Towards Collaboration with AI to Explore New Features of Dementia That Cannot Be Found from Medical Viewpoint

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Abstract

This paper focuses on collaboration between human and AI and shows its potential of exploring new features that cannot be found by either human experts or AI. Concretely, this paper focuses on dementia and shows that new features of dementia based on heartrate cannot be found from the medical viewpoint but can be found from hints based on the analysis of AI. Through an analysis of heartrate of both dementia patients and healthy subjects, the following implications have been revealed: (1) an ability of dementia patients to maintain a stable heartrate as homeostasis is weaker than that of healthy subjects; and (2) the time-series features of heartrate obtained by AI (i.e., the statistical analysis and machine learning) is needed to be interpreted (by human) to find a potential symptom of dementia.

Introduction

Do you think that generative AI (GenAI) is mainly used for writing documents faster or creating interesting images? The current situation of using GenAI has dramatically changed according to the article of Harvard Business Review (Zao-Sanders, 2025), which analyzed how people were really using GenAI and compared the 100 use cases in 2025 with those in 2024. This article revealed a fundamental shift of using GenAI from a *tool for productivity* to a *companion* and a *guide for improving life*. Concretely, the top four of the use cases in 2025 include "therapy/companionship" (the 1st rank from the 2nd rank in 2024), "organizing my life" (the 2nd rank as new use case), "finding purpose" (the 3rd rank as new use case), and "enhanced learning" (the 4th rank from the 8th rank in 2024), while those in 2024 include "generating idea" (the 1st rank which drops to the 6th rank in 2025) "therapy/companionship" (the 2nd rank which is risen to the 1st rank in 2025), "specific search" (the 3rd rank which drops to the 13th rank in 2025), and "editing text" (the 4th rank which drops to the 45th rank in 2025). This result shows that GenAI is clearly shifted to be used for improving inner fulfillment and mental health from doing something effectively.

When focusing on the above use cases in 2025, in particular, GenAI is used as *a conversation partner* (mainly as a listener) in the use case of "therapy/companionship", while it is used for *creating better life* in the use cases of "organizing my life," "finding purpose," and "enhanced learning." This is because the primary purpose of therapy/companionship is to recover mental condition of users and/or prevent them to feel lonely by listening to users, which is fundamentally different from creating better life. Considering the use case of "healthier living" (the 10th rank in 2025 which is risen from the 75th rank in 2024) in addition to the three use cases, our expectation to AI including GenAI becomes to support us to create better life.

Towards this goal, it goes without saying that it is important to check our health, manage it, and hopefully maximize it, because better life cannot be created without good health condition. For this issue, for example, we take care of our health by exercising and avoiding high-calorie meals. However, it is difficult to know an effect of such activities soon, which prevents us from continuing such activities. More importantly, it is important to know our health condition before getting sick. This is especially true for diseases that has no known treatment such as dementia, and even GenAI cannot solve this problem due to a lack of known treatment.

To address this issue, this paper focuses on dementia and introduces our dementia detection method (Matsuda et al., 2023) with describing how collaboration between human and AI are essential to develop it. Concretely, the proposed method detects dementias according to their heartrates during sleep which are acquired from a mattress sensor placed on bed, and it has a potential of providing hints of new features of dementia through the analysis of AI. What should be noted here is that (1) new symptoms of dementia based on heartrate cannot be found from the medical viewpoint because medical doctors focus on the main symptom of dementia such as a decrease of cognitive function, which cannot be evaluated by heartrate; (2) collaboration between human and AI has a potential of finding new symptoms of dementia.

This paper is organized as follows. The next section analyzes the time-series features of heartrate data obtained from the human subject experiments, and provides the results of detecting dementia patients. Section 3 interprets the found time-series features to new symptoms of dementia. Finally, our conclusion is given in Section 4.

What Does AI Find? - Analyzing Time-Series Features of Heartrate Data

Data Set of Human Subject Experiments

To investigate features of heartrate found in dementia, we conduct the two human subject experiments which were approved by the ethics community of St. Marianna University and the University of Electro Communications.

