tables IV, V and VI. Table IV presents the confusion matrix for the classification task of the eating pattern, based on the value of coefficient α. Detection accuracy is 90%, which is significantly higher than the top accuracy of 83% reported for the algorithms in [7]. Table V presents the confusion matrix for the classification task of coefficient β; detection accuracy

[2] http://www.mandometer.com/



(a) Bite event (b) FA event (c) Artifact event

Fig. 2: Probability density functions for the parameters of the PCFG events. They have been determined based on statistical analysis of the available recordings and their ground truth.

TABLE IV: Confusion matrix for coefficient α (eating pattern). Overall accuracy is 90.35%

		Predicted			
		C_1^α	C_2^α	C_3^α	C_4^α
Actual	C_1^α	3	0	0	0
	C_2^α	0	5	1	0
	C_3^α	0	1	57	6
	C_4^α	0	1	2	38

TABLE V: Confusion matrix for coefficient β. Overall accuracy is 87.72%

		Predicted				
		C_1^β	C_2^β	C_3^β	C_4^β	C_5^β
Actual	C_1^β	0	0	0	0	0
	C_2^β	1	11	2	1	0
	C_3^β	0	5	35	3	0
	C_4^β	0	0	2	53	0
	C_5^β	0	0	0	0	1

is 88%. Table VI presents the MAD and StdAD across all meals, for each of the remaining three indicators: total FI in grams, meal duration in seconds, and average bite size in grams.

These results indicate that the effectiveness of the PCFG algorithm is very high. Confusion in the eating pattern is minimal, and for most misclassified meals the predicted class is adjacent to the actual, indicating a relatively small error of the actual value of the α coefficient. The same is true for the classification based on the β coefficient. Finally, the effectiveness of the algorithm on the rest of the indicators is also high, as indicated be the MAD of total FI which is only 10 grams (it was 26 grams for the best case in [7]), and the MAD of the average bite size which is less than 1 gram.

TABLE VI: MAD and StdAD of indicators

Indicator	MAD	StdAD
Total food intake (grams)	10.00	30.74
Duration (seconds)	16.49	30.84
Average bite size (grams)	0.61	1.37

V. Conclusions

The Mandometer treatment is one of the most effective methods against OB and EDs. It is based on analysing continuous meal weight recordings and constructing the FI curve of the meal, and has been shown to achieve very high remission rates, and very low relapse rates as well. In this work we have presented an algorithm that automatically constructs the FI curve based solely on the Mandometer recordings. The effectiveness of the algorithm has been demonstrated on a large dataset that includes normal, OB and AN cases of varying BMI.

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