GutIO: Toward Sensing and Inducing Gut Feelings with Abdominal Sounds

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Abstract

Gastric interoception, the perception of gastric sensations, influences both emotions and intuition. Despite its potential for novel interaction design, gut sensing for influencing gastric interoception remains underexplored. In this work we present two initial investigations toward GutIO, gut interfaces that can sense abdominal sounds associated with gut feelings and manipulate gastric interoception through haptic feedback. We collected 12 hours of abdominal sounds from six participants watching emotion-inducing movies to identify abdominal sound characteristics corresponding to gut-feelings. Using these, we created four abdominal-sound-driven haptic feedback patterns and studied their effects on perceived gastric sensations, emotions, and intuition with 12 participants. Results showed that our haptic feedback is perceived as more realistic, and strongly influences perceptions of gastric activities. This work demonstrates the potential of detecting gut feelings through abdominal sounds and influencing gastric interoception, opening new possibilities for interaction design.

CCS Concepts

• **Human-centered computing** → *Interaction paradigms*; *Interaction devices.*

Keywords

Brain Computer Interface, gut-brain connection, emotion, gut feelings

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1 Introduction

Have you ever felt butterflies in your stomach before an important event? Is it anticipation, anxiety, or perhaps your gut's way of warning you of danger? These common sensations, often dismissed as mere quirks, are actually profound examples of how our body is communicating with us.

The gut, often referred to as the "second brain", constantly sends signals to the brain, informing it of the body's internal state. Aside from the air that we breathe in, everything else that enters our body has to go through the digestive system. Gastric signals, therefore, play a key role in the maintenance of the body's homeostasis [22]. These signals, together with signals from other internal organs, such as cardiac signals from the heart, endocrine signals from the endocrine glands, and blood glucose levels from the pancreas, comprise the interoception — the collection of internal feelings from internal organs. Interoception provides the brain with important information of the body's internal state, shaping various affective and cognitive processes [14].

The bidirectional relationship between the gastrointestinal tract (GI) and emotions is well-evidenced. On the one hand, stress and emotions have been shown to disrupt contraction and blood flow in the GI tract [2, 29]. On the other hand, gut signals influence feelings, emotions, and decision-making through the interoception pathway [4]. For instance, the sensation of "butterflies in the stomach" can be interpreted as anxiety before an exam, or romantic attraction when meeting someone new. These **gut feelings, defined as the sensations that arise from the gut area**, are more than just metaphors; they are real physiological responses that influence our emotions and decision-making [22].

Gastric signals influence and are influenced by the movements of the intestines, which in turn produce audible sounds called abdominal sounds. Abdominal sounds, therefore, represent a direct and measurable output of gut activities. These sounds reflect the dynamic state of the digestive system; their patterns can vary based on stress [7], and other physiological conditions. Abdominal sounds have been well used in the medical field to diagnose problems in the GI tract [20]. However, their use in HCI literature remains limited, and little is known about how they are related to affective states other than stress.

In this paper, we report two preliminary studies that provide first understanding about the relationship between abdominal sounds and emotional gut feelings, aiming to shed light on the potential of gut interfaces and gastric interoception in HCI. In Study 1, we investigate whether emotions indeed create detectable changes in abdominal sounds. We asked 6 participants to each watch an emotionally charged movie. The movies were between 1.5 and 2 hours long. During this time, we strapped a measuring device to their abdomen, which collected their gut's sounds during the movie. Altogether, we collected approximately 12 hours of abdominal sound recordings. We then extracted sound features and analyzed their distributions to quantify changes in their signature. Our findings show that there is a shift in abdominal sound signatures during the moments when users feel emotions and gut feelings. Based on our analysis of the acoustic features of abdominal sounds, we identified 4 clusters of abdominal sounds experienced during gut feelings and created 4 abdominal-sound-driven haptic patterns based on these clusters.

In Study 2 (n=12), we investigated the effects of these haptic patterns on users' perceived gastric sensations. We found that applying these abdominal-sound-driven haptic patterns to the abdomen area can remind users' of gastric feelings, such as an upset stomach, satiation, and hunger compared to our baseline. In this paper, we contribute with:

(1) insights into the relationship between abdominal sounds and gut feelings and the possibility of sensing emotions using sounds.
(2) insights on the ability to mimick gut feelings through abdominal-sound-driven haptic feedback.

We believe that our on-going work motivates further investigations towards gut interfaces in HCI and hope it sparks new ideas on how gut interfaces could be explored in context of affective computing applications like emotion regulation in the future.

