# Feasibility of Meal Onset Detection using Electrocardiograms

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***Abstract*—Information about meal onset is required for the artificial pancreas in efficient blood glucose level control (BGL). In this paper, we explore the effectiveness of electrocardiogram (ECG) signals for the detection of meal onset. In order to detect electrocardiographic changes during the meal ingestion, ECG signals were recorded before, during, and after the meal intake in healthy volunteers using three electrodes in Einthoven's configuration in four subjects. Six-time domain ECG features were extracted from segments of 20 s duration. These six features were given to a least-squares support vector machine for classification into meal-related ECG and no-meal ECG. The proposed approach achieves a classification accuracy of 84.82%, suggesting that ECG signal carry significant information that can be used to discriminate between meal and non-meal related events. Additionally, the average detection time (from actual meal start to meal onset detection) was only 3.47 min. Our preliminary results suggest that ECG-based meal discrimination information can be used in an artificial pancreas to improve its performance. It may also be used in continuous glucose monitoring systems to remind users of a forgotten meal insulin bolus.**

***Keywords*— artificial pancreas; meal onset detection; electrocardiogram.**

## I. Introduction

Type 1 diabetes mellitus (DM1) is a chronic disease in which the pancreas does not produce insulin. It is characterized by elevated blood glucose levels. Long-term diabetes leads to serious damage to the heart, kidneys, blood vessels, eyes, and nerves [1]. Regulation of blood glucose levels in a diabetic patient is very important to mitigate the adverse effects of diabetes.

Patients with DM1 need an external insulin injection to regulate blood glucose level (BGL). Manual insulin dosing is a tedious process. Also, manual insulin dosing is not feasible for children and old people, who often tend to forget or do not have the capability to do it. Hybrid artificial pancreas (AP) is developed for the control of BGL. Hybrid AP uses information about meal as input from continuous glucose monitoring (CGM) to decide insulin infusion [2]. Due to the slow absorption of insulin by subcutaneous tissue and the slow dynamics of glucose sensors, insulin should be infused prior to meal start to reduce postprandial glucose excursions [3], [4]. Thus, both the two available hybrid AP systems (Minimed 780G from Medtronic and t: slim with Control IQ from Tandem Diabetes Care) require manual intervention to inform the control system about meal onset and meal content (typically, grams of carbohydrates ingested), which can be often forgotten and along with carbohydrates estimation remains a challenge.

In recent years, several automated meal detection approaches have been developed [5]. The methods in [4], [6] have employed CGM values for the detection of the onset of meals. The disadvantage of CGM-based approaches is the delay associated with the detection of meal onset, which usually is 30-40 min. In the best case, the CGM-based approach requires approximately 10 min to detect meal onset [6]. Bowel sound-based approaches have been explored in [7], [8] for the detection of meal onset. The major drawback of existing abdominal sound-based approaches to detect the onset of meals is that their performance deteriorates in the presence of ambient sounds. Alternatively, in this work, we explore the utility of the electrocardiogram (ECG) for improved and rapid meal onset detection.

In the past few decades, researchers have focused their efforts on studying the effect of food on ECG. Food consumption induces significant changes in ECG activity. Specifically, the QT interval, heart rate, and RR interval are altered after food intake. These changes appear to coincide with the beginning of meals and can last up to four hours [9],

[10]. Our hypothesis is that changes occurring in ECG signals during meal can be distinguished by employing suitable signal processing and machine learning algorithms. Therefore, we explore the utility of an ECG for improved and rapid meal onset detection. To the best of our knowledge, this is the first work to explore electrocardiograms for meal onset detection.

The rest of this paper is organized as follows. Section II details the data acquisition and describes the proposed ECG based meal detection approach. Section III presents the results with discussion. Finally, the conclusion is drawn in Section IV.

## II. METHODOLOGY

### *A. Data Acquisition*

In order to acquire ECG signals, we have used a commercially available ProComp Infiniti system (Thought Technology Ltd). The signals are sampled at a rate of 2048 samples/s.

