BRIEF PAPER Special Section on Recent Advances in Simulation Techniques and Their Applications for Electronics

Heart Rate Control System for Walking with Real-Time Heart Rate Prediction

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SUMMARY In recent years, the declining birthrate and aging population have become serious problems in Japan. To solve these problems, we have developed a system based on edge AI. This system predicts the future heart rate during walking in real time and provides feedback to improve the quality of exercise and extend healthy life expectancy. In this paper, we predicted the heart rate in real time based on the proposed system and provided feedback. Experiments were conducted without and with the predicted heart rate, and a comparison was made to demonstrate the effectiveness of the predicted heart rate.

key words: *healthcare, IoT technology, edge computing, artificial intelligence, heart rate*

1. Introduction

In recent years, Japan has been experiencing a declining birthrate and an aging population problem that is becoming increasingly serious. Population trends in Japan show an increase in the elderly population aged 65 and over and a decrease in the population aged 14 and under [1]. The population of the elderly is also expected to increase based on population estimates for 2020 and beyond. The increase in the elderly population is expected to lead to an increase in nursing care and medical expenses. Therefore, it is thought that extending healthy life expectancy and minimizing the period during which people require nursing care through health promotion will be a solution to the problem of declining birthrates and aging society. In general, healthy life expectancy is defined as “the period during which a person can live without being limited in daily life by health problems” [2]. The difference between average life expectancy and healthy life expectancy is the “period during which one is not healthy” when one’s daily life is restricted. The difference between average life expectancy and healthy life expectancy in Japan is about 10 years for both men and women [3]. Extending healthy life expectancy would reduce the cost of nursing care and medical care, thereby reducing the burden on the working population.

Given the above, there is a wide range of research on exercise support for health promotion. Research on guiding walking pace includes a Walk Navigation System by Shoe-shaped Interface for Inducing a Walking Cycle [4] and Walk-In Music [5]. In [4], a shoe-shaped device was used to generate vibrations on the instep, and it was shown that a constant walking pace can be induced by changing the pace of these vibrations. However, this requires a special device. In [5], a drum sound is generated in accordance with the walking pace, successfully inducing a constant walking pace. Studies that predict heart rate and provide feedback based on the results include MPTrain [6], IM4Sports music system [7], and a Heart Rate Prediction for Easy Walking Route Planning [8]. [6] and [7] use music with a suitable tempo as needed so that the user can continue exercising at a heart rate within a certain range. The user can naturally perform an effective workout simply by matching his or her pace to the tempo of the music being played. The above system, however, is performed on a treadmill, and assumes an environment in which the heart rate is relatively easy to predict. [8] conducted an experiment assuming a real road environment with sudden changes in walking speed and road gradient. By predicting the future heart rate without using the current heart rate, walking can be easily performed without the need to wear a heart rate monitor. However, the prediction accuracy is low because current heart rate data is not used for prediction. In addition, the feedback method only recommends an appropriate route from among three patterns of walking routes, and no specific feedback is provided. Existing healthcare systems such as Apple Watch [9] and RunKeeper [10] mainly collect data such as heart rate and visualize and manage the data. Although the heart rate from the past to the present is displayed, the future heart rate cannot be predicted. When abnormal data is found in the collected data, it is picked up and displayed, but specific feedback has not been realized.

In this research, we aim to construct a system that predicts the heart rate during walking in real time, guides the walking pace with specific feedback based on the results, and controls the heart rate to provide walking at a load suitable for each individual.

2. Proposed Technology

In this research, we are considering building a system based on edge artificial intelligence (AI). The system configuration is shown in Fig. 1. At the edge, various sensor data such as heart rate, acceleration, etc. are collected, and the heart rate is predicted from the data and feedback is provided in real time. In the cloud domain, a new learning model is constructed from the sensor data collected in the edge domain. By reflecting the newly created learning model in

Manuscript received November 3, 2023.
Manuscript revised February 21, 2024.
Manuscript publicized April 23, 2024.

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DOI: 10.1587/transele.2023ESS0002

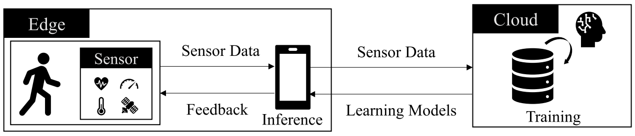

Fig. 1 System configuration

the edge area, we believe that the performance of both the edge and cloud areas can be improved. In addition, to enable outdoor prediction, we will build a more general model that takes external factors into account using elevation data and aim to provide specific feedback using a walking pitch. This will enable specific, real-time feedback that is not possible with existing healthcare systems.