2 Background and Related Work

2.1 Sensing Abdominal Sounds

Abdominal Sounds have been used extensively to diagnose issues in the GI tract [18, 20, 28]. Wearable devices and automated sound processing methods for monitoring abdominal sounds have recently attracted attention from the research community [6, 28, 33, 37]. Although abdominal sounds are within hearing range, they come from inside the body, and as such, their signal strength is significantly weakened by the layers of muscle, fat, and abdomen lining. A common approach to recording abdominal sounds is to use an electrical stethoscope [7, 28] or a microphone that is embedded in a traditional stethoscope/stethocsope-like device to amplify the signal [33]. The recording device is often placed in the lower quadrants of the stomach [1].

Despite the potential of this method to detect emotional states, the use of abdominal sounds in affective computing remains scarce. The relationship between abdominal sounds and stress has only recently begun to be explored, with some early work from [7]. In face of recent findings about the close connection between the gut and the brain, as well as the fact that that butterflies and hunger are often accompanied by churrings of the gut, we attempt to explore in this work whether those abdominal sounds could be sensed through gut interfaces to capture these visceral feelings.

2.2 Interoception Manipulation

While the human experience is shaped by both external and internal signals, HCI research has predominantly focused on using external sensory inputs such as sight, sound, touch, taste, and smell to create novel interactions [3, 9, 30, 38]. Recently, internal signal manipulation, such as interoception manipulation, has garnered more attention from HCI researchers and practitioners, with applications mainly in the area of emotion regulation and cognitive capacity enhancement [5, 11–13, 15, 23]. Within the space of interoception manipulation, cardiac interoception (the perception of one's own heart rate) [13] and breathing pace have been explored [15, 23, 24]. For example, [13] designed a wrist-worn device that tapped onto users' wrist rhythmically and in doing so it manipulated their perception of their heart rate. [23] changed user's breathing pace by designing a belt that provided haptic feedback that mimicked user's breathing pace and gave them guidance for their breathing exercise.

Haptic feedback has been used extensively to replicate social touch as well as to deliver affective messages [27, 32]. Work in this area has shown that haptic feedback can communicate and modulate user's affective states through thermal and particularly through vibrotactile feedack [12, 15, 35, 36, 38, 39]. Although various haptic patterns have been designed as a means to communicate affective states, they mostly convey the affective meaning of a social touch, such as stroking [17], squeezing [34, 35], or caressing [10]. Haptic patterns that replicate inner feelings such as gut feelings have not been explored yet. Our work adds new insights to this body of work by exploring how haptic patterns applied to the stomach area are associated with different physical and emotional gut feelings.

3 Study 1: Sounds of the Butterflies

The aim of this study is to evaluate the feasibility of detecting gut feeling moments from abdominal sounds. We induced emotional states in participants using emotionally charged movies and recorded their abdominal sounds. We then analyzed sound features during three types of moments: emotional gut feeling moments (emotions with felt visceral sensations), emotion-only moments (emotions without noticeable visceral sensations), and neutral moments (no emotional response). We hypothesize that if emotional gut feelings indeed create changes in abdominal sounds, we will see a significant shift in the distributions of sound features during these gut feeling moments. The larger the distance between these distributions, the more effectively they can be discriminated and detected in machine learning models, serving as a foundation for automated detection.

3.1 Participants

Six participants (4 females, 2 males) aged between 25-32 and from diverse cultural backgrounds (2 Europeans, 2 Indians, 1 Southeast Asian, 1 New Zealander) were recruited from the university pool. Participants started the study one hour after their last meal to stabalize bowel motility and reduce digestive sounds [31]. None of the participants reported having inflammatory bowel disease.

3.2 Materials

To account for cultural differences in the experience of watching movies, participants filled out a short survey prior to the study with the following questions: (1) What are the *saddest/scariest/most emotional* movies that you have ever watched? (2) On the scale of 1 to 5, how *sad/scared/emotional* do you think it would be if you were to watch it again? The movie with the highest emotional intensity was selected as movie material to be played for the individual participant. The final list of movies chosen by participants was P1: "Train to Busan" (Yeon, 2016), P2: "Past Lives" (Song, 2023), P3: "Me Before You" (Sharrock, 2016), P4: "It's Okay to Not Be Okay, Ep. 9" (Korean: Psycho but It's Okay, Park, 2020), P5: "The Conjuring" (Wan, 2013), and P6: "Midsommar" (Aster, 2019).

