Pilot Study of Early Meal Onset Detection from Abdominal Sounds

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***Abstract*—A typical artificial pancreas depends only on the continuous glucose monitoring (CGM) value for insulin dosing. However, both the insulin infusion and the glucose sensing are subject to time delays and slow dynamics. An automated and reliable meal onset information could enhance the control outcome of artificial pancreas by making it possible to infuse insulin earlier and thereby avoid large postprandial glucose excursions.**

In this study we employ abdominal sounds recorded in two healthy volunteers with a condenser microphone and propose an automated approach for meal onset detection from abdominal sounds. We use the Mel-frequency cepstral coefficients (MFCCs) and wavelet entropy extracted from the abdominal sounds as features. These features are fed to a simple feed forward neural network for discriminating meal from no-meal abdominal sounds.

This approach detects meal onset with an average delay of 4.3 minutes in our limited number of subjects. More importantly, it provides lesser response delay than the state-of-the-art CGM based approach, which achieved a response delay ranging from 30-40 minutes. The preliminary results indicate that the proposed abdominal sound-based approach may provide early meal onset information. This can be exploited in an artificial pancreas through allowable earlier meal insulin boluses, resulting in improved glycemic control.

Keywords*— *meal onset detection; abdominal sounds; artificial pancreas; Mel-frequency cepstral coefficients; Neural Networks.

I. Introduction

Diabetes mellitus type 1 (DM1), also known as type1 diabetes, is a chronic condition in which the pancreas fails to produce sufficient insulin. DM1 patients need external insulin injection to regulate the blood glucose level. Manual insulin dosing is a tedious process. Alternatively, researchers have developed a semi-automated system, called a hybrid artificial pancreas (AP) for controlling blood glucose level (BGL) [1]. The artificial pancreas uses continuous glucose monitoring (CGM) where the sensors are placed in the subcutaneous tissue, and the insulin is also infused in the same tissue. Due to the slow absorption and effect of insulin in this tissue, as well as the slow dynamics of these glucose sensors, insulin should be infused ahead of the meal in order to reduce postprandial glucose excursions [2]. The hybrid AP requires the patients to give meal information (estimate the amount of carbohydrates) to the system in order to achieve this. However, this is a burden to the patients, and it is notoriously unreliable. Since the meal onset information is required for the artificial pancreas in efficient BGL control, researchers have focused their efforts towards early automated meal detection. Methodologies in [3-4], have explored CGM data-based approaches for the meal onset detection. There is a delay of 40 minutes between actual meal intake and reliable meal detection [5]. Kölle et al. proposed a CGM based methodology [6] that detects meals with a delay of 10 minutes. However, this approach needs clinical verification. In order to control BGL efficiently, it is very important to further mitigate the delay between actual meal intake and reliable meal detection.

Sounds from the abdomen, or gastrointestinal sounds, are normally caused by transport of food, liquids and gas in the intestines during digestion. Of late, many researchers have studied the characteristics of abdominal sounds [7-8]. However, their main focus is towards the diagnosis of gastric disorders. Further, these works have reported the results corresponding to pre- and postprandial sounds, which did not include the actual time of meal intake. In contrast to the above works, the focus of the work presented in the current paper is early meal detection using abdominal sounds. To the best of author's knowledge Mamun and McFarlane [9] were the first to explore the sound recordings for meal detection. They developed a bowel-sound detector circuit, aiming to use it in an artificial pancreas. More recently, Kölle et al. proposed an abdominal sound-based early meal detection using power spectral density features and support vector machines [10]. The abdominal sound-based approach detected meals with a mean delay of 10 minutes.

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

II. METHODOLOGY

A. Data Acquisition

In order to record the sound signals from the abdomen, we employed a Sennheiser MKE2 P-C condenser microphone, which was fixed in the chest-piece of a stethoscope as shown in Fig.1. This assembly was attached to the upper right quadrant of the abdomen using a medical tape. This quadrant was chosen to effectively capture the sounds originating from the region where the stomach ends in the duodenum. A digital audio recorder 722 (Sound Devices LLC, Reedsburg, Wisconsin, US) was used to digitize the sound signals into samples with a sampling frequency of 32000 Hz and 24-bit precision. In order to reduce the computational complexity of the meal detection approach, these signals are decimated to 4000 Hz.

