Towards Modeling Human Biorhythms Using Non-Invasive Approaches

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***Abstract*—Biorhythms in humans hold vital importance that is directly related to a person's health and well-being. This paper introduces a novel dataset for modeling biorhythms while focusing primarily on using an ingestible pill to monitor core body temperature and four physiological signals. We use two different settings to label our data to develop different scenarios of energization and enervation. We propose an approach that could potentially act as a reliable alternative to the usage of core temperature pills and genome sequencing while avoiding their invasiveness and complexities. We also explore the effect of the data size on the overall performance. Our findings indicate that our proposed approach is reliable and feasible, and presents future promise in using less invasive approaches to monitor and predict the circadian state of humans.**

***Index Terms*—multimodal dataset, circadian state detection, physiological sensors, ingestible core body temperature pill, machine learning classification**

I. Introduction

Projections estimate that by 2030, nearly 14% of all Americans might be diagnosed with some type of diabetes [1] and that nearly one out of two Americans will have obesity [2]. Multiple studies have shown that disruptions to the human body's circadian clock are linked to increased risks of diabetes, obesity, and cardiovascular diseases [3], [4]. This has led to a rise in developing means to better model various aspects of the human state, with the global wearables market reaching $26.8 billion in 2022 alone, with COVID-19 accelerating adoption trends even further [5]. Circadian rhythms that dictate physical and mental changes over a 24-hour period in humans are hence of particular interest, as better understanding could lead to better treatments for sleep disorders, jet lag, mental health disorders, and obesity, among others [6], [7]. Accordingly, we are motivated to analyze and model human biorhythms in this research.

Currently, modeling the circadian state requires intensive genome-sequencing approaches to identify [8], which is not feasible on a wider scale. Similarly, measurements of compounds in saliva have also been shown to model circadian rhythm but require sampling of saliva whenever a subject's circadian state is to be determined [9]. The usage of core body temperature pills has been identified as another alternative to monitor temperatures and identify circadian rhythms in firefighters [10]. Research by Khals et al. also demonstrated that core body temperatures are impacted by the circadian state [11]. While approved by the Federal Drug and Food Administration, the pills themselves are invasive, expensive, and prone to unforeseen complications as well [12]. However, most of this research was conducted in the context of medical-based studies, where highly sophisticated and relatively costly laboratories are required to model these states and apply such invasive approaches. Motivated by the aforementioned challenges and the lack of proper alternative approaches, this research aims to find other means to model the circadian state through physiological signals using surface-contact-based sensors that are not invasive, safer, and cheaper to deploy at larger scales.

While past research has primarily focused on using machine learning via features extracted from gene sequencing, to our knowledge, our research is the first to model biorhythms in an everyday setting using multiple modalities and supervised machine learning in order to classify a subject's current circadian state. Our analysis indicates that our suggested alternative methods are reliable and promising, and present a major step in feasible monitoring of biorhythms. In particular, this paper presents four main novel contributions:

- A multimodal dataset that captures visual, audio, thermal, and physiological data, as well as a variety of surveys related to sleep, behavior, and demographics across 16 subjects spread across multiple sessions to model circadian state,
- Monitor core body temperatures across 12 of the subjects alongside the above-mentioned modalities through an ingestible pill as they conduct their activities over the course of a day,
- A systematic procedure to monitor four physiological signals to use in the modeling and classification of human biorhythms,

- Analysis and comparison of modeling the circadian state through a time-based hypothesis and self-reported sleepiness score using the ingestible pill and the physiological sensors.

II. Related Work

Research has been conducted to monitor and analyze human biorhythms. Genome sequencing approaches were used to identify changes in the genes that regulate the body's rhythmic clock [13], However, the approach is limited due to the need to collect tissue samples to determine any disruptions. Other approaches through the means of using saliva to analyze the periodicity of clock genes were used to model the periodic nature of circadian rhythm [14]. However, their usage is still limited because of the need to collect samples and to have specific equipment and resources to properly analyze them. A common limitation also lies in the inability to continuously monitor the state of the subjects.

The use of core body temperature measurements was hence explored, with research by Refinetti and Menaker having established that core body temperatures are affected by circadian rhythms [15]. McKenzie and Osgood determined that core body temperature monitoring pills could be used to effectively monitor core body temperature, performing as accurately as rectal thermometers, while also being more acceptable by patients [16]. Coyne et al. also used ingestible pills to monitor body temperatures to determine menstrual cycles by detecting changes in circadian rhythms [17]. This approach could not provide more instant depictions of the circadian state, focusing more on the cyclic variations over a longer timeframe instead. While accurate when administered correctly [18], there are significant financial costs, invasiveness, and limitations associated with using a pill for monitoring the subject state reliably [19].