3.3 Method

The study was conducted in a quiet room. Upon arrival, participants were briefed on the procedure and explained the definition of gut feelings. An electronic stetoscope was mounted on the torso of the participant, with the head placed 10 cm on the left of their navel. The belt's postion and tightness was calibrated to ensure comfort to the particiapnt as well as a clear sound recording. Participants additionally wore an E4 watch[1] at their dominant arm to label their experience and record physiological signals. A Garmin watch on the non-dominant arm served as timer.

After mounting all devices, participants were instructed to comfortably sit down on a reclining chair. They were asked to meditate for 10 minutes with lights turned off and cultivate bodily awareness with focus on the abdomen area via a guided meditation video[2]. Abdominal sounds during this phase were recorded as baseline. . Afterward the participants watched the chosen movie comfortably on an Ultra High Definition 60-inch monitor without talking. Participants were told to press the event marker button on the E4 watch once whenever they felt an emotional moment without any gut feelings, or press twice if they experienced a gut feeling (a gut activity during an emotional moment). Every 10 minutes the Garmin watch buzzed, and participants were asked to report their valence/arousal using the modified Self-Assessment Manikin scale [8]. The study was approved by the university's Institutional Review Board committee (IRB Number: IRB:NUS-2024-586).

3.4 Results

The entire study lasted 2-3 hours on average and a total of 13 hours of labeled data was recorded. After processing and cleaning the data from artifacts, 11.5 hours of sound data was left for our analysis. The complete data processing procedure can be found in Appendix A.1. From the labeled data we derived three groups of sound samples: (1) **Emotional-Only (EM)** where participants did feel emotional change but no gut feelings, (2) **Gut Feeling (GF)** where participants felt emotions and gut feelings, and (3) **No Feeling (NF)** sound samples that were neither labeled as EM or GF.

[1]https://www.empatica.com/research/e4/
[2]Guided meditation video by Head Space (https://www.youtube.com/watch?v=QHkXvPq2pQE)

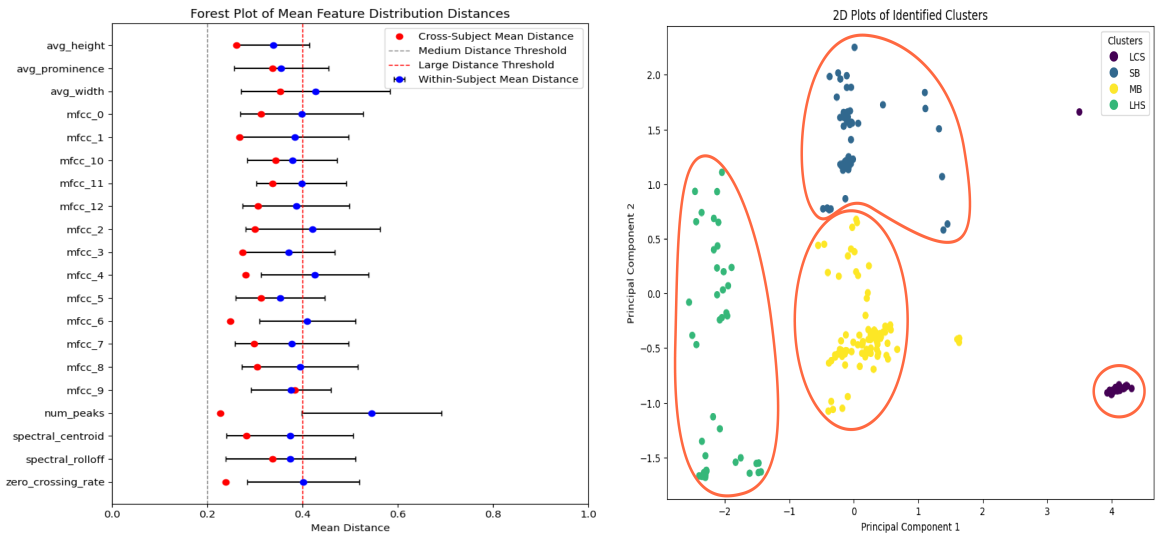
Participant	P1	P2	P3	P4	P5	P6
Emotion-Only	10	14	50	7	20	14
Gut-Feelings	9	24	11	1	17	8