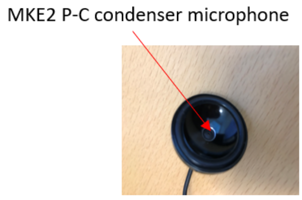

Fig. 1. MKE2 P-C condenser microphone fixed on the chest piece of stethoscope

The bowel sounds used in our experiments are collected from two volunteers enrolled in a pilot study approved by the Regional Ethical Committee These subjects self-reported to have no gastrointestinal disorders. On the day of recording, the subjects had their usual breakfast and fasted until lunch. The bowel sound data is recorded during the regular lunch time of the individuals. The recordings from subject 1 are done in an echo-free recording room, while the recordings of subject 2 are done in a typical lunchroom.

Abdominal sounds were recorded in a total of eight meals; four meals from each of the volunteers. The protocol of the recording is shown in Fig. 2. Each recording starts with a fasting period of approximately after 20 minutes, after which the subjects started eating their food for a maximum of 15 minutes. This is followed by a 45 minutes' digesting period. Therefore, a typical recording contains abdominal sound data corresponding to 80 minutes. Further, we have also noted the meal onset time of each recording.

The sound signals are segmented into smaller segments each of 20 seconds (80000 samples) with an overlap of 10 seconds between consecutive samples. These segments are further processed to discriminate the meal and no-meal sounds.

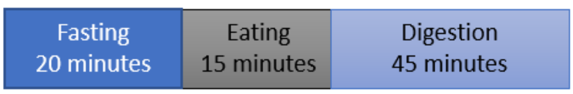

Fig. 2. Protoccol of the recording

B. Feature extraction

The block diagram of the proposed approach for meal onset detection from abdominal sounds is shown in Fig. 3. We extract two sets of features; Mel-frequency cepstral coefficients (MFCC) and wavelet transform-based entropy features from each abdominal sound segment. The extracted features are combined by using simple feature concatenation technique to get a final feature vector representation. The final feature vector extracted from each segment is given to a feedforward neural network for discriminating meal and no-meal abdominal sounds. Details of individual stages of processing involved in our approach are as follows:

Mel-frequency cepstral coefficients

MFCC are widely used classical features in automatic speech and speaker recognition. The effectiveness of the MFCCs in various speech related tasks motivated us to explore them for sound-based automatic meal detection. The steps involved in the computation of MFCC features are as follows:

i. Firstly, the signal is divided into overlapping segments known as frames. These frames are multiplied with a window function to avoid the discontinuities at the start and end of the frames.

ii. Power spectrum is computed from each of these windowed frames.

iii. These power spectra are then passed through a filter bank that is linearly spaced in Mel scale. The log energy is computed from each of the filter outputs.

iv. Finally, the discrete cosine transform (DCT) of these log filter bank energies is computed to get the MFCCs.

Further details on MFCC computation can be found in [11]. Since the dominant part of abdominal sound signal energy lies between 100–500 Hz [12], the MFCC coefficients corresponding to the aforementioned frequency range are used in our experiments and the rest are discarded. Here, the first five MFCCs extracted from the abdominal sound segments are used in this work.

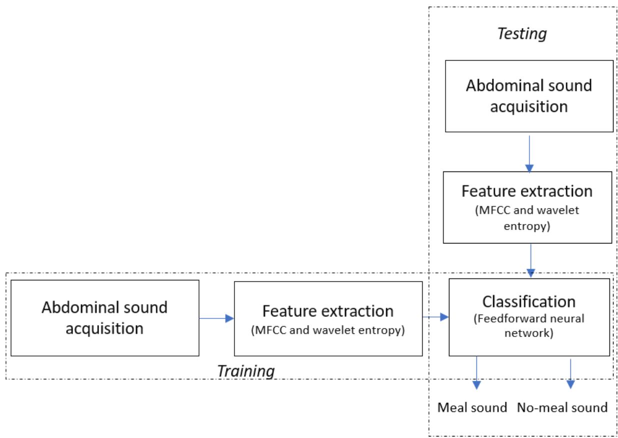

Fig. 3. Block diagram of the proposed meal detection approach

Wavelet entropy

In addition to the MFCCs, we also extract wavelet transform (WT) based features. The WT transforms the time domain signal to wavelet domain [13]. The abdominal sound signals are passed through the low pass filter (LPF) and high pass filter (HPF). Subsequently, the output signals obtained at the end of LPF and HPF are down-sampled by a factor of 2. This process converts the signals to approximate (low pass) and detail (high pass) coefficients. This procedure forms the level-one of decomposition. For the next level of decomposition, the approximate coefficients are again passed through the LPF and HPF, and the same process is repeated to compute the next level of DWT coefficients. In the proposed approach, a 3-level Haar wavelet-based DWT is used for decomposing the sound segment. After decomposing the signal into detail and approximation coefficients, Shannon entropy [14] computed from the approximation coefficients is used along with MFCC coefficients to discriminate meal and no-meal sounds. The detail coefficients are discarded to reduce the effect of noise on the meal detection.