Furthermore, usage of these pills has been limited to controlled lab assessments [16], specific applications in sports [10], [20], or in direct temperature applications such as providing a ground truth [21]. We aim to present our dataset which consists primarily of college students while they engage in everyday activities to be more representative of the expected core temperature data in normal circumstances.

Work by Slywia et al. explored the effect of circadian rhythms on physiological signals [22] to allow for less invasive means of monitoring. There have also been attempts to better model human states in applications, such as emotion, alertness, stress, deception, drowsiness, and distraction detection [23], among others, through physiological sensors and noncontact modalities, such as audio and vision [24] and other means [25]. However, existing Work is quite limited in modeling the biorhythms through physiological sensors or non-invasive approaches in general.

III. Dataset

We assembled a dataset from 16 diverse subjects in a simulated setting, approved for research by the University of Michigan's institutional review board. This approval included using a core body temperature monitoring pill for consenting subjects. The subjects were required to come in for a total of six recording sessions, as described in Table I. Morning sessions were planned for 90 minutes after waking, between 7-11 AM. Evening sessions, typically post-work and sunset were set for 8 hours post morning session, between 5-9 PM. Baseline and afternoon sessions, typically 11 AM-4 PM, were flexibly arranged based on the subject's preference. The initial session was the baseline, with the remaining sessions arranged as needed in the following days/weeks. One set of morning and evening sessions constituted a dual session on the same day, while other sessions were on different days for diverse data collection.

TABLE I
Recording Setup

Session Type	Session Time	Recording Type
Baseline		2 minute Baseline Recording
Single Session	Morning Evening Afternoon	2 minute Silent Recording, 5 minute Active Recording
Dual Session	Morning Evening	
	6 Sessions Total	37 minutes of Data Collected

Subjects were instructed to avoid caffeine, alcohol, and drugs prior to and during the two-week recording period to ensure accurate measurements. We recorded various modalities to capture a broad scope of features, including hardware such as multiple RGB and thermal cameras, a Lavalier mic, four physiological sensors, and an ingestible sensor pill. Recordings took place in a climate-controlled lab to maintain constant temperature, humidity, and lighting. The first session required subjects to sit silently for at least two minutes. Subsequent sessions involved silent behavior (quiet sitting and natural breathing for at least two minutes) and active behavior (five-minute free-flowing dialogue on any topic). This ensured data capture during both silence and conversation at various times.

Subjects also had to sign consent forms to authorize the usage of their data. Additionally, throughout a subject's set of recordings, they were required to fill out multiple surveys pertaining to their demographics, sleep and activity patterns, and emotion and tiredness levels. Of these, the most pertinent ones are the Karolinska Sleep Questionnaire (KSQ) [26] taken at the baseline recording session, and the Karolinska Sleepiness Scale (KSS) [27] taken at every non-baseline recording session. The physiological signals and core body temperature pill data are the main focus of this paper and are explained in further detail in Sections III-A and III-B.

In total, we collected 16 baseline recordings, and active and silent recordings for 16 subjects across 48 morning sessions, 48 evening sessions, and 16 afternoon sessions. Out of those, 12 subjects who took the temperature monitoring pill had 12 sessions each in the morning and evening, for a total of 24 sessions, concurrently with their core body temperature transmitting data as well.

A. Physiological Signal Monitoring Setup

All physiological signals were captured using the Biograph Infiniti physiological modality recording suite from Thought Technology, capable of recording the following signals:

1) Blood Volume Pulse (BVP) - 2048Hz
2) Respiration Rate - 256Hz upscaled to 2048Hz
3) Skin Conductance - 256Hz upscaled to 2048Hz
4) Skin Temperature - 256Hz upscaled to 2048Hz

The respiration rate sensor was fastened to the subject's midsection, while the other sensors were attached to the non-dominant hand of the subject. The Bio Infiniti software automatically upscales the sampling rate of the respiration, skin conductance, and skin temperature sensors to align with the higher sampling rate of the heart rate sensor.

B. CorTemp Pill Temperature Monitoring Setup

Of the 16 subjects, 12 ingested the CorTemp pill, a core body temperature sensor from HQ, Inc. This pill wirelessly transmits temperature data in Fahrenheit (°F) every 10 seconds to a belt-worn device. Subjects ingested the pill an hour before bedtime on the night before dual recording sessions, then activated the recorder and wore the belt to collect data. Despite some data losses due to movement, the high transmission rate ensured sufficient data capture for our analysis.