3. Heart Rate Prediction Experiment

3.1 Experimental Method

First, we predicted heart rate during walking. 6 healthy male adults aged 21-23 years walked a designated course for approximately 60 minutes several times and collected data. Because the burden level during walking is easily affected by walking speed and gradient [11], five types of data were collected: heart rate [bpm], elevation [m], average pace [m/sec], instantaneous pace [m/sec], and pitch [step/sec]. Heart rate was collected using POLAR H10, and elevation, average pace, instantaneous pace, and pitch were collected using the iPhone's built-in sensor. All data acquisition intervals were set to 1 [sec]. The heart rate sensor was attached to the chest and the waist pouch to the abdomen, and the iPhone was stored in the waist pouch.

3.2 Neural Network

We used a CNN (Convolutional Neural Network) [12] to construct a heart rate prediction model. Table 1 shows the prediction model used in this experiment. Table 2 shows the training parameters. When dealing with time-series data as in this experiment, RNN (Recurrent Neural Network) systems such as LSTM (Long Short-Term Memory) [13] and transformer systems [14] can be used. The data handled in this research is non-stationary data without periodicity, which is a weak point of RNN systems. Also, since real-time performance is important in this research, it is impossible to guarantee real-time performance in large-scale networks such as transformer systems. However, CNNs can generally be represented as FIR filters, even for non-stationary data, so there are few disadvantages, and the amount of computation can be kept relatively low. For these reasons, CNN was employed in this experiment. The input data were the sensor data from $t - t_1$ [sec] to t [sec], and the output data were the heart rate (predicted value) at $t + t_2$ [sec]. The combination of t_1 and t_2 was changed to compare the prediction accuracy, and the relationship between input/output time was investigated.

Table 1 Learning parameters

Parameter	Setting
Loss function	Huber loss
Optimizer	Adam
Learning rate	0.001
Epoch	100

Table 2 Prediction models

Layer	Filter size	Stride size	Output size
Input			600, 5
Convolutional	5	1	600, 8
Batch normalization			600, 8
Max pooling	2	2	300, 8
Convolutional	5	1	300, 8
Batch normalization			300, 8
Max pooling	2	2	150, 8
Convolutional	5	1	150, 8
Batch normalization			150, 8
Max pooling	2	2	75, 8
Convolutional	5	1	75, 8
Batch normalization			75, 8
Max pooling	2	2	38, 8
Convolutional	5	1	38, 8
Batch normalization			38, 8
Max pooling	2	2	19, 8
Flatten			95
Fully connected			32
Fully connected			1

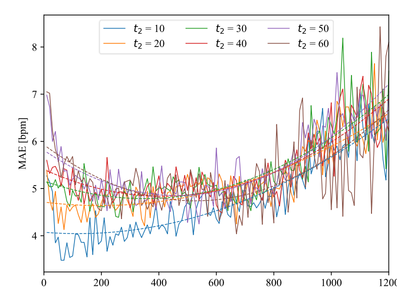

Fig. 2 Average of MAE at each input/output time

3.3 Experimental Results

The heart rate was predicted by changing t_1 from 10 [sec] to 600 [sec] in 10 [sec] increments and t_2 from 10 [sec] to 60 [sec] in 10 [sec] increments. Ten predictions were made for each combination, and the average error between the predicted and measured values is shown in Fig. 2. The dashed line in Fig. 2 is a quadratic approximation. Figure 2 shows that the number of input data (t_1 [sec]) at which the average absolute error is minimized is different for each output time (t_2 [sec]), indicating that there is an appropriate time for each. The overall increase in the mean absolute error with increasing output time (t_2 [sec]) indicates that the prediction becomes more difficult as the prediction time increases. The minimum values obtained from the quadratic approximation in Fig. 2 are shown in Fig. 3. Each point in Fig. 3 represents the minimum value, and the solid line represents a linear ap-

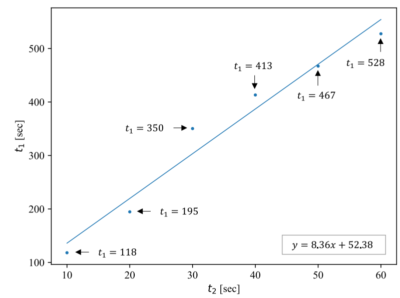

Fig. 3 Minimum value of MAE at each input/output time

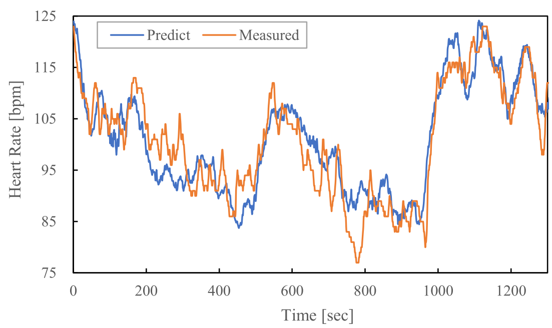

Fig. 4 Prediction result

proximation of each point. Figure 3 shows that as the output time (t_2 [sec]) increases, the number of required input data (t_1 [sec]) also increases.