From the first human subject experiment, the data set composed of 124 days of the heartrate during sleep of one dementia patient (who develops Alzheimer dementia (AD)) were obtained (n = 124), while that of 39 days of the heartrate during sleep of 21 healthy subjects were obtained (n = 39). In the dementia patients, in particular, the heartrate is composed of one AD patient (80s). In the healthy subjects, on the other hand, the heartrate is composed of seven days of three elderly subjects (60s-70s), 18 days of 10 middle-aged subjects (40s-50s), and 14 days of eight young subjects (20s-30s). The data of the heartrate and body movement were obtained from the mattress sensor by *EMFIT Ltd*., and the heartrate during sleep was extracted from the sleeping time to waking up time, determined by the body movement.

From the second human subject experiment, the data set composed of 81 days of the heartrate during sleep of two dementia patients (who develop AD and Lewy bodies (DLB) dementia, respectively) were obtained (n =81), while that of 27 days of the heartrate during sleep of 9 healthy subjects were obtained (n = 27). In the dementia patients, in particular, the heartrate is composed of 76 days of one AD patient (80s) and 5 days of one DLB patient (70s). In the healthy subjects, on the other hand, the heartrate is composed of 10 days of two elderly subjects (60s-70s), seven days of one middle-aged subject (50s-60s), and 10 days of six young subjects (20s-30s). The data of the heartrate and body movement were obtained from the mattress sensor by *FutureInk Corporation*, and the heartrate during sleep was extracted from the sleeping time to waking up time, determined by the body movement as the same the first human subject experiment.

In order to find general features of heartrate in dementia, the experimental facility in the first human subject experiment is different from that of the second human subject experiment, and the data of the heartrate and body movement were obtained from the EMFIT Ltd sensor in the first human subject experiment, which is different from the FutureInk Corporation sensor in the second human subject experiment.

Time-series Features of Dementia

Since it is generally unknown what kinds of features of heartrate that dementia patients have, our experiment employed the "tsfresh" python library composed of 794 time-series features and conducted the statistical analysis of 794 time-series features in terms of classifying between dementia patients and healthy subjects. As shown in Fig. 1, the heartrate data is extracted in the 10 minutes window to calculate its time-series features by shifting its window by one minute. Using these data, Mann-Whitney U-test was conducted after checking that the sample of features did not match the normal distribution by ShapiroWilk test. After the statistical analysis, the top 10th time-series features with the smallest p-values are selected. However, since these p-values are very close to each other, Random Forest (RF) (Breiman, 2001) as one of a machine learning (ML) techniques is employed using the top 10th time-series features to select the most important time-series feature(s) among the top 10th ones. For this issue, our experiment trained RF to classify dementia patients with healthy subjects using the top 10th time-series features, and calculate the *feature importance* of the time-series features which shows how each time-series feature contributes to the classification between dementia patients with healthy subjects.

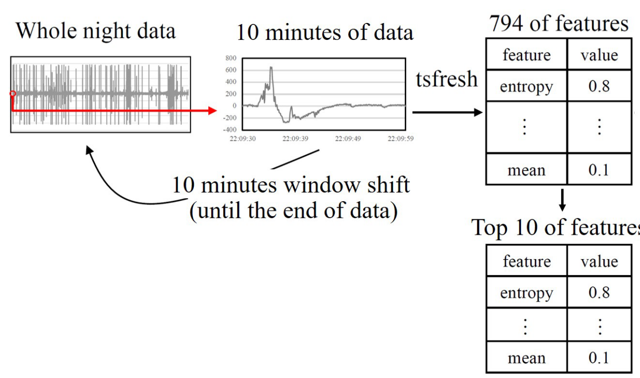

Figure 1: Time-series features calculation

Selected Time-series Features

Through the above analysis of the time-series features of heartrate data obtained in the first human subject experiment, our previous work selected the following two features that have the 1st and 2nd highest feature importance values

(Matsuda et al., 2023) because these values are very close each other. Note that this paper regards these two features as the ones found by AI.

- **Partial auto-correlation coefficient of lag 2 (x_{pac})**
  x_{pac} is the auto-correlation between time-series data (x_t) and its lag 2 data (x_{t-2}) by excluding its lag 1 data (x_{t-1}) as shown in Eq. (1). In general, a_k is calculated as the auto-correlation between a_t and its lag k value x_{t-k} by excluding the middle variable $\{x_{t-1}, \ldots, x_{t-k+1}\}$ as shown in Eq. (2) (Box et al., 2015).