Subjects wore the belt overnight and during the next day for simultaneous session data and temperature recording. They also noted events like eating, drinking, exercising, and belt-off times via a number pad on the recorder, as it was hypothesized these could change the body temperature. The recorder and belt were returned post-evening session or the next day. The ingested pill safely passes through the digestive system in 1-2 days.

IV. Methodology

A. Physiological Signals Feature Extraction

From the BVP signal, we extracted 49 features including ten from the inter-beat intervals, three from the raw BVP amplitude, 12 related to heart rate (HR) and heart rate variability (HRV) temporal statistics and specific frequency-related data, and 24 depicting spectral power stats from various frequency bands (<0.04 Hz, 0.04-0.15 Hz, 0.15-0.4 Hz). Power-related statistics like total power, mean, standard deviation and power percentages were calculated per band. A total of 18 statistical features to model the temporal behavior of the respiration, skin conductance, and skin temperature channels are extracted as well. Finally, four statistical features to model the combined behavior of the heart rate and respiration rate signals are extracted to make a total of 4 core signal features and 73 extracted features.

The physiological data was segmented into 4-second and 8-second sequential segments using a sampling rate of 16Hz, which were chosen after a hyperparameter search to determine suitable segment sizes. This agrees with past literature that states that smaller segments model physiological signals better [28], [29] and also allows for efficient classification of a subject's state. Each segment represents one data point which was the mean value for each of the core and extracted features. Table II lists the number of data points extracted for all recording sessions across all 16 subjects and all sessions as well as for the sessions that coincide with the core temperature pill data collection.

TABLE II
Number of data points for Physiological Signals

	All Recordings (16 subjects, All Sessions)		Recordings w/ Pill (12 subjects, Dual Session Only)	
Segment Size	Time 2-Class	KSS Labels	Time 2-Class	KSS Labels
4 seconds	8005	10613	1415	2876
8 seconds	3939	5219	1415	2876

B. CorTemp Pill Temperature Data Processing

Data stored in the recorder is extracted using the CorTrack II program to extract relevant temperature and event data per subject. Table III shows the mean core body temperatures that were recorded across the 12 subjects across different time spans. We see that on average, the core body temperature is lower during the night, likely when the subjects were asleep than during the day by around 1.2 °F. All subjects had a recorded lower body temperature at night. We also see that the core body temperature tends to rise slowly over the course of the day, with a 0.252 °F average increase between the first and second halves of the day. This agrees with the literature that also measured a drop in body temperatures at night [30], [31].

TABLE III
Recorded Mean Core Body Temperatures across 12 Subjects

	Night (Before 8AM)	Day (After 8AM)	Day - 1st Half (8AM-2PM)	Day - 2nd Half (2PM-8PM)
Mean Temp.	97.698	98.943	98.884	99.136

After processing the extracted temperature data and in order to use this data for classification, we took all the pill temperature data that occurred within an hour window (± 30 minutes) of the morning and evening dual sessions that were recorded in the lab for the day. This was done in order to have a fair comparison between the performance of the core pill data and the proposed physiological signals using machine learning. For each corresponding lab (morning/Evening) session's window, we calculated a single data point of the pill core temperature with the mean, standard deviation, minimum value, maximum value, 25% percentile value, and 75% percentile value of the temperature data recorded to form six extracted features. This gave us a total of 12 data points each for the morning and evening sessions for 12 subjects.

C. Experimental Setup

Two hypotheses were used to model the circadian state of a subject through their energized and enervated levels to use as target labels, for a total of five types of labels:

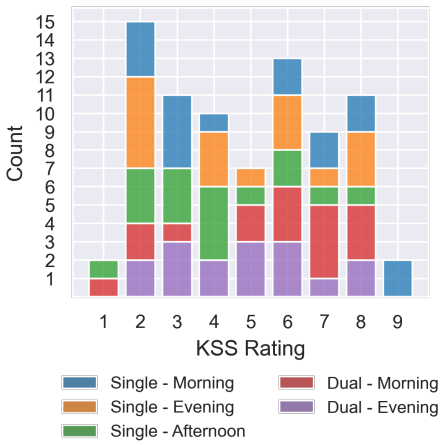

Fig. 1. Self-reported KSS Sleepiness Rating (Extremely Alert (1) to Very Sleepy (9))