Based on these results, we calculated the appropriate input and output data and constructed a prediction model for this experiment. Figure 4 shows the results of the actual heart rate prediction. In the prediction shown in Fig. 4, $t_1 = 600$ and $t_2 = 60$. Figure 4 shows that the measured values (orange) and predicted values (blue) show similar trends. The average absolute error between the measured and predicted values in Fig. 4 was 3.85 [bpm]. The mean absolute error was 9.92 [bpm] when the prediction was made using heart rate alone.

4. Heart Rate Control Experiment

4.1 Experimental Method

Next, the future heart rate was predicted in real time, and the walking pitch was guided based on the result of the prediction. Six healthy male adults aged 21 to 23 years were subjects in this experiment. The subjects walked on a specified course for approximately 60 minutes. Because sensor data from the previous 10 minutes were necessary to predict heart rate, feedback began 10 minutes after the start of the experiment. Feedback was provided using a metronome-like sound. Subjects were instructed to walk in time with the sound, and the walking pitch was guided so that the heart rate fell within the target range. The following shows how the heart rate range and walking pitch were determined.

Table 3 Parameter determination method

(a) Uses current and predicted heart rate

HR	PHR	Δp
$HR > UHR$	$PHR > UHR$	-0.25
	$LHR \leq PHR \leq UHR$	-0.2
	$PHR < LHR$	-0.15
$LHR \leq HR \leq UHR$	$PHR > UHR$	-0.1
	$LHR \leq PHR \leq UHR$	0
	$PHR < LHR$	0.1
$HR < LHR$	$PHR > UHR$	0.15
	$LHR \leq PHR \leq UHR$	0.2
	$PHR < LHR$	0.25

(b) Use current heart rate

HR	Δp
$HR > UHR$	-0.2
$LHR \leq HR \leq UHR$	0
$HR < LHR$	0.2

4.2 Heart Rate Range Determination Method

The Karvonen method [15] exists as a method to express exercise intensity using heart rate. Exercise intensity is correlated with oxygen uptake. However, measurement of oxygen uptake may not be possible at some medical institutions or facilities. Therefore, heart rate is used as an index of exercise intensity in place of oxygen uptake. The Karvonen method calculates exercise intensity using heart rate. Equation (1) shows the formula for the Karvonen method.

$$EL = \frac{(HR - RHR)}{(MHR - RHR)} \times 100 \quad (1)$$

In Eq. (1), EL represents Exercise Loads, HR represents Heart Rate, RHR represents Resting Heart Rate, and MHR represents Maximum Heart Rate. EL = 0.5 is appropriate for setting the exercise intensity for endurance exercise. The upper and lower limits of the target heart rate are determined using the Karvonen method, and feedback is provided to keep the heart rate within these limits. In this experiment, the lower heart rate limit was set at an exercise intensity of 0.45 and the upper heart rate limit at an exercise intensity of 0.55.

4.3 Walking Pitch Determination Method

In this experiment, walking pitch is used as a method to change the heart rate during walking by feedback. When the walking pitch was changed by 20 [step/min], a change in heart rate of approximately 10~20 [bpm] was observed [16]. Based on the above, in this experiment, the walking pitch was changed as shown in Eq. (2). FP [step/sec] in Eq. (2) represents Feedback Pitch and CP [step/sec] represents Current Pitch.

$$FP = CP + \Delta p \quad (2)$$

Table 3 shows how Δp [step/sec] in Eq. (1) is determined. Table 3 (a) shows the case where the current and predicted heart rates were used to determine Δp, and Table 3 (b) shows the case where only the current heart rate was used. The two patterns shown in Table 1 were tested and compared. In Table 1, HR stands for Heart Rate, PHR for Predict Heart Rate, UHR for Upper Heart Rate, and LHR for Lower Heart Rate.

