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Exploring the Potential of a Wrist-Worn Optical Sensor for Measuring Daily Life Activities

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Profile

Tomoko　Funayama

- Occupational therapist.
- Experience with Therapy: For the disabled and older people in hospitals, nursing homes, and their homes, I worked.
- Current affiliation: Department of Occupational Therapy, Faculty of Medical Sciences, Teikyo University of Science.
- Research: I have been researching with engineering specialists on the use of digital wearable devices to support people with disabilities.
  - ➢ Step Measurement Using a Household Floor Mat and Shoe Sensors, T. Funayama, Y. Uchida, and Y. Kogure, International Journal on Advances in Life Sciences, Vol. 15, No. 1 & 2,Issue 5, pp. 33-43, 2023.
  - ➢ Monitoring of Daily Health-condition with WearableDevice and Network, T. Funayama, Y. Uchida, Y. Kogure, Rehabilitation International 24th World Congress,2022
  - ➢ Application of the human-machine interface technology to occupational therapy, T. Funayama, N. homma, Y. Kogure, Y. Uchida, 16th International Congress of the World Federation of Occupational Therapists, 2014

Our Projects

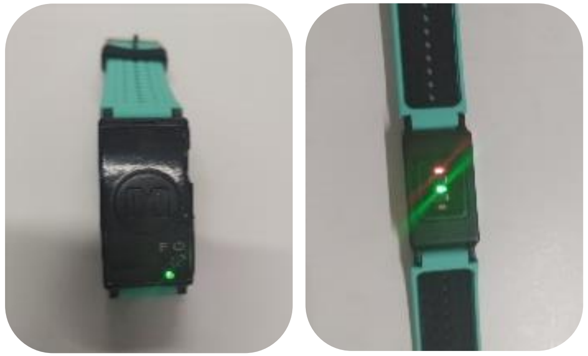
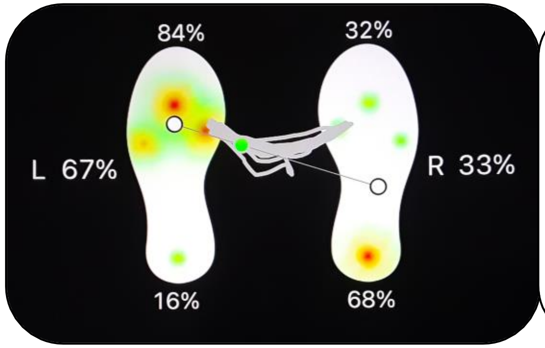


Figure 1. Wristwatch type optical and acceleration sensors

We have been researching the assessment of physical activity using digital wearable devices for individuals with disabilities and health concerns. This research is conducted in partnership with occupational and physical therapists from hospitals, experts in human-machine interfaces (HMIs), specialists in data processing, medical doctors, and other professionals.