$$x_{pac} = \alpha_2 = \frac{Cov(x_t, x_{t-2}|x_{t-1})}{\sqrt{Var(x_t|x_{t-1})Var(x_{t-2}|x_{t-1})}} \quad (1)$$

$$\alpha_k = \frac{Cov(x_t, x_{t-k}|x_{t-1}, \ldots, x_{t-k+1})}{\sqrt{Var(x_t|x_{t-1}, \ldots, x_{t-k+1})Var(x_{t-k}|x_{t-1}, \ldots, x_{t-k+1})}} \quad (2)$$

- **Number of CWT (Continuous Wavelet Transform) peak (x_{ncp})**
  x_{ncp} is the number of peaks of CWT which detects the temporal changes in frequency and power spectrum (scalogram) (Sharma et al., 2021). In CWT, the Mexican hat function (ricker) is generally employed as the mother wavelet function. The founded peaks of CWT are shown in the red marks of Fig. 2.

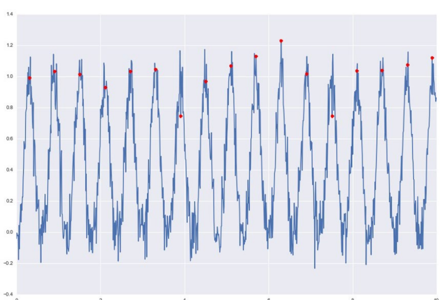

Figure 2: The peaks (red marks) of continuous wavelet transform (CWT)

Dementia Detection

To investigate whether x_{pac} and x_{ncp} contributes to detecting dementia patients, this paper employs our previous method (Matsuda et al., 2023) to train RF to classify dementia patients with healthy subjects using x_{pac} and x_{ncp}. As the difference compared to RF, our method is composed of multiple RFs, each of which is trained with the heartrate data in the assigned period of time, and classifies dementia patients if a ratio of classifying dementia patients among all RFs is equal or larger than a certain percentage (e.g., 0.6 in this experiment); otherwise classifies healthy subjects. Such multiple RFs contribute to reducing the accidental wrong training of RFs. As the general setting of RF, this paper conducts the five-fold cross-validation, which divides into five groups (folds) with one used for validation and four for training and calculates the average of accuracy after repeating the cycle of training and evaluation five times. To balance the class between the dementia patients and the healthy subjects, the weight for each class was calculated and applied when training RF. The depth and the number of RF decision trees were set to 2 and 100, respectively.

As the evaluation criteria, the accuracy, precision, recall (sensitivity), specificity, and F1-score are employed for each human subject experiment. Concretely, these criteria are calculated with the data set composed of 124 days of the dementia (AD) patient (n = 124) and 39 days of healthy subjects (n = 39) in the first human subject experiment, and with the data set composed of 81 days of the dementia (AD and DLB) patients (n = 81) and 27 days of healthy subjects (n = 27) in the second human subject experiment.

Fig. 3 shows the accuracy, precision, recall (sensitivity), specificity, and F1-score of the two human subject experiments. In detail, the blue and orange bars indicate the results of the first and second human subject experiments, respectively. From this figure, dementia can be detected with a high accuracy (i.e., 87.5% in the first experiment and 84.3% in the second experiment) even if the data sets are different, the used facilities are different, the used mattress sensors are different (i.e., EMFIT sensor in the first experiment and FutureInk sensor in the second experiment), and the types of dementia are different (i.e., only AD patient in the first experiment and both AD and DLB patients in the second experiment). From the medical viewpoint, in particular, the recall (sensitivity) is very important because it represents the percentage of not overlooking dementia patients (i.e., the percentage of correctly identifying dementia patients among the dementia patients). For this issue, the recall is quite high in both the human subject experiments (i.e., 92.8% in the first experiment and 88.9% in the second experiment). Since the recall (specificity) of the PCR test for COVID-19 is around 80%, x_{pac} and x_{ncp} contributes to detecting dementia patients with a higher probability than the PCR test.

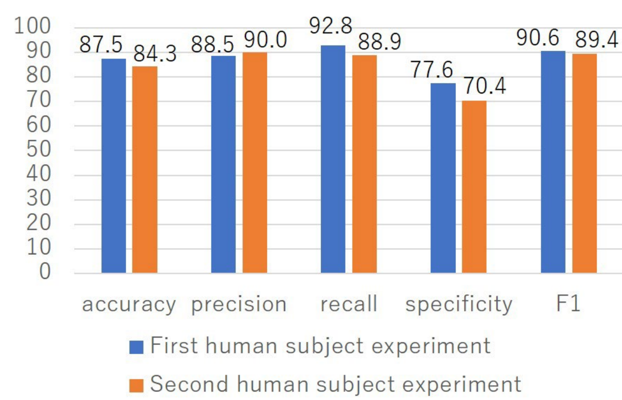

Figure 3: Accuracy, precision, recall (sensitivity), specificity, and F1-score in dementia detection