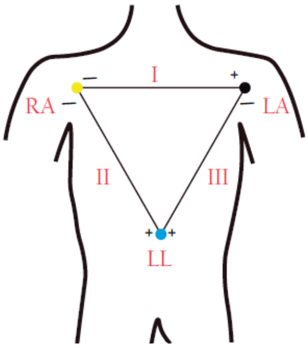


Fig. 1. ECG configuration used in data acquisition.


Fig. 2. Protocol for data acquisition.

In our work, we have connected an ECG sensor (T9306M) together with a sensor extender cable (T8720M) to channel one for acquiring ECG data. The three ECG electrodes are attached to the human body in an Einthoven configuration, as shown in Fig. 1.

The ECG signals used in our experiments are collected from four volunteers enrolled in a study approved by the Regional Ethics Committee of Norway (REK-midt, ref. 2019-778). The participants were asked to sign a consent form before participating in data acquisition. These subjects' self-reported that they had no known cardiac disorders. On the day of the recording, the subjects had their usual breakfast and subsequently fasted until lunch. ECG data was recorded during the regular lunchtime of the individuals. Subjects were asked to reduce body movements (other than eating) to a minimum during their food intake. Each recording starts with a fasting period of about 15 min, after which the subjects started taking their food for a maximum of 15 min. This is followed by a 40 min digesting period. Therefore, a typical recording contains ECG data corresponding to 70 min. In addition, the meal onset time for each recording has been recorded. The data acquisition protocol is shown in Fig. 2.

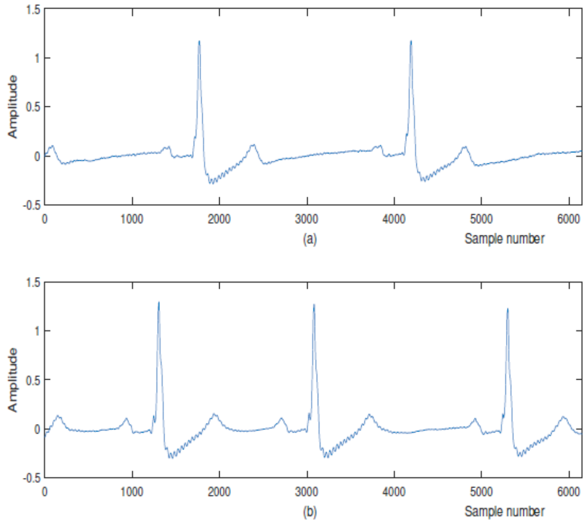


Fig. 3. A sample raw ECG segment corresponding to (a) no-meal/resting state (b) meal state.

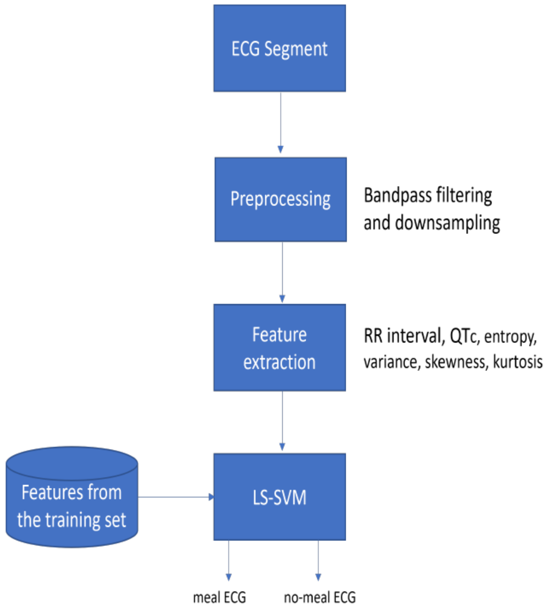


Fig. 4. Block diagram of the proposed ECG-based meal detection approach.