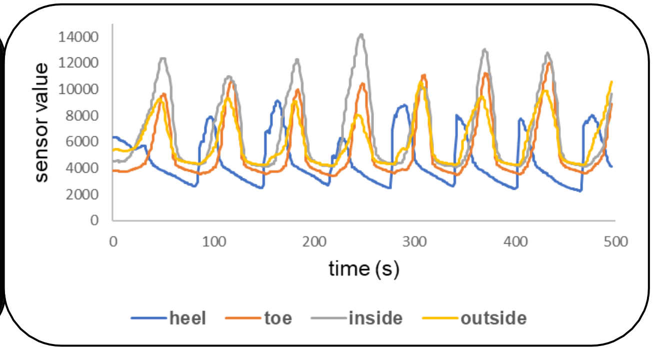


Figure 2. Smart Insoles

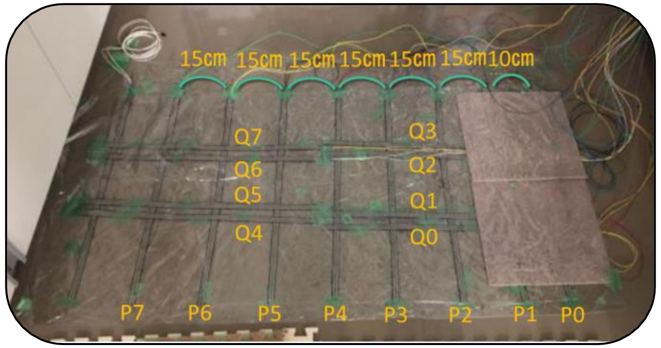


Figure 3. Floor mat type pressure sensor

Introduction / Purpose

- To enhance the quality of life for individuals with health-related issues, it's crucial to examine the reciprocal relationship between health conditions and daily activities and make necessary adjustments.
- Life activities are not inherently categorized as good or bad for one's health; they depend on factors such as health condition, activity intensity, habits, adaptation, and environment.
- Recently, wearable sensors have been developed and commercialized for monitoring and supporting older adults and individuals with health issues.
- In this study, we conducted an exploratory investigation using a wrist-worn wearable device equipped with optical sensors in the context of individuals' daily routines.
- Purpose: We studied the heart rate and Fourier analysis and examined the relationship between the condition and activity. We suggest certain aspects of the measurement methodology for use during daily activities.

Experimental Method

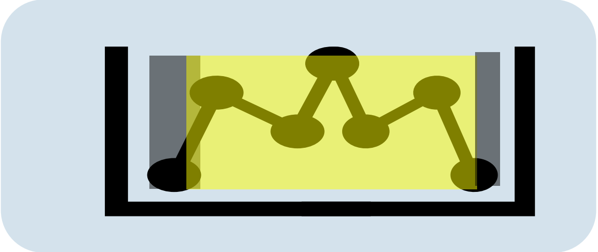
Devices

- **Device Used for Measurement:** Maxim Integrated MAXREFDES103.
- **Optical Lights:** Green, red, and infrared LEDs. Green LED produces green and green2 data.
- **Heart Rate Calculation:** Calculated and provided as a value using MAXREFDES103.
- **Data Content:** Includes three-axis accelerometer data (x, y, z). Heart rate. SpO2. Timestamps.
- **Sampling Frequency:** 25 Hz.
- **Data Sources Used :** Green light sensor data. Heart rate. Timestamps.

MAXREFDES103

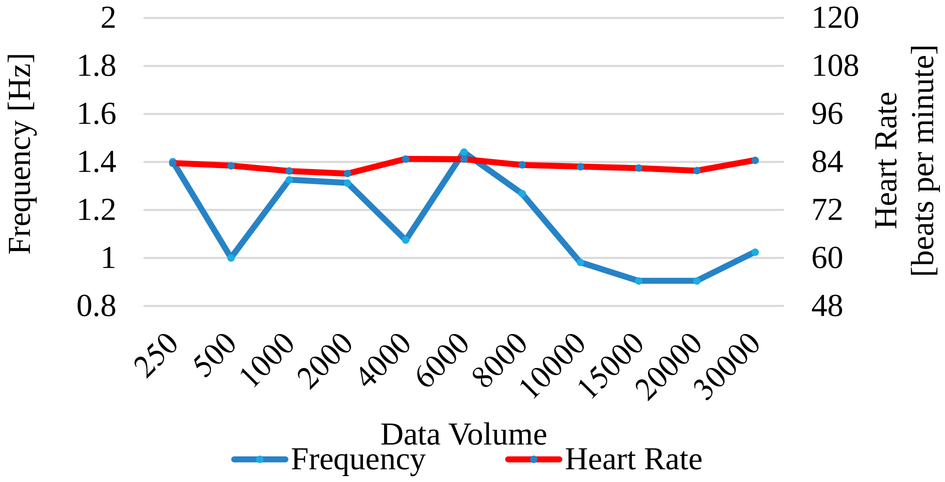
Measurements

- The subject, a man in his 60s, used a MAXREFDES103 device to measure his daily life activities, as determined by his judgment. Simultaneously, corresponding situations were recorded.
- Self-perceived health conditions, stress levels, activity details, duration, and location from Google Form records were used. Health conditions and stress levels were rated on a scale of 1 to 10, with a free-text field.
- The initial two minutes, comprising 3000 data points, and the final 1000 data points from the device were excluded. Fourier analysis was performed using the numpy.fft.fft function in Python.