Table 1: Number of Events Marked During the Movie Watching Sessions

3.4.1 Frequency of Emotional and Gut Feeling Events. The strong varience in valence (V) and arousal (A) data within individual subjects (mean $\sigma_A^2 = 1.28$, mean $\sigma_V^2 = 0.91$) show that the chosen movies were able to induce different emotional levels in the participants. Each participant reported between 8 and 61 events with an average number of $M = 30.83$ ($SD = 18.65$) marked events. On average each participant reported that 37.23% ($SD = 19.14$) of emotional events were accompanied by gut feelings. P2 reported the highest amount of gutfeeling events with 24 out of 38 labeled events (63.16%), and P4 reported the lowest amount of perceived gutfeeling events with 1 out of 7 labeled events marked as emotional and gut feelings (12.50%). Table 1 shows the numbers and types of events marked by participants.

3.4.2 Feasibility of Detecting Gut Feelings. To determine whether it could be possible to automatically recognize gutfeelings based on recorded sound data from the gut, we analyzed our samples based on 20 sound features commonly extracted from audio data to analyse their similarity and dissimilarities between 3 classes of interest. These included temporal features such as the number of peaks and the peak width, as well as spectral features such as the 13 Frequency Cepstral Coefficients (MFCC) `mfcc_0-13`, spectral centroid, and spectral rolloff (see Appendix A.2 for more details). We analysed the changes of individual features between the three groups (EM, GF, NF) by calculating their pair-wise Jensen-Shannon (JS) distribution distances[21]. This analysis is done at the cross-subject level (all participant samples), as well as at the individual subject level (samples analyze per participant). The full list of feature distribution distances can be found in Table 1 (see Appendix A.1).

We found that most features have a moderate JS-distance between the classes ($d > 0.2$) for both within-subject level and cross-subject level, except for distances between No Feeling class and Emotional-Only class of P3. Moreover, for each feature, we calculated the average distance of all 8×3=18 within-subject comparison pairs to find features that have consistent discriminative power between classes. We visualized the summary of the mean and standard deviation of JS-distance for each feature across 18 within-subject comparison pairs and contrasted with the distance of cross-subject (red dots) in Figure 1(a). Although each feature had varying JS-distances across participants, `num_peaks, avg_width, mfcc_0, mfcc_2, mfcc_4, mfcc_6` had a large mean distance between the three sound sample groups ($d >= 0.4$). Notably, `num_peaks` distributions consistently show large distances for most participants, ($JS_{num\_peaks}(NF||GF) > 0.4$ for 5 out of 6 participants), suggesting that increased gut activities took places during moments where users reported to experienced gut feelings. Our results hence hint that those features could contribute towards training a classifier that automatically recognizes gutfeelings. Interestingly, we observed a



(a) Mean within-subject Jensen-Shannon distance

(b) Gut Feeling Sound Clusters

Figure 1: (a) Forest plot for mean feature distribution distance across classes and individuals. Red dots marked the mean of distribution distances of feature when all participant's data were combined (b) Visualization of Abdominal Sound Clusters. LCS: Long Continuous Sounds, SB: Single Bursts, MB: Multiple Bursts, LHS: Long Harmonic Sounds

neutralization effect of feature distances in cross-subject: the distance between groups shrank in all features. This could indicate that a per participant calibration may help detect gutfeelings in indivdual users. Our work with regards to this is still on-going.

3.4.3 Gut Feeling Sound Characteristics. To understand the sound characteristics of abdominal sounds experienced during gut feelings moments, we clustered these gut feelings sound segments to determine their characteristics using K-mean clustering. We used Elbow method with silhouette score analysis to determine the ideal numbers of clusters. We found that 4 clusters has the right balance of stability and separation score. Analysing the sound segments at the centroid of each cluster, we found the dominant characteristics of these clusters are:

- Single Bursts: Characterised by separate high-amplitude sound bursts.
- Multiple Bursts: Characterised by multiple high-amplitude sound bursts close to each other.
- Long Continuous Sounds: Characterised by low frequency long rumbling sounds.
- Long Harmonic Sounds: Characterised by consistent harmonic frequencies.

4 Study 2: Inducing Gut Feelings

As we observed distinct characteristics of abdominal sounds during gut feeling moments, we wanted to understand whether we can use these characteristics to create haptic patterns that can influence users' perception of gut feelings.

4.1 Participants

12 participants (6 males, 6 females) aged between 22-38 years ($M = 28$) were recruited through convenience sampling. All started the study at least one hour after their last meal, reporting to be neither full nor hungry. Participants rated their gastric interoception awareness between "Poor" (2/12), "Average" (8/12), "High" (2/12), and rated their familarity with haptic feedback from "Not at all" (1/12), "Slightly Familiar" (1/12), "Moderately Familiar" (6/12) , "Familiar" (2/12) and "Extremely Familiar" (2/12) .