What Do x_{pac} and x_{ncp} Mean? – Interpreting Time-Series Features of Heartrate Data

Analyzing Time-series Features

In order to clarify why x_{pac} and x_{ncp} can detect dementia patients, i.e., how x_{pac} and x_{ncp} of dementia patients are different from those of healthy subjects, Fig. 4 shows x_{pac} and x_{ncp} together with $REF.x_{pac}$, $REF.x_{ncp}$, and the heartrate within 500 seconds (≒ 8 minutes) of one healthy subject and one dementia patient. Note that $REF.x_{pac}$ and $REF.x_{ncp}$ are the reference values of x_{pac} and x_{ncp} (i.e., $REF.x_{pac} = -0.06$ and $REF.x_{ncp} = 47$) to directly compare the two graphs of healthy subjects and dementia patients. In this figure, the horizontal axis indicates a time, while the left and right vertical axes indicate x_{pac} and x_{ncp}, respectively. The green, red, and blue lines indicate x_{pac}, x_{ncp}, and the heartrate, respectively, while the green and red dotted lines indicate $REF.x_{pac}$ and $REF.x_{ncp}$, respectively. The upper and lower graphs show the results of a healthy subject and a dementia (AD) patient, respectively. From this figure, the time-series features of the healthy subject and the dementia patient are summarized as follows, each of which is mostly found in other healthy subjects and dementia patients:

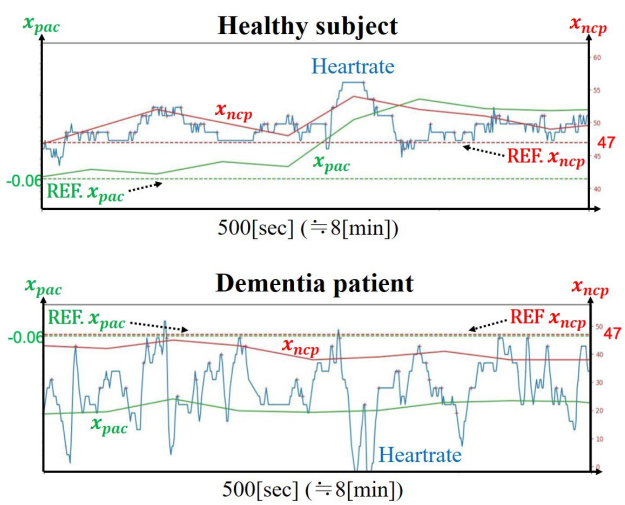

Figure 4: x_{pac} and x_{ncp} of healthy subject and dementia patient

- **<u>P</u>artial <u>a</u>uto-<u>c</u>orrelation coefficient of lag 2 (x_{pac})**

  x_{pac} of the healthy subject is around zero (which is slightly larger than the reference value ($REF.x_{pac} = -0.06$)), while that of dementia patient is negative (which is smaller than −0.06). This result means the heartrate of the healthy subject between *t* and *t – 2* is not correlated, while the heartrate of the dementia patient between *t* and *t – 2* is (*negatively*) correlated. From this opposite tendency, dementia patients can be detected according to x_{pac} of the healthy subject and the dementia patients because they are clearly different.

- **<u>N</u>umber of <u>C</u>WT <u>p</u>eak (x_{ncp})**

  x_{ncp} of the healthy subject is larger than the reference value ($REF.x_{ncp} = 47$), while that of the dementia patient is smaller than 47. This result means that the number of peaks of the heartrate of healthy subject is larger than that of the dementia patient. From this different tendency, dementia patients can be detected according to x_{ncp} of the healthy subject and the dementia patients because they are clearly different.