RESULTS

Data Interval Used for Analysis



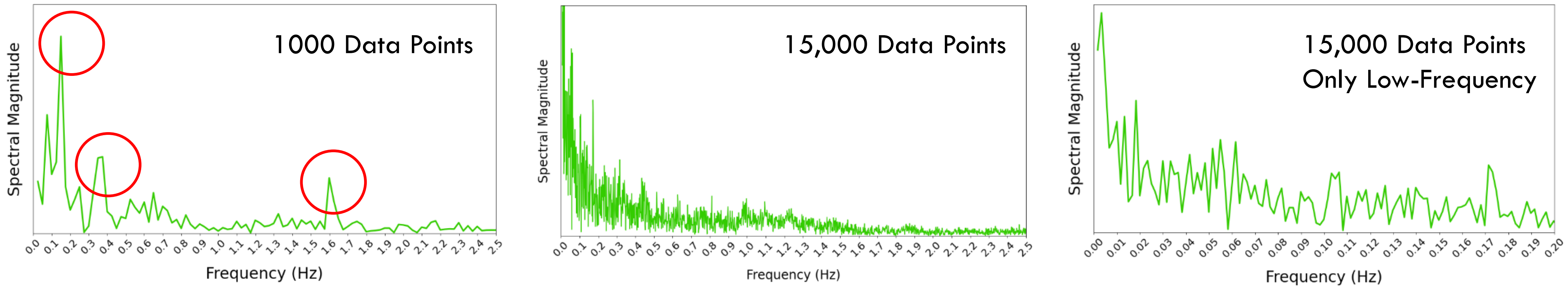
0.9-2.5 Hz Frequency at maximum spectral and heart rate.

- During daily activities, extensive measurements generate a large dataset.
- We divided this data and identified heart rate-influenced frequencies using Fourier analysis in the 0.9 Hz to 2.5 Hz range. These frequencies were compared to device-calculated heart rates.

- Data division occurred at intervals of 250 to 30,000 data. With more data points, the device-calculated heart rates diverged from the actual ones. With 250 data points, heart rates closely matched, often up to 1000 points. However, beyond 2000 points, inconsistencies arose.
- Factors contributing to this include longer measurement times, a greater variety of heart rates, and the influence of Fourier analysis, aside from the heart rate mixing at 0.9-2.5 Hz.

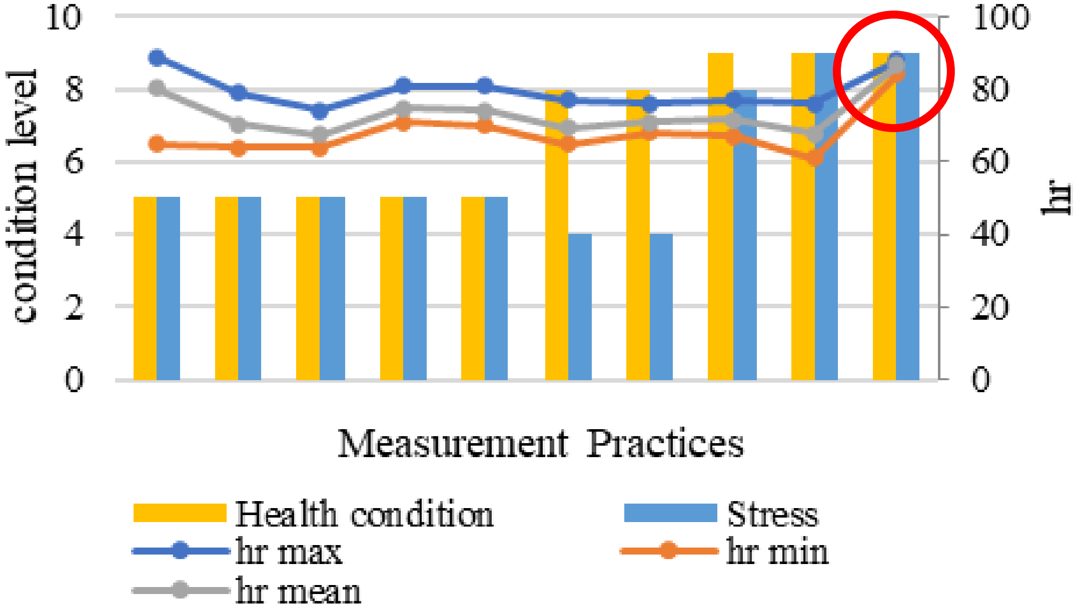
Characteristic Frequency Bands

- The number of data points was set to 1000, 2000, 4000, 6000, 8000, 10000, 15000, and 20000 or more, each of which was Fourier-analyzed to examine the spectral intensity and frequency band characteristics.