In order to obtain the final feature representation, MFCC coefficients and wavelet entropy are combined using feature concatenation technique [15].

C. Classification: Feed-forward neural network

The final feature vector obtained in the previous stage is fed to the feedforward neural network (FNN) [16]. More specifically, we have used FNN with backpropogation training algorithm and two hidden layers with five and three neurons, respectively.

D. Validation

In order to verify the utility of abdominal sounds for early meal detection, we have performed leave-one-out cross-validation approach on the sound data collected from each volunteer separately. Since, we have collected abdominal sounds of each volunteer in four sessions, one recording is kept for testing in each iteration. More specifically, the feature-set extracted from the sound data corresponding to one session is used for testing, while feature-set extracted from the two sessions is used for the training and features extracted from one session are used for validation.

In meal detection for fully automated artificial pancreas the outcome of false classification is asymmetric: If an algorithm fails to detect a meal, it has no immediate consequences other than that the postprandial period will be poorly regulated by the control system, which contributes to long-term complications. On the other hand, a false meal detection could trigger an inappropriate insulin injection which might cause immediate hypoglycemia. Therefore, instead of directly using true positives, true negatives and classification accuracies, we define the following performance metrics for evaluation of the proposed meal detection approach:

a. *True positive meal (TPM):* A meal is detected as true positive meal only if four consecutive sound segments after meal onset are classified as meal-sound.
b. *False positive meal (FPM):* A false positive meal occurs if four consecutive segments before the start of a meal are classified into meal-sound.
c. *Response delay (RD):* The time delay from actual meal onset to the time of detection by the proposed method.
d. *False negative meal (FNM):* A false negative meal occurs if there are no four consecutive segments after the start of meal classified as meal-sound.

III. Results and Discussion

The results of the abdominal sound-based meal detection approach are shown in Table 1. The response delay reported in the table is the mean of the response delays computed from the leave-one-out approach. The proposed approach has achieved a meal detection accuracy of 75% and 50% for subject 1 and 2 respectively. Similarly, meals were detected with a delay of 6.6 minutes and 2 minutes in subjects 1 and 2, respectively. It can be inferred from the results that abdominal sounds might be used for the meal detection. As expected, the meal detection performs better in noise-free conditions (subject 1).

In summary, our pilot study indicates that abdominal sound bears promise as a basis for early meal detection. The abdominal sounds-based approach provides a shorter response delay than CGM based approaches [5-6]. More importantly, our approach has outperformed the existing abdominal sound-based approach [10]. However, the approach in [10], has been tested on a larger dataset, so the present results should not be considered conclusive. In the future, abdominal sounds may be combined with other modalities like CGM in order to increase safety and robustness.

The proposed meal detection approach was tested on a small dataset collected in two healthy volunteers. It needs to be tested on larger dataset before applying this for clinical purposes. Also, the meal detection accuracy needs to be improved, since it would be dangerous to inject meal insulin based on a false positive meal detection.

Typically, meals are ingested by the patients in locations where e.g. door sound, speech, and the sound of other people eating would affect the performance of the meal detection approach. Thus, the method needs thorough testing under such noisy conditions, and active or passive noise cancellation methods will likely need to be applied to achieve acceptable robustness.

TABLE I. Performance evaluation of the proposed abdominal sound-based meal detection approach

Subject Number	***TPM***	***FPM***	***FNM***	***RD***
1 (Noise-free)	75%	25%	0	6.6 minutes
2 (Noisy)	50%	50%	25%	2 minutes

IV. Conclusion

In this paper, we have investigated the feasibility of analyzing abdominal sounds for early meal onset detection. The MFCC and wavelet entropy-based method were explored for the detection of meal from sound signals. In our tests on a small dataset, the proposed approach detects the meals with a mean delay of 4.3 minutes with a detection accuracy of 75% in a constrained environment. In addition, our approach provides lesser response delay than the state-of-the-art CGM based approach, which achieved a response delay ranging from 30-40 minutes.

The preliminary results presented in this paper indicate that abdominal sounds may be applicable for early meal onset detection. In future work, the proposed method should be studied and validated on a larger dataset. Thereafter, it is required to test and enhance the performance of the proposed abdominal sound-based approach under more noisy and realistic conditions.

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