The ECG signals are segmented into smaller segments each of 10, 20, and 30 s. These segments are annotated as meal or no-meal ECG segments. The segments before the start of the meal are annotated as no-meal, otherwise, they are annotated as meal-based ECG segment. Each of these ECG segments is further processed to discriminate between the meal and no-meal ECG segment. Examples of raw ECG segments taken from the meal and no-meal case are depicted in Fig. 3. From. the figure, one can visualize the change in RR-interval, QT, and heartbeat in the ECG signal of no-meal and meal cases.

TABLE I. LENGTH OF SEGMENT VS CLASSIFICATION ACCURACY

| Length of ECG segment (s) | Accuracy (%) |
|---|---|
| 10 | 83.61 |
| 20 | 84.82 |
| 30 | 84.94 |

TABLE II. PERFORMANCE EVALUATION OF THE PROPOSED ECG BASED MEAL DETECTION APPROACH

| Number of Meals | TPM | FPM | FNM | Average RD |
|---|---|---|---|---|
| 7 | 7 (100%) | 2 (28.57%) | 0 | 3.47 min |

## *B. Proposed Approach*

The block diagram of the proposed approach for the detection of electrocardiographic changes during meal intake is shown in Fig. 4. In the proposed approach, we have extracted a set of statistical features from the pre-processed ECG segment. These statistical features extracted from the ECG segment are fed to a least-squares support vector machine (LSSVM) for classification purpose. More details of our approach are given below.

- Pre-processing: In this stage, the ECG signal is processed through $6^{th}$ order Butterworth bandpass filter with lower and upper cutoff frequencies of 0.5 and 200 Hz to remove unwanted noise and baseline wandering in the ECG signal. The resultant ECG signal is downsampled to 256 samples/s to reduce the computational complexity.

- Feature Extraction: As RR interval and QT are found to be affected during the meal intake [9], [10], we used average values of RR interval and QTc (corrected QT interval [11]) extracted from ECG segment as features. Additionally, the entropy, variance, skewness and kurtosis computed from the ECG segment [12] are also used as features. In total, six features were computed for each ECG segment.

- Classification: These statistical features extracted from the ECG segment are fed to a LS-SVM classifier [13] with radial basis function to determine whether the ECG segment corresponds.

# III. RESULTS AND DISCUSSION

## *A. Experimental Results*

In our experiments, we recorded ECG signals during 11 meals. ECG signals corresponding to one of the meals was discarded as it was corrupted with high amount of noise due to loose contact between electrodes, motion artifacts. Out of the remaining 10 recordings, 3 were used for training, and 7 were reserved for testing. The data was partitioned such that the data corresponding to the same person do not appear in both the testing and training sets. We have performed two set of experiments to validate proposed approach. The first set of experiments are performed to show the effect of different ECG segment length used on the classification accuracy. The classification accuracy obtained for segments lengths of 10, 20, and 30s is shown in the table I. It can be observed that the proposed approach has achieved the highest classification accuracy of 84.94% when the segment length is 30s. However, the improvement in classification accuracy is marginal when the segment length is changed from 20s to 30s. Although the increase in segment length has increased classification accuracy, it also increases the response delay (RD) which is the time delay from actual meal onset to the time of detection by the proposed approach. Therefore, for further analysis, we have restricted the length of ECG segments to 20s. The 3Dscatter plot of three features variance, skewness and kurtosis is shown in Fig. 5. It can be observed that the clusters belonging to the meal and no-meal classes are well separated. There are some outliers in the scatter plot, which may be due to the presence of noise due to cable movement.

The second set of experiments were performed to measure the delay associated with meal detection. Notice that the outcome of the meal detection approach in a fully automated artificial pancreas is asymmetric: If the method fails to detect a meal (false negative), it has no immediate effects other than that the postprandial period will be poorly regulated by the system, which affects results mostly in the long term. On the contrary, a false positive meal detection could trigger an inappropriate insulin injection that might cause hypoglycemia, a dangerous situation in short term. Therefore, instead of employing classification accuracy, true positives, and true negatives, we employ the following metrics for performance evaluation of our meal detection approach [7], [8]:

- True positive meal (TPM): A meal is detected as a true positive meal only if four consecutive ECG segments after a true meal start are classified as meal-related ECG.