- Peaks were observed near 1.5 Hz, 0.3 Hz, 0.1 Hz, and occasionally below 0.1 Hz with increments of 0.01 Hz, with an occasional peak around 0.01 Hz below 0.1 Hz.

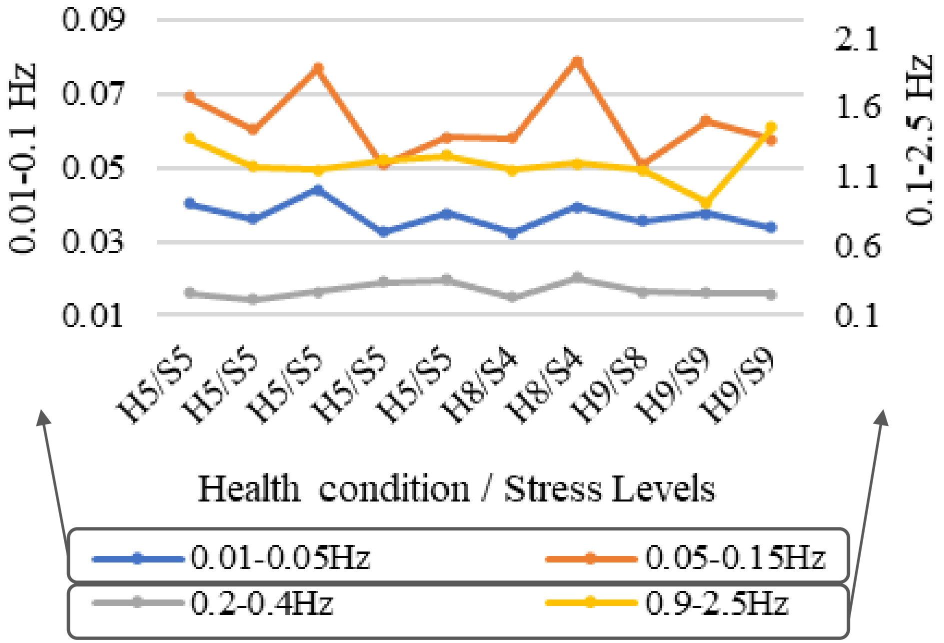
Frequency Characteristics due to Health Condition and Stress



- Compared health (states 8 and 9) and stress (states 4 and 5) on a 10-point scale using heart rate. Due to the absence of data for states rated 3 or below, states 4 and 5 were used for comparison.

- High heart rates occurred during times of poor health and high stress, but no clear correlation was found.
- Even in relatively good health, maximum heart rates remained high.

Health, Stress, and Fourier Analysis Results

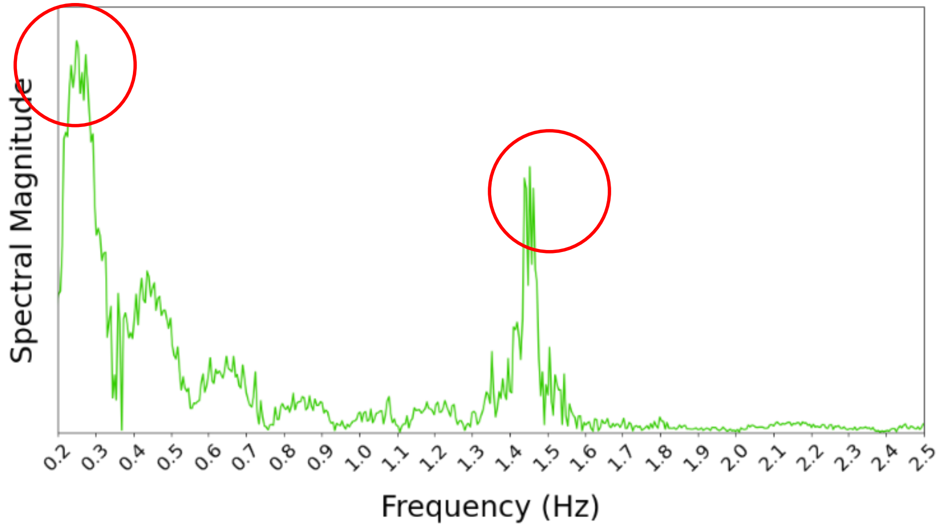


- Examined self-perceived health conditions, stress, and Fourier results.
- Extracted peak spectral intensity frequencies in 0.01-0.05 Hz, 0.05-0.15 Hz, 0.2-0.4 Hz, and 0.9-2.5 Hz ranges.
- Graph's X-axis: Slash right is stress levels (1-10) , left is health conditions (1-10) . H / S : H = health, S = stress.