4.2 Haptic Patterns

Gut Feeling Patterns: The centroid segments of the identified clusters in Study 1 (see section 3.4.3) were used to create 4 sound patterns, namely: short *single bursts (SB)*, *multiple bursts (MB)*, *long continuous sound (LCS)*, *long harmonic sound (LHS)*, with a duration of 20 seconds each. We adjusted the sound intensity until we had the most naturalistic haptic feelings. We arrived at an additional 500Hz low-pass filter and a 24dB intensity reduction. The spectrograms of these patterns are included in figure 3 (Appendix A.3).

Baseline: We use white-noise as our baseline, as it possessed a full spectrum of frequencies. We used the sample white-noise showed in Wikipedia[3] and reduced the intensity to match the intensity of the sound-driven patterns.

4.3 Method

The second study was conducted in the same quite environment as the initial study. This time particiants sat down on a reclining chair[4] and different haptic patterns were rendered to the participants using

[3]https://en.wikipedia.org/wiki/White_noise
[4]https://www.ikea.com/sg/en/cat/poaeng-series-07472/

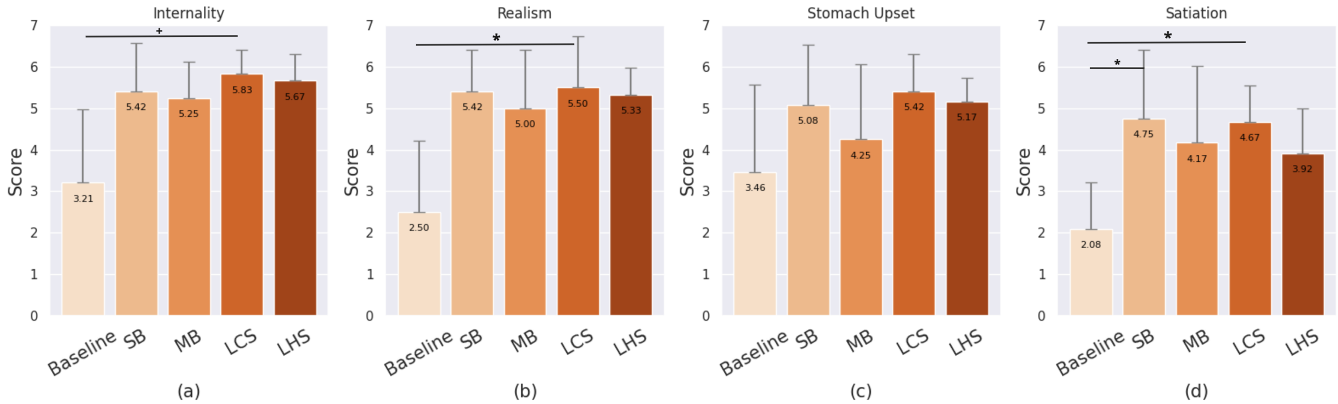


Figure 2: Score of Internality, Realism, Stomach Upset and Satiation for Baseline, Single Bursts (SB), Multiple Bursts (MB), Long Continuous Sounds (LCS), Long Harmonic Sounds (LHS) and White Noise (WN). $^{+}p < 0.06$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

two voice-coil actuators (SolidDrive SD1[5]) similar to [25]. One transducer was fixed at the back of the chair and one mounted on the participant's stomach with the help of a waist belt, right at their navel similar to the electronic stetoscope in study 1. The participants were asked to wear noise-canceling headphones playing white-noise to isolate noise from the actuators.

Participants used a laptop computer on their lap to begin the next trail and rate rendered haptic patterns based on different criteria. Upon pressing a button participants could initiate the next trail. In each trial, one out of five haptic patterns was randomly played. After playing a haptic pattern, participants rated the experience of the haptic pattern based on different critera on a 7-point Likert scale. The criteria comprised questions about:

Internality: Whether the sensations felt as if they occurred internally (inside the body). *Realism*: Whether the sensations felt natural, as if produced by their own body. *Gastric Interoception*: Whether the sensations mimicked their experiences in different gastric states, including: hunger, satiation, and stomach upset. The questions for these criteria can be found in Appendix A.3. The study ended after the participants had experienced and rated each pattern once. The order of the patterns was randomized.