Interpreting x_{pac} and x_{ncp}

The experimental result and the above analysis show that x_{pac} and x_{ncp} contributes to detecting dementia patients, but it is unknow what is the meaning of x_{pac} and x_{ncp} from the medical viewpoint. To clarify this issue, this section focuses on the heartrate in Fig. 4. From the two graphs, the heartrate of a healthy subject in the upper graph tends to keep it as the same rate or quickly put back into the original rate in many periods of time even though it slightly increases and decreases in a certain period of time (e.g., 1 minutes). On the other hand, the heartrate of a dementia patient in the lower graph is hard to can keep it as the same rate or quickly put back into the original rate, which fluctuates significantly over a short period of time (e.g., 20 to 30 seconds). This different tendency may suggest that healthy subjects have a *strong* homeostasis to keep the heartrate as the same rate while the dementia patients have a *weak* homeostasis. In other words, the rhythm of keeping the same rate of heartrate in healthy subjects is *stable* while that in dementia patients is *unstable*. What should be noted here is that the circadian rhythm of the melatonin secretion in healthy subjects is also *stable* (i.e., a melatonin secretion is high in midnight and low in noon) while that in AD patients is also *unstable* (i.e., a melatonin secretion is high/low in unspecified time) (Mishima, et al. 1999). This fact supports to explain the different tendency of heartrate.

Relating x_{pac} to the different tendency of heartrate, the heartrate in the healthy subject at *t* is mostly the same as the heartrate at *t – 2* as *t* increases (i.e., they are not correlated), while the heartrate in the dementia patient at *t* mostly increases/decreases from the heartrate at *t – 2* as *t* increases (i.e., they are correlated). Relating x_{ncp} to the different tendency of heartrate, on the other hand, the number of the peaks of the heartrate in the healthy subject is high due to the fact that the heartrate is quickly put back into the original rate many times, while that in the dementia patient is low due to the fact that the heartrate increases and decreases over a short period of time.

These associations suggest that the new symptom of dementia can be a *weak* homeostasis of the heartrate, but x_{pac}

and x_{ncp} do not directly related to the *weak* homeostasis. In other words, some kinds of features of dementia patients (i.e., x_{pac} and x_{ncp} in this experiment) can be found by AI (i.e., the statistical analysis and ML in this experiment) but they are hard to be related to symptoms of dementia. This requires humans to interpret the features found by AI to symptoms of dementia. As the same time, humans (medical doctors) are also hard to find new symptoms of dementia based on heartrate because they focus on the main symptom of dementia such as a decrease of cognitive function. This indicates that collaboration between human and AI is indispensable for finding new symptoms of dementia, which can be found from hints based on the analysis of AI.

Conclusion

This paper focused on collaboration between human and AI and showed its potential of exploring new features that cannot be found by either human experts or AI. Concretely, this paper focused on dementia and showed that new symptoms of dementia based on heartrate cannot be found from the medical viewpoint but can be found from hints based on the analysis of AI. Through an analysis of heartrate of both dementia patients and healthy subjects, the following implications have been revealed: (1) an ability of dementia patients to maintain a stable heartrate as homeostasis is weaker than that of healthy subjects; and (2) the time-series features of heartrate obtained by AI (i.e., the statistical analysis and machine learning) is needed to be interpreted (by human) to find a potential symptom of dementia.

What should be noticed here is that this paper just finds a potential symptom of dementia, therefore the next step must be pursued in the near future in addition to (1) generalize the found potential symptom by increasing the number of dementia patients and healthy subjects; and (2) validate the found potential symptom from the medical viewpoint.

Acknowledgments

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References

Box, G.E.P., Jenkins, G.M., Reinsel, G.C., and Ljung, G.M. 2015. *Time series analysis: forecasting and control*, John Wiley & Sons.

Breiman, L. 2001. "Random forests," *Machine learning*, 45(1):5–32.

Matsuda, N., Nakari, I., and Takadama, K., Katayama, K., Shiraishi, M., Ohira, Y. 2023. "Alzheimer Dementia Detection Based on Time-series Instability of Heart Rate," *The 45th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC2023)*.

Mishima, K., Tozawa, T., Satoh K, Matsumoto, Y., Hishikawa, Y., and Okawa, M. 1999. "Melatonin secretion rhythm disorders in patients with senile dementia of Alzheimer's type with disturbed sleep-waking," *Biological Psychiatry*, 45:417-421.

Sharma, M., Patel, S., and Acharya, U.R. 2021. "Expert System for Detection of Congestive Heart Failure Using Optimal Wavelet and Heart Rate Variability Signals for Wireless Cloud-based Environment," Expert Systems, page12903.

Zao-Sanders. M. 2025. "How People Are Really Using Gen AI in 2025," *Harvard Business Review*, April 9. https://hbr.org/2025/04/how-people-are-really-using-gen-ai-in-2025.