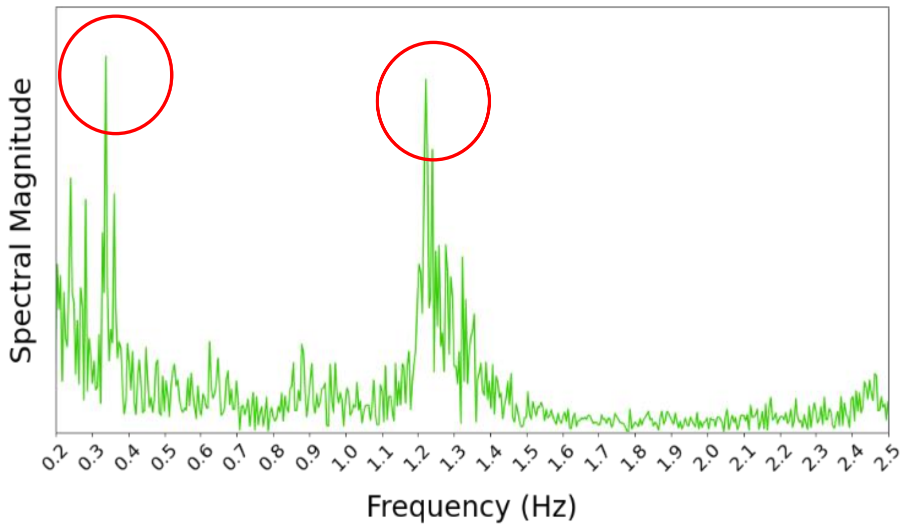
- No obvious features were observed over the entire frequency range.

Analyzing Fourier Spectra for Health Comparison

- Compared Fourier analysis in poor and good health with around 5000 data points



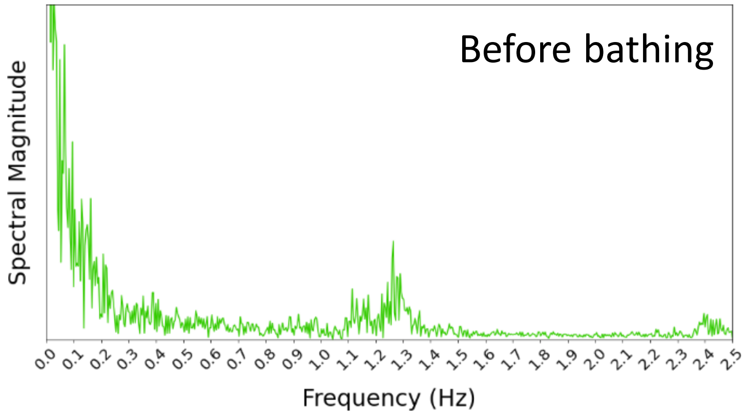
Fourier analysis results for poor health.

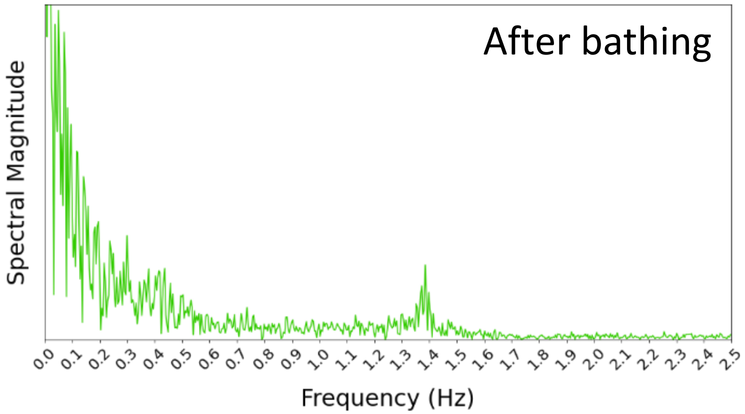


Fourier analysis results for good health.