4.4 Results

We use repeated measures ANOVA to find the main effect of haptic patterns; Shapiro-Wilk tests to check normality, and Friedman tests when normality was violated. Post-hoc Wilcoxon signed-rank tests with Holm correction was used to identify specific differences between haptic patterns. We plotted the score of 4 key criteria where we found significant positive results, namely: Internality, Realism, Stomach Upset and Satiation in Figure 2.

4.4.1 Internality. The average internality scores range from 3.8 (Baseline) to 5.83 (LCS). Internality scores were not normally distributed (Shapiro-Wilk test, $p < 0.05$). The Friedman test showed a significant main effect of haptic patterns on internality ($\chi^2(2) = 16.47, p = 0.0024$). Post-hoc analysis showed marginal differences in internality scores. Differences were observed between baseline and LCS ($Z = 1.25, p = 0.056$) and between baseline and LHS ($Z = 1.88, p = 0.071$).

4.4.2 Realism. The average realism scores were above neutral for all but the Baseline (M=3.42, SD=1.73). Realism scores ranged from 5.0 (MB) to 5.5 (LCS) for other patterns. The ratings of Realism did not satisfy the normality assumption ($p < 0.05$), and a significant main effect of haptic patterns and realism ($\chi^2(2)$=16.28, $p = 0.0027$) was found using Friedman test. Post-hoc analysis showed significant differences in realism scores between Baseline and LCS ($Z = 1.25, p < 0.05$), and marginal differences between Baseline and LHS ($Z = 1.25, p = 0.055$).

4.4.3 Gastric Interoception. Normality assumption was not satisfied in hunger, "stomach upset", satiation subscores of *Gastric Interoception*. Friedman tests showed no significant main effect in hunger ($p = 0.08$) or "stomach upset"($p = 0.68$), but a significant main effect on satiation ($\chi^2(2)$=18.32, $p < 0.05$). Post-hoc analysis showed significant differences between Baseline and LCS ($Z = 3.05, p < 0.05$), and marginal differences between Baseline and SB ($Z = 1.25, p = 0.050$)

5 Discussion and Limitations

In study 1, we explored a new class of affective states, namely, emotional gut feelings. Although popular in our modern society, gut feelings have not been formally induced and studied in the literature. Our study successfully induced this type of feeling through movie experiences played to the participants. Analysing the acoustic characteristic of abdominal sounds, we showed that emotions and gut feelings created a shift in sound features, evidenced in the moderate to large JS-distance of sound feature distribution between classes. This suggests that abdominal sounds could be used to detect emotional gut feelings. The findings in study 1 lend support to the emerging literature on gut-brain connection [4, 16], in which the GI tract plays the role of both the *"influencer"* and *"influencee"*. The difference between emotional class and gut feeling class points toward the nuanced differences in emotional states when they are experienced with and without gut feelings. Within the gut feeling class, we could identify four different types of abdominal sound

[5]https://soliddrive.mseaudio.com/sd-1sm-ti.html

characteristics, which could provide insights into different internal body states using future gut interfaces.

In study 2, we showed that abdominal sounds could in turn be used to influence the perceptions of gut feelings inside participants. All sound-driven patterns demonstrated high Internality scores (above 5), with the highest score for long continuous sound pattern (LCS) ($M = 5.83, SD = 0.87$). Moreover, haptic patterns derived from abdominal sounds were rated significantly higher in the score of Realism, enabling these patterns to easily blend in users' perceptions and consider the sensations to come from their own bodies. Compared to white-noise, sensations created by abdominal sounds are more likely to be perceived as satiation sensations. Together with the high Internality and Realism score, abdominal sound patterns showed promising cabability to manipulate users' gastric interoceptions. This capability could spark interesting applications in the future, such as dietary intervention (e.g., making users feel hungry or full), empathy communication (e.g. communicating users' inner feelings over the distance), immersive experiences, and many more.

Our preliminiary investigations still entail several limitations. Study 1 was conducted with a limited number of participants (n=6). Even though we recorded each participant for an extended period of time, we obtained relatively small numbers of gut feeling moments, with 11 moments per participant on average, limiting our ability to generalize the sound characteristic of all gut feeling moments. As we were mostly concered with emotional gut feelings, we do not discern the type of emotions (positive, negative, neutral) that participants reported, limiting our ability to investigate further the sutble differences in sound features in these emotional states. Our second study also consisted of a smaller number of participants (n=12), and our findings are limited to a lab setting. Although we were able to show the potential of influencing users' gastric interoception using haptic feedback, it is unclear how this feedback may influence users' emotions, perceptions, and decision-making in real-life scenarios yet. Our work therefore motivates more investigations regarding these areas. Gut sensing and stimulation devices could offer a way to interface with our body more seamlessly and intimately and explore new interesting applications such as emotion regulation or dietary intervention in the field of HCI and affective computing in the future.

