Validation of the Use of Heart Rate Variability Measurements during Meal Intake in Humans

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Abstract

Food intake is an essential function for a living organism. Analyzing food intake provides an estimation of a healthy or unhealthy lifestyle of a person. Misbalanced eating behavior often is a result from psychological disturbances like mental stress. To plan a proper therapy, the reasons for this misbalance have to be investigated. As the activity of the autonomous nerve system (ANS) affects food intake, this activity should be monitored in combination with food intake to get a deeper insight on eating disorders. This could help to understand the complex interactions between different eating stimuli and food intake. However, the ANS itself is affected by food intake as well. To quantify this influence, ECG recordings of 81 participants were taken before, during and after a short meal session. Heart rate variability (HRV) values were calculated as a measurement of ANS activity and analyzed. From the recordings, clusters could be built based on the trends of the HRV parameters SDNN, RMSSD, pNN50 and total power. In the biggest cluster, the values of these parameters tend to decrease during food intake and increase afterwards. In a second cluster, these HRV values increased from the resting period to the eating period and from the eating period to the second resting period. This showed that food intake influences the ANS activity in a defined way.

1.   Introduction

Eating and drinking are basic functions for life. Food and liquid intake keep up the energy balance of an organism. Disturbed eating behaviour has severe impact on the health state of the organism. Objective monitoring of the human food intake behaviour is beneficial for many reasons: The food intake behaviour is a sign for a healthy or an unhealthy way of live. Commonly, misbehaviour in food intake has psychological reasons. Hence, it can be influenced by psychological therapy. Additionally, the eating and drinking behaviour can be measured objectively. The analysis of these measurements might provide proper knowledge for the therapy of maladapted food intake.

There were many approaches to monitor human food intake behaviour objectively by body worn sensor systems: [1], [2], [3], [4], [5]. However, neither of these studies investigated food intake under different psychological conditions. We wanted to study the influence of different psychological conditions, especially mental stress, on the eating behaviour. These investigations should give deeper insight into the complex interaction of different eating stimuli and the food intake behaviour. Conclusions for a healthier way of eating might be drawn from these studies. Woda et al. [6] suggested the mastication frequency to be a key parameter for the evaluation of healthy mastication. Hence, we evaluated different methods to detect chew events by a wearable sensor to calculate the mastication frequency [7]. According to [8], the activity of the autonomic nervous system (ANS) influences human food intake considerably. Therefore, this activity has to be measured for our future investigations.

It is a well-known fact that the view of food and the perspective of food intake cause vegetative reactions of an organism. The process of food intake, the effect of saturation and the onset of digestion also cause such reactions, but with some temporal delay. In measurements of the activity of the ANS during food intake, these vegetative reactions are systematic perturbations. They have to be determined and the measurements must be corrected from these influences. A potential way to measure the activity of the ANS continuously might be the use of a wearable electrocardiogram (ECG) recorder. The analysis of the heart rate variability (HRV) provides insight to the processes of the ANS. Using ECG recordings has an additional benefit: Simultaneous recordings of the chewing activity and the ECG provide the potential of combined analyses of the mastication frequency and the HRV. This multi-parameter monitoring approach might be a valuable way for long time studies of the influence of the ANS activity on the eating behaviour. The recent developments of body area networks provide the requirements for this kind of multi parameter monitoring systems.

The present study contains preliminary investigations for the simultaneous measurement of the chewing

frequency and the HRV. Special emphasis was placed on the question, whether short time analysis of the HRV of randomly chosen healthy participants might be used to divide the participants in groups due to their vegetative reactions. Another important question was which parameters of the HRV were suitable for this cluster formation. The aim of the present study was to optimize the HRV analysis during food intake and to prepare a suitable method for evaluations of the ANS activity in a future study with simultaneous measurements of the chewing frequency and the ECG.

2. Methods

2.1. Recording procedure

Subjects of the investigation were 83 healthy volunteers (62 male, 21 female) aged 23 to 63 years (mean: 32.1). Participants were invited to a single recording session of 1 to 1.5 hours duration. They were not allowed to eat anything for at least three hours before the start of a session. Participants had to sit down at a quiet office room's table with the test food on it. ECG recordings were taken from the chest of the participant. The session was divided into three consecutive parts. The first and the last 20 minutes of the sessions were used as reference. Participants were allowed to talk with the investigator or to read a newspaper. After the first 20 minutes, the participants were instructed to eat and drink as much of the given food and beverages as they wanted. Eating and drinking should be performed as usual for at least 5 minutes and up to 30 minutes of duration. A wearable chewing sound sensor system [5] was applied to the right ear of the participant during this phase. Sandwiches with cheese and chocolate biscuits were offered to the participants. They were allowed to drink a beverage of their choice during the eating phase.