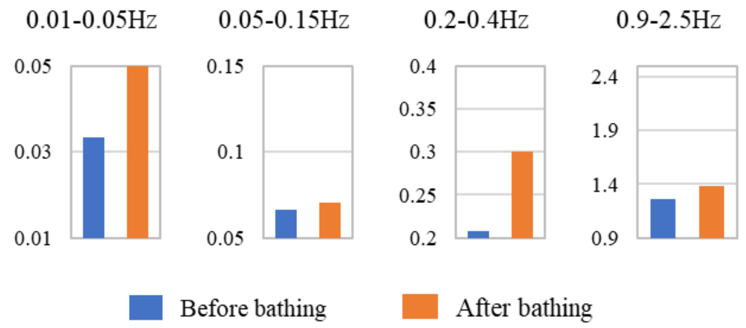
- Poor health periods had jagged and fluctuating peaks in heart rate and respiration frequencies, while good health periods occasionally showed sharp peaks.
- No consistent patterns were found across all instances.

Frequency Band Changes Due to Bathing





Bathing's effects on frequency bands: Fourier analysis with 6000 data points.



Frequency of the strongest of the spectrum in each frequency band

FREQUENCY DIFFERENCES BASED ON DATA POINTS

	250 data	1000 data	6000 data
0.2-0.4Hz Before Bathing	0.20	0.37	0.21
0.2-0.4Hz After Bathing	0.20	0.30	0.30
0.9-2.5Hz Before Bathing	1.20	1.27	1.27
0.9-2.5Hz After Bathing	1.30	1.02	1.39

- Frequencies in all bands, 0.01-0.05 Hz, 0.05-0.15 Hz, 0.2-0.4 Hz, and 0.9-2.5 Hz, increased after bathing in the case of 6000 data points.
- The frequency varied depending on the data segmentation method used

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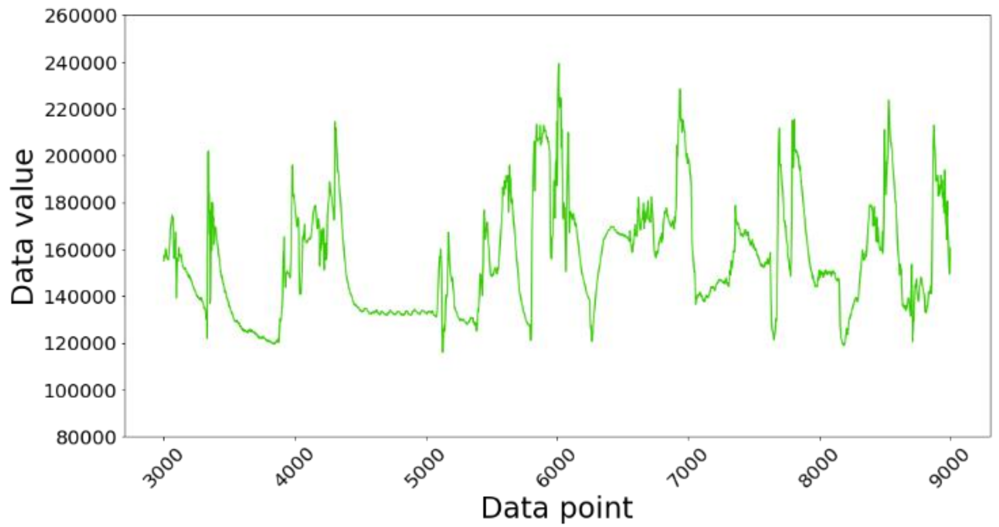
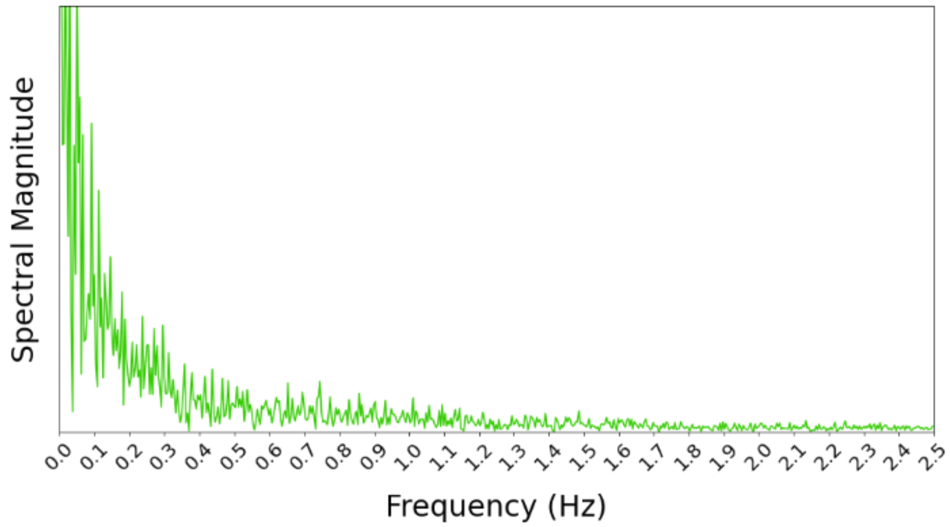
Frequency Characteristics due to driving a car