1) Time - The Time 2-Class label assumes that subjects in the morning are more energized, and are enervated by the end of the day. This was reasoned to apply as our primary demographic of subjects was college students with full schedules comprising of courses and part-time work. This is correlated with the KSQ survey responses where a majority of the subjects reported wake-up times between 7-8 AM, and bedtimes to be between 11 PM to 12 AM. This setting is also verified and confirmed with Medical School faculty at the University of Michigan who are active in conducting sleep-based research.
2) KSS - Subjects were asked to rate their sleepiness level from a scale of 1 (Extremely alert) to 9 (Very sleepy) each session. The distribution of the KSS ratings can be seen in Fig. 1. Using this self-indicated rating, we construct two binary and two trinary classification schemes as follows:
    a) KSS 5-4 - Scores from 1 through 5 are considered to be energized, and 6 through 9 are considered to be enervated.
    b) KSS 4-D1-4 - Scores from 1 through 4 are considered to be energized, and 6 through 9 are considered to be enervated. Sessions, where subjects recorded a score of 5 (Neither sleepy nor alert), would be discarded from the dataset.
    c) KSS 4-1-4 - Scores from 1 through 4 are considered to be energized, and 6 through 9 are considered to be enervated, with those with a score of 5 forming a third 'neutral' state of neither energization nor enervation.
    d) KSS 3-3-3 - Scores from 1 through 3 are considered to be energized, scores from 7 through 9 are considered to be enervated, and scores from 4 through 6 are considered to be a third 'neutral' state of neither energization nor enervation.

It should be noted that the Time 2-Class label is balanced in the ratio of 2:2:1 for the Morning:Evening:Afternoon split as a result of the experimental setup for the recordings. Since KSS ratings were self-reported by the subjects, their distributions are hence more imbalanced across their splits. It could also be noted that interestingly some subjects labeled their morning recording as "(9) Very Sleepy" and vice versa. This was another motivation why we used different labeling settings to be able to address these interpersonal variations.

We tested three supervised machine learning models, a simple baseline classifier to provide a baseline reference, a random forest classifier (RF) [32], and a gradient-boosted classifier (XGB) [33]. A Leave-One-Subject-Out Cross Validation (LOSO CV) data split was used, where for each fold, all of the data of one subject was used in testing, while the rest of the data from the other subjects were used in training. This implies that the classifiers would have to classify data for a subject never seen before in any way during training.

V. Experimental Results & Analysis

To compare the performance of the physiological signals against the core body temperature, we used one slice of our data consisting of the 12 subject's core body temperatures that corresponded to the morning and evening physiological recordings as shown in Fig. 2. Furthermore, to understand how having more data might affect the overall performance, we compared the performance of the physiological signals when using the smaller 12-subject subset of the data against the full set of physiological data for all 16 subjects and all recordings as shown in Fig. 3.

Fig. 2. Performance metrics for classification for CorTemp Core Body Temperature versus Physiological Signals (12 Subjects).

In Fig. 2 and Fig. 3, we plot the accuracy, mean recall, and mean F1 score for each target label to visualize the performance. We use recall to determine the sensitivity of the classifier, with a higher recall score indicating that the number of true positives is higher. The F1 score is calculated as the harmonic mean of precision and recall, which gives us the most balanced representation of accuracy for a classifier, even in the cases of imbalanced datasets. A higher F1 score is hence the strongest metric to determine the performance of a classifier. The different modalities are represented in different hues, and the classifier type is represented using different marker styles.

A. Core Body Temperature Vs. Physio. Signals Classification

In Fig. 2 we observe that the CorTemp pill performs very well against the Time 2-Class label with a mean F1 score of over 80% with the RF classifier. The physiological 4-second segmented signals achieve a ∼71.6% mean F1 score using the XGB classifier. This demonstrates the viability of using physiological signals as a method to identify a subject's state as a much less invasive approach compared to taking a temperature monitoring pill.

We also observe a similar trend when using the KSS labels, as in the binary KSS 5-4 label where the CorTemp pill has a mean F1 score of ∼69.3% using the RF classifier, while the physiological 8-second segmented signals using the XGB classifier has a mean F1 score of ∼55.68%, which are both significantly higher than the baseline of ∼39.2%. Interestingly, for the trinary KSS 3-3-3 label, the physiological 8-second segmented signals using the XGB classifier even outperforms the CorTemp pill, with a mean F1 score of ∼48.2% compared to ∼43.3% against a baseline of ∼21.4%.