- False positive meal (FPM): A false positive meal occurs if four consecutive ECG segments before the start of a true meal are classified into meal-related ECG.

- False negative meal (FNM): A false negative meal occurs if there are no four consecutive segments after the start of a true meal classified as meal-related ECG.

The results of the proposed ECG-based meal detection approach are shown in Table II. The ECG-based meal detection has achieved a true positive meal detection accuracy of 100% detecting all 7 meals but 2 with false positives. The meals were detected with an average response delay of 3.47 min.

## *B. Discussion*

Our experimental results suggest that the information extracted from ECG signals is very effective in meal detection in a constrained environment with less training data. Our system detects 5 out of 7 meals The ECG-based meal detection approach provides a better response delay than the existing CGM-based approaches [4], [6] and abdominal sounds-based approaches [7], [8]. Another advantage of the proposed approach is that the ECG signal is robust to environmental noise, unlike sound-based approaches [7], [8]. On the other hand, 2 out of 7 meals (28.57 %) resulted in false positive meals, which needs to be improved.

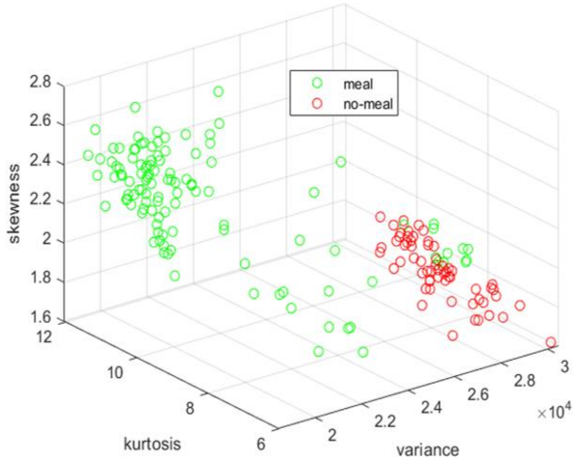


Fig. 5. Scatter plot of the features (skewness, variance and kurtosis) computed from meal and no-meal classes.

As the proposed approach is found to be effective in detecting meal onset with less delay, it can be explored in continuous monitoring systems to remind users of a forgotten meal insulin bolus. Although the proposed approach was found to be effective in detecting meal onset, note that the data set used in this study is collected in healthy volunteers without any self-reported history of cardiac disorders. Also, volunteers are asked to restrict their movements (activities other than eating) while eating. The proposed approach needs to be tested on a larger and more diverse data set before applying this for clinical purposes. As a part of our future work, we plan to test our approach on a dataset which contains ECG data in diabetic patients, cardiac arrhythmia's and ECG data taken in an unconstrained eating environment. Robustness can be tested by including, for example, physical exercise and 'eating simulations' (situations where the subject pretends to eat or does activities similar to eating). Furthermore, the performance of the proposed meal detection approach needs to be improvised in terms of FPM and classification accuracy, since it would be dangerous to inject insulin based on a FPM. Therefore, we plan to employ advanced deep learning techniques for improving the performance of ECG-based meal onset detection.

## IV. Conclusion

In this paper, we have investigated the utility of ECG signals for meal onset detection. Our experimental results suggest that ECG signals carry discriminative information that aids in the detection of meal onset. In addition, the ECG-based meal onset detection approach has provided less response delay than the abdominal sound-based and CGM-based approaches. Our preliminary results suggest that ECG-based information is useful in discriminating meal and non-meal in a constrained environment. In the future, we plan to investigate the utility of ECG signals in a larger and more diverse dataset.

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