The raw data during car driving.



Fourier analysis data during car driving.

- During car driving, the wrist wearing the device moves frequently because of steering wheel manipulation. The Figure of raw data shows repeated significant fluctuations.
- The effect of each frequency band was also examined. No clear peaks were found in all frequency ranges, including 0.01-0.05 Hz, 0.05-0.15 Hz, 0.2-0.4 Hz, and 0.9-2.5 Hz.

Discussion

More data points resulted in larger discrepancies between device-calculated heart rates and spectral frequencies.

- Possible factors
  - Longer measurement duration led to device movement and unstable data.
  - Interference from non-pulse rate factors within the 0.9-2.5 Hz frequency range.
  - Increased pulse rate variety and occurrences led to measurement variations.
  - Fourier analysis characteristics, such as quick variations within brief timeframes, were also influential.

Examined spectral intensity and frequency bands using Fourier analysis. With 1000 data points (equivalent to 40 s), peaks at around 1.5 Hz, 0.3 Hz, and 0.1 Hz observed. Larger datasets (e.g., 15000) occasionally showed peaks near 0.01 Hz.

- Frequencies around 1.5 Hz related to pulse rate, 0.3 Hz to respiration.
- The 0.1 Hz peak might relate to MWSA from blood pressure. Frequencies: 0.15-0.45 Hz (HF, parasympathetic control), 0.04-0.15 Hz (LF, sympathetic control), <0.1 Hz (myogenic/neurohumoral factors). However, daily activity measurements are influenced by various factors and may not accurately represent specific biological information.

In terms of health condition and stress, sharp peaks that were not observed during periods of poor health were observed during periods of good health.

- It is possible that during poor health conditions, the heart rate is not stable and the heart rate variation increases, whereas during good health conditions, there are times when the heart rate is stable at a certain level.
- No clear relationship found between Fourier analysis and health.
- Stress is known to impact biological information, but it varies among individuals.
- Lack of change in biological data doesn't necessarily indicate unchanged health.
- Individual differences, subjective awareness, low correlation, measurement challenges, and device limitations may influence these findings.

In the investigation before and after bathing, with 6000 data points, the frequency at the peak spectrum was higher in all frequency ranges of 0.01-0.05 Hz, 0.05-0.15 Hz, 0.2-0.4 Hz, and 0.9-2.5 Hz compared to before bathing.

- It can be inferred that the frequency is higher after bathing; however, depending on the extracted data to be analyzed, such as when movement is involved, the results may not match.

No distinctive results were observed while driving.

- Possible reasons include external factors like upper limb movement during steering, vehicle vibration, and outdoor lighting.
- Analyzing data in short intervals when upper limbs are stationary may yield more distinct results.

Conclusion

1. Rest and activity measurements differ, but long-term data is valuable for daily life. Consider activity, perceived health condition, and stress and their responses.
2. In addition to frequencies of 1 Hz, 0.3 Hz, and 0.1 Hz, the analysis should include low-frequency ranges, such as 0.01 Hz.
3. Exclude data with significant device movements or rapid changes.
4. Divide and analyze data at various intervals (10 s, 1 min, 10 min).
5. Compare activity and rest changes, recovery times, and external factors.
6. Human behavior varies, and activity impacts are influenced by individual traits. Big data enables objective judgments from flexible activity data. Continue investigating activity-health relationships for lifestyle pathology and health promotion understanding.

Acknowledgments

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Thank you for reading