TABLE IV
SELF-REPORTED KSQ CHRONOTYPE AND MEAN KSS SCORES

Self-reported Chronotype	Count	Mean KSS Score	
		Morning	Evening
Extreme morning type	2	5.5	7
More morning than evening type	2	5.5	5
Neither morning nor evening type	5	6.4	4
More evening than morning type	2	4.5	3
Extreme evening type	1	7	7

The lower performance when using KSS labels could be attributed to a possible dissonance between a subject's self-reported rating, versus their self-reported chronotype from the KSQ survey they took during the baseline session. From Table IV, we see that self-reported chronotypes do not line up with the expected changes in KSS scores for the 12 subjects who took the body temperature monitoring pill. For example, the subjects who reported themselves to be of the "Neither morning nor evening type" had a higher mean difference in their KSS scores compared to those who reported themselves to be "More evening than morning type". We also see that subjects who reported themselves as "More morning than evening-type" would self-report being slightly more tired during their morning session than in the evening session. Furthermore, subjects irrespective of chronotype tended to only report themselves to be more tired than alert for the morning sessions. This indicates that there could be inconsistencies in how they perceived their energy levels over the course of a day, making the KSS label harder to model as a means to detect circadian state, especially with a smaller number of subjects.

B. Effect of Concatenated Dataset Vs. Full Dataset for Classification using Physio. Signals

In Fig. 3 we see that for the Time 2-Class label, having more data does not correlate to better performance, as the physiological 4-second segmented signals using the full dataset using the RF classifier drops to a mean F1 score of ∼60.4%. Moreover, both RF and XGB classifiers are meta-classifiers

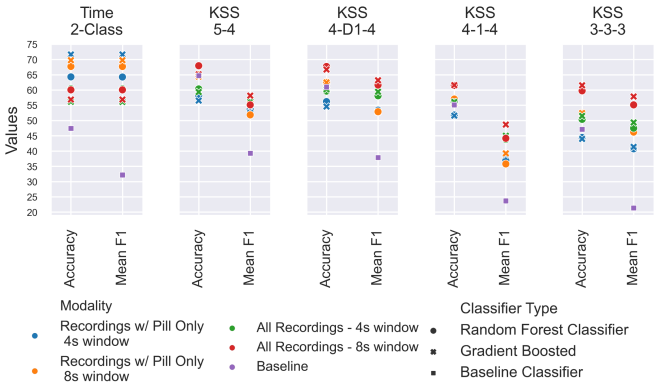

Fig. 3. Performance metrics for classification for Physiological Signals Limited to Recordings w/ Pill versus All Recordings (16 Subjects).

that avoid overfitting the data. The lower performance can be likely attributed to the nature of the LOSO CV approach, where having more distinct subjects in the training dataset also results in the over-generalization of the knowledge the classifier can extract from the features. This subsequently causes the model to perform worse when attempting to classify a subject's data not seen before in training. It also highlights the significant effect of inter-personal variations on developing global models.

Similarly, we do not see a significant gain in performance for the KSS 5-4 label with the mean F1 score being ∼58.1%, when using physiological 8-second segmented signals with the full dataset and XGB classifier. As discussed previously, this is likely due to the KSS label being a product of a self-reported score that does not match the subject's chronotype.

VI. CONCLUSION

Our research aims to model biorhythms non-invasively, avoiding restrictive and invasive methods, such as genome sequencing, saliva sampling, or temperature monitoring. We offer a novel, cost-effective, and large-scale applicable method using surface-contact sensors. Significantly, we built a dataset of 16 subjects' physiological and behavioral parameters, including the core body temperatures of 12 subjects from an ingestible pill. We propose a systematic protocol to observe four specific physiological signals for the modeling and classification of human biorhythms. Lastly, we conducted a preliminary analysis and comparison of our method against using the core body temperature monitoring pill to model and classify the circadian state.

Our mean F1 score for the Time 2-Class label exceeded 80% and about 69.3% for the KSS 5-4 label using the pill; for physiological 4-second segmented signals, the scores were approximately 71.6% and 55.68%, respectively. Despite core temperature pills yielding higher performances, our approach generates closely comparable results while avoiding the pills' associated challenges and invasiveness. Moreover, our results indicate that additional data might not necessarily contribute to better performance due to the noticeable interpersonal variations between the subjects, guiding us toward future

personalization exploration. The Time label outperformed the KSS label, suggesting self-reported scores might be inaccurate due to potential energy evaluation difficulty or confusion around individual biorhythms.

VII. Future Work

Our future work will aim to enhance performance using deep learning, examine the effects of personalization and data splits to optimize model training, and train models using specific sessions while testing other sessions and days for the same subject. Furthermore, We aim to create multimodal and non-contact methods using collected audio, visual, and thermal modalities for the comprehensive detection of human biorhythms.

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