Table 4 Temperature at time of experiment [°C]

Subject	Expt1		Expt2	
	(I)	(II)	(I)	(II)
A	12	11	25	26
B	7	9	27	26
C	12	13	26	26
D	13	8	27	31
E	5	10	25	31
F	14	7	31	29

Table 5 Feedback comparison results

Subject	Evaluation item	Expt1		Expt2	
		(I)	(II)	(I)	(II)
A	Range Probability [%]	26.97	59.48	36.81	67.95
	Mean Error [bpm]	6.03	2.12	4.74	0.90
B	Range Probability [%]	83.91	86.15	71.36	72.34
	Mean Error [bpm]	0.45	0.20	0.88	0.87
C	Range Probability [%]	79.95	85.74	61.35	86.53
	Mean Error [bpm]	0.53	0.26	1.66	0.42
D	Range Probability [%]	78.19	24.24	79.90	75.17
	Mean Error [bpm]	0.59	5.39	0.80	1.09
E	Range Probability [%]	60.04	54.04	67.58	49.74
	Mean Error [bpm]	2.38	2.48	1.74	5.96
F	Range Probability [%]	7.62	0.00	34.42	46.64
	Mean Error [bpm]	13.19	49.23	5.94	3.10

4.4 Experimental Results

In this experiment, heart rate control experiments were conducted with two patterns, one without prediction and the other with prediction, and the results were compared. As shown in Table 1 (b), the feedback pitch was determined using only the current heart rate for the experimental pattern without prediction, while the feedback pitch with prediction was determined using the current heart rate and the predicted heart rate as shown in Table 1 (a). In this paper, we refer to the case without prediction as (I) and the case with prediction as (II). Experiments were conducted using only heart rate data for prediction in Experiment 1 and five types of sensor data for prediction in Experiment 2. The temperatures at the time of each experiment are shown in Table 4.

Table 5 shows the results of calculating the range probability and mean error from the heart rate at the time of feedback. The range probability in Table 3 represents the probability of a heart rate falling within the target heart rate range. The mean error represents the averaged error of the heart rates that are outside the target range, as shown in Eq. (3). The HE (High Error) and LE (Low Error) in Eq. (3) are obtained from Eq. (4) and (5).

$$ME = \frac{1}{N}\sum_{i=0}^{N} HE_i + LE_i \tag{3}$$

$$HE = \begin{cases} 0, & HR \leq UHR \\ HR - UHR, & HR > UHR \end{cases} \tag{4}$$

$$LE = \begin{cases} 0, & HR \geq LHR \\ LHR - HR, & HR < LHR \end{cases} \tag{5}$$

From Experiment 1 in Table 5 shows that subjects A, B, and C have higher range probabilities for feedback using predicted heart rate. The mean error was smaller for feedback using predicted heart rate, suggesting that the accuracy of heart rate control was increased by using predicted heart rate for feedback. However, for subjects D, E, and F, the range probability of feedback without predicted heart rate was higher, indicating that the mean error was smaller. This can be attributed to the effect of temperature. Subjects A, B, and C had no difference in temperature during the experiment, but subjects D, E, and F had a larger difference in temperature during the experiment. It is thought that the high temperatures increased the heart rate variability and made it difficult to control the heart rate.

Table 6 Amount of variation

Subject	Range Probability		Mean Error	
	Expt1	Expt2	Expt1	Expt2
A	32.50	31.14	-3.91	-3.84
B	2.24	0.98	-0.25	-0.01
C	5.79	25.18	-0.26	-1.24
D	-53.94	-4.73	4.80	0.29
E	-6.00	-17.84	0.09	4.22
F	-7.62	12.22	36.05	-2.84

Next, we investigated the effect of heart rate prediction accuracy on heart rate control. The differences between condition (I) and condition (II) in range probability and mean error for each experiment are shown in Table 6. Focusing on Subjects A, B, and C, whose heart rate control accuracy was higher in Condition (II) than in Condition (I) in both Experiments 1 and 2, the difference in range probability was larger for Subject C in Experiment 2, where heart rate prediction accuracy was higher, and the difference in mean error was smaller. However, for Subjects A and B, Experiment 1, which had lower heart rate prediction accuracy, resulted in a higher increase in accuracy. This can be attributed to the effects of the feedback method and temperature. Since there were only a few types of feedback methods in this experiment, three patterns for condition (I) and nine patterns for condition (II), we believe that the effects of differences in prediction accuracy were not reflected in this experiment. We intend to improve the feedback method and continue to investigate the effect of heart rate prediction accuracy on heart rate control. We would also like to consider external factors such as temperature, humidity, and weather, as well as individual differences in age, gender, and exercise history.

5. Conclusion

In this paper, as the initial phase in the implementation of the system, a heart rate prediction model was developed, and heart rate regulation was conducted using the said model. The precision of heart rate control was augmented through the integration of feedback based on the heart rate prediction model. The establishment of this technology is anticipated to enhance the extension of healthy life expectancy and alleviate the financial burden associated with nursing care and medical services.

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