2.2. HRV analysis

To calculate HRV we used an ambulant 3 channel ECG recording device, which was developed at the Fraunhofer Institute for Photonic Microsystems [9]. A sampling frequency of 250 Hz and an amplitude quantification of 12 bit were used at an analog recording bandwidth of 0.5-40 Hz. Heart beat annotation was done using a wavelet min-max-pair based automated QRS detector [10]. The ECG signal and the QRS annotations were presented to a cardiologist, who manually selected segments of 2.5 minutes duration for each of the three above mentioned phases, only including consecutive normal beats. Single trigger errors were corrected during this selection, to provide a clean series of RR-intervals for each segment. Records with no clean segment of normal beats for each of the phases or more than 7 corrections

were excluded from analysis.

Next, the corrected RR-interval series were checked for supraventricular ectopic beats (SVES). To identify potential SVES we used the 20%-threshold for subsequent RR-interval deviation [11], [12], [13]. Datasets with the occurrence of potential SVES were entirely rejected from HRV analysis, to prevent wrong conclusions about the ANS. The following HRV parameters were calculated on the selected segments:

Time domain HRV parameters were taken from [14]:

MeanNN is the average value of all normal beat intervals (NN-intervals). In fact, it is the reciprocal value of the mean heart rate.

$$meanNN = \frac{1}{n}\sum_{i=1}^{n} NN_i \,, \qquad (1)$$

where n denotes the number of intervals NN of two consecutive normal beats within the current segment. SDNN stands for standard deviation of all NN-intervals within the evaluated phase.

$$SDNN = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(NN_i - meanNN\right)^2} \quad (2)$$

RMSSD is the root mean square of successive differences.

$$RMSSD = \sqrt{\frac{1}{n-1}\sum_{i=2}^{n}\left(NN_i - NN_{i-1}\right)^2} \quad (3)$$

pNN50 represents the percentage of NN-intervals within the current segment differing more than 50 ms to their preceding NN-interval.

$$pNN50 = \frac{\sum_{i=2}^{n} h(i)}{n-1}\cdot 100\,, \qquad (4)$$

where

$$h(i) = \begin{cases} 1, \text{if } \left|NN_i - NN_{i-1}\right| > 50\,\text{ms} \\ 0, \text{if } \left|NN_i - NN_{i-1}\right| \leq 50\,\text{ms} \end{cases}. \qquad (5)$$

As a parameter for nonlinear analysis of the HRV, the Shannon entropy SE was taken from [15].

For calculation of HRV parameters from frequency domain, four steps were necessary. Equidistant resampling was done at 10 Hz sampling frequency using a linear interpolation algorithm. The higher sampling frequency was selected to allow a high resolution frequency filtering in the next step and to ensure proper handling of high frequency signal details. Depending on the desired frequency content for different parameters, the resampled tachogram was filtered with 10th order Butterworth filters. The power components were selected with 3 dB cut-off frequencies of 0.15 Hz to 0.4 Hz (HF power) and 0.04 Hz to 0.15 Hz (LF power). To reduce computational costs, the filtered tachograms were downsampled to an equidistant sampling frequency of 1 Hz, ensuring all spectral content up to 0.5 Hz according

to the Nyquist-Theory. With the frequency content of interest being located between 0 Hz and 0.4 Hz, the frequency domain parameters of the HRV were well represented by this sampling rate. Power spectrum density was estimated using Welch's method with 8 sub segments and an overlap of 50 % using a Hann window. The following HRV parameters from frequency domain were calculated according to [14]:

The total power corresponded to a spectrum between 0 Hz and 0.4 Hz, representing HF (high frequency), LF (low frequency) as well as VLF components (very low frequency). Note that this value was in fact not holding any 0 Hz component, since we estimated the PSD based on an unbiased tachogram to attain better quality for the remaining frequency spectrum. LF power represented the low frequency components between 0.04 Hz and 0.15 Hz. The HF power corresponded to frequencies between 0.15 Hz and 0.4 Hz. LF/HF was the ratio of LF power and HF power. LFn and HFn were normalized LF and HF power,

$$LFn = \frac{LF}{LF + HF}, \qquad (6)$$

$$HFn = \frac{HF}{LF + HF}. \qquad (7)$$

2.3. Clustering procedure

Clustering was carried out manually based on the changes of each parameter from the first reference phase (A) to the eating phase (B) and from this phase to the second reference phase (C). Clusters were built of participants with similar trends of HRV parameters during the three phases. Additionally, we took care of low variances of the absolute values of HRV parameters of interest within a cluster. For each cluster, we evaluated the significance of changes of the HRV parameters from A to B and from B to C using the Wilcoxon test for combined measurements. Additionally, significance of the difference of these changes between different clusters was evaluated using the Mann-Whitney U test for independent measurements. Significance level was set to 0.05. All tests of significance were done using IBM SPSS version 19.

3. Results

Out of the 83 datasets 42 records were rejected by the cardiologist because of overall bad signal quality, there was no clear 2.5 minute segment in one of the three phases or it was necessary to correct more than 7 beat triggers. In 14 of the remaining records, one or more beats within a segment exceeded the 20%-RR-deviation threshold. They were excluded from analysis, too. Overall, 27 ECG recordings were usable for HRV analysis.

In nearly all 27 ECG recordings, meanNN was reduced during phase B. Hence, heart rate was higher during food intake. The ECG recordings could be divided into two clusters and an additional rejection cluster. Cluster 1 consisted of 14 participants and cluster 2 contained 4 participants. Nine recordings could neither be added to one of these clusters, nor build an own cluster. Hence, these recordings built the rejection cluster. The division was made based on the trends of the parameters SDNN, RMSSD and pNN50. In cluster 1 all three parameters started at a medium level in phase A and were significantly reduced in phase B. From phase B to C, there was a significant increase of the parameters (SDNN: $p<0.005$, RMSSD: $p<0.0005$, pNN50: $p<0.0005$). The values of phase A and C were not significantly different. Cluster 2 showed a significant increase of all three values from phase A to B and from B to C (SDNN: $p<0.05$, RMSSD: $p<0.01$, pNN50: $p<0.01$), starting at low levels in phase A. Both groups differed significantly in the change of SDNN, RMSSD and pNN50 from phase A to B (SDNN: $p<0.05$, RMSSD: $p<0.001$, pNN50: $p<0.005$). The change of these values from phase B to C was not significantly different. In frequency domain parameters, there were significant changes in total power of both clusters. In cluster 1 a decrease from phase A to B ($p<0.0005$) and an increase from phase B to C ($p<0.0005$) could be observed. Cluster 2 showed significant increases of total power from phase A to B ($p<0.01$) and from B to C ($p<0.01$). Both clusters differed significantly considering the change of total power from phase A to B ($p<0.001$). Changes of the other parameters presented in section 2.2 were not significant or could not be used to distinguish the clusters in a significant way.

4. Discussion

The given results showed that the HRV parameters were influenced in a defined way by eating food. Two clusters could be divided by significant differences of the HRV parameters SDNN, RMSSD, pNN50 and total power. Many recordings had to be rejected from analysis due to bad signal quality or the risk of having irregularities within the heart beat series. However, we were able to form clusters from the recordings and group the participants due to their HRV trends. Therefore, the HRV analysis from ECG recordings was seen to be a suitable way for estimating reactions of the ANS due to food intake and related processes. Especially, the parameters SDNN, RMSSD, pNN50 and total power might be used in future studies to estimate the activity of the ANS. A physiological interpretation of the HRV trends could not be made, yet. For this task, additional biochemical parameters, like the salivary cortisol level, have to be drawn. However, this will be done in future work.

5. Conclusions

Eating behaviour is a substantial parameter of a healthy lifestyle. Especially, the activity of the autonomous nerve function had been found to influence food intake. However, ANS activity itself is influenced by the key stimulus of food intake. We took recordings of ECG from 83 participants during a short meal session to quantify the influence of food intake to heart rate variability. Based on calculated HRV trends, we were able to form clusters of the recordings. The methodological approach was able to recognize different types of reactions of the ANS to food intake. HRV measurements were seen to be a suitable method for the estimation of ANS activity during food intake. It is assumed that HRV analysis could provide a suitable method to measure mental stress during food intake.

Acknowledgements

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