6 Conclusion

In this paper, we showed that emotions (with and without gut feelings) create detectable changes in abdominal sounds, laying the foundation to use abdominal sounds as a new modality to detect emotional gut feelings. Secondly, we were able to extract distinct characteristics of gut feeling moments and use this understanding to create haptic patterns that could effectively mimick familiar gastric experiences. The findings of our studies encurage future work to explore gut interfaces as a new modality for sensing emotions and interacting with inner feelings through sensations in the abdomen.

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A Appendix

A.1 Data Preprocessing

A total of 13 hours of data were recorded. Audio segments that were heavily contaminated by the environment (e.g., background conversations, rustling sounds, movement artifacts) were removed manually. After cleaning, there were 11 hours of clean sound data. Following prior works [19, 28], we applied a second-order Butterworth filter on our data with a lowpass cutoff at 2000 Hz and a highpass cutoff at 50 Hz. The choice of the cutoff is due to the fact that the frequency range of abdominal sounds is 50 Hz to 2000 Hz [1, 26]. We divided the data into 20-second segments with a sliding window of 1 second (i.e. 19 seconds overlaping between 2 consecutive segments), which resulted in a total of 40,787 audio segments. We assigned the labels for these audio segments as follows: NF (no feeling) if there were no event marked; GF (gut feeling) if there were two event markers within the segment; EM (emotion only feeling) if only one event is marked within the segment. We had a total of 37185 NF segments, 1420 GF segments and 2182 EM segments.

A.2 Feature Extraction

We obtained the spectrogram of each audio segment and computed 20 standard temporal and spectral features using `scikit-learn` and `librosa` libraries in `python`. These features include:

(1) Temporal features: number of peaks in the energy envelope (`num_peaks`), average peak height (`avg_height`), average peak width (`avg_width`), average peak prominence (`avg_prominent`),
(2) Spectral features: 13 Mel Frequency Cepstral Coefficients (MFCC) featrues (`mfcc_0-12`), spectral mass centroid (`spectral_centroid`), zero crossing rate (`zero_crossing_rate`) and spectral roll off (`spectral_rolloff`).

A.3 Sound Patterns

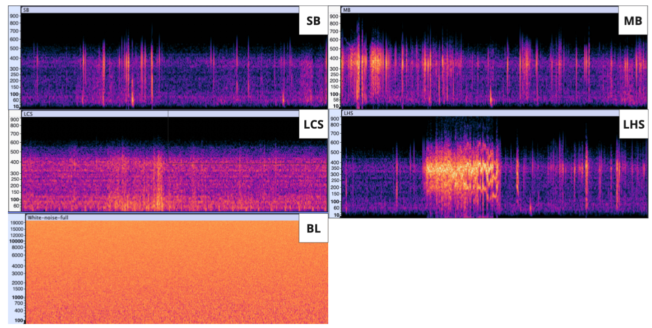

Figure 3: Spectrograms of haptic patterns used. BL: Baseline, SB: Single Bursts, MB: Multiple Bursts, LCS: Long Continuous Sounds, LHS: Long Harmonic Sounds

A.4 JS Distance

A.5 Questionnaire

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Feature	P1			P2			P3			P4			P5			P6			ALL		
	NE	NG	EG	NE	NG	EG	NE	NG	EG	NE	NG	EG	NE	NG	EG	NE	NG	EG	NE	NG	EG
avg_height	0.30	0.31	0.33	0.29	0.24	0.30	0.24	0.40	0.28	0.31	0.52	0.44	0.37	0.35	0.26	0.29	0.44	0.43	0.35	0.23	0.21
avg_prominence	0.29	0.33	0.33	0.29	0.28	0.31	0.18	0.34	0.25	0.44	0.52	0.45	0.44	0.49	0.25	0.27	0.50	0.44	0.45	0.33	0.23
avg_width	0.52	0.51	0.44	0.45	0.29	0.40	0.14	0.30	0.24	0.51	0.77	0.71	0.32	0.36	0.24	0.47	0.52	0.52	0.47	0.24	0.35
mfcc_0	0.45	0.58	0.54	0.30	0.21	0.32	0.21	0.32	0.32	0.47	0.59	0.60	0.29	0.23	0.31	0.45	0.43	0.54	0.28	0.27	0.38
mfcc_1	0.41	0.47	0.51	0.37	0.28	0.36	0.18	0.29	0.30	0.43	0.62	0.60	0.36	0.29	0.29	0.32	0.34	0.47	0.28	0.26	0.27
mfcc_10	0.34	0.38	0.39	0.38	0.24	0.35	0.18	0.29	0.35	0.33	0.55	0.58	0.37	0.38	0.34	0.41	0.45	0.49	0.27	0.38	0.37
mfcc_11	0.41	0.34	0.30	0.30	0.35	0.38	0.38	0.37	0.24	0.44	0.63	0.61	0.38	0.38	0.44	0.33	0.42	0.45	0.28	0.34	0.39
mfcc_12	0.36	0.26	0.37	0.35	0.27	0.39	0.26	0.39	0.34	0.34	0.62	0.60	0.33	0.28	0.32	0.40	0.57	0.52	0.30	0.27	0.34
mfcc_2	0.33	0.57	0.58	0.44	0.30	0.43	0.16	0.28	0.27	0.47	0.64	0.59	0.26	0.31	0.33	0.51	0.55	0.57	0.31	0.26	0.33
mfcc_3	0.33	0.39	0.30	0.33	0.38	0.35	0.23	0.32	0.36	0.36	0.59	0.60	0.32	0.34	0.22	0.35	0.42	0.45	0.26	0.31	0.25
mfcc_4	0.33	0.51	0.49	0.36	0.26	0.43	0.40	0.37	0.32	0.45	0.71	0.59	0.40	0.47	0.26	0.35	0.54	0.42	0.30	0.21	0.33
mfcc_5	0.30	0.36	0.32	0.35	0.29	0.40	0.15	0.27	0.29	0.34	0.53	0.58	0.30	0.34	0.38	0.42	0.34	0.38	0.40	0.24	0.29
mfcc_6	0.35	0.40	0.51	0.43	0.33	0.35	0.33	0.45	0.38	0.50	0.63	0.54	0.27	0.32	0.31	0.28	0.50	0.50	0.19	0.28	0.27
mfcc_7	0.38	0.46	0.53	0.34	0.27	0.28	0.17	0.23	0.21	0.35	0.62	0.59	0.39	0.35	0.36	0.41	0.40	0.45	0.32	0.24	0.34
mfcc_8	0.29	0.38	0.43	0.31	0.33	0.27	0.19	0.32	0.30	0.41	0.63	0.59	0.33	0.39	0.31	0.53	0.52	0.57	0.29	0.25	0.38
mfcc_9	0.29	0.50	0.46	0.36	0.29	0.41	0.20	0.29	0.36	0.30	0.51	0.49	0.34	0.36	0.40	0.33	0.43	0.45	0.44	0.31	0.40
num_peaks	0.43	0.58	0.59	0.57	0.49	0.57	0.23	0.32	0.32	0.61	0.52	0.44	0.77	0.59	0.67	0.67	0.67	0.76	0.27	0.14	0.27
spectral_centroid	0.38	0.38	0.30	0.53	0.29	0.39	0.14	0.27	0.29	0.57	0.67	0.57	0.21	0.31	0.35	0.26	0.39	0.40	0.34	0.29	0.21
spectral_rolloff	0.31	0.36	0.32	0.44	0.37	0.37	0.15	0.27	0.29	0.65	0.70	0.53	0.20	0.31	0.35	0.30	0.43	0.38	0.27	0.37	0.37
zero_crossing_rate	0.34	0.27	0.38	0.46	0.39	0.54	0.17	0.22	0.26	0.48	0.61	0.60	0.41	0.48	0.39	0.42	0.34	0.44	0.23	0.27	0.22

Table 1: JS distance (JSD) between emotion class distributions for within-subject (P1-P6) and cross-subject(ALL). NE: JSD between No feeling class and Emotion only class; NG: JSD between No feeling class and Gut feeling class, EG: JSD between Emotion-only class and Gut feeling class.

Category	**Type**	**Statement**: This feels like the feeling that I have when
Gastric Interoception	Hunger	I am hungry
	Stomach Upset	I feel my stomach is upset
	Satiation	I am full and my stomach is digesting food

Table 2: Categories, Emotions, and Corresponding Questions