Verification of Pulse Rate Estimation Accuracy for Human-recorder

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Abstract

Rescue workers at disaster sites and construction site operators routinely perform demanding tasks. They become fatigued due to these demanding tasks. This fatigue causes discomfort and a lack of motivation at work which affects both work efficiency and safety. Therefore, it is necessary to constantly monitor their physical condition. Several existing technologies are known to detect fatigue using a face image or wearable device. However, these systems have several issues. Recording the face carries a risk of invading the subject's privacy, and it is inconvenient to constantly wear a wearable device. In recent years, a head-mounted camera which is attached to a helmet is widespread. Therefore, a human-recorder has been proposed to obtain the user's biometric information and to detect fatigue from the head-mounted camera. The human-recorder extracts head sway in a video recorded by the head-mounted camera, and analyzes the time change of head sway. In this paper, the estimated pulse rate is calculated using the human-recorder to confirm that the pulse rate can be estimate in real time. Furthermore, the effect on the accuracy of the pulse rate estimation is verified by the camera frame rate. From the results, it was verified that the pulse rate can be estimated using the human-recorder. Also, it was confirmed that pulse rate estimation is possible regardless of the camera frame rate.

Keywords

Human-recorder, Pulse rate estimation, Optical flow, Frequency analysis

1. Introduction

Rescue workers at disaster sites and construction site operators routinely perform demanding tasks. They become fatigued due to these demanding tasks. This fatigue causes discomfort and a lack of motivation at work which affects both work efficiency and safety [1]. Therefore, it is necessary to constantly monitor their physical condition. Several existing technologies are known to detect fatigue. One method involves analyzing a recorded video of a face to extract changes in brightness values related to the pulse, and then analyzing the fluctuations of these changes to detect fatigue [2]. Another method uses wearable devices to measure heart rate and detect fatigue based on the obtained heart rate [3]. However, these systems have several issues. Recording the face may cause privacy issues, and it is inconvenient to constantly wear a wearable device. In recent years, a head-mounted camera which is attached to a helmet is widespread [4]. A video recorded by this camera is used sharing and recording real-time experiences at work

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sites. Also, it can be used hands-free operation. Therefore, a human-recorder has been proposed to obtain the user's biometric information for fatigue detection using the head-mounted camera [5, 6, 7]. The human-recorder extracts head sway in a video recorded by the head-mounted camera, and analyzes the time change of head sway. In this paper, the estimated pulse rate is calculated using the human-recorder to confirm that the pulse rate can be estimate in real time. Furthermore, the effect on the accuracy of the pulse rate estimation is verified by the camera frame rate. This analysis is important because it supports more practical and real-time use at disaster sites and construction site.

2. Human-recorder for pulse estimation

Figure 1 shows an overview of the human-recorder for pulse rate estimation. The human-recorder analyzes video recorded by a head-mounted camera to estimate pulse rate. This system processes the recorded video through the following steps.

(1) The feature point $f_1(x_1, y_1)$ is determined from the first frame in the recorded video. The feature coordinate point $f_n(x_n, y_n)$ each frame in the recorded video is calculated using optical flow.

(2) The time change of the feature coordinate point in x-coordinate is extracted and applying frequency analysis. From the result of frequency analysis, the user's pulse rate is estimated.

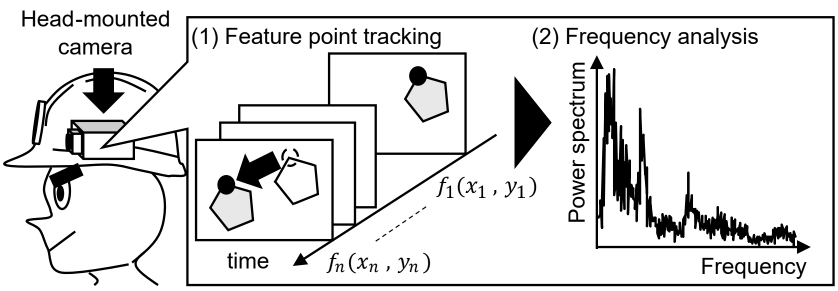

Figure 1: Human-recorder for pulse estimation

2.1. The feature coordinate point calculation using optical flow

Figure 2 (a) and (b) shows optical flow processing. The head sway is analyzed by tracking the feature coordinate point using optical flow. Optical flow processing is a method that calculates the feature coordinate point between temporally consecutive images in recorded video. Optical flow is expressed as equation (1).

$$
\begin{aligned}
&\frac{\partial I}{\partial x}u + \frac{\partial I}{\partial y}v + \frac{\partial I}{\partial t} = 0 \\
&I(x, y, t) = I(x + \Delta x, y + \Delta y, t + \Delta t) \\
&u = \frac{dx}{dt}, \quad v = \frac{dy}{dt}
\end{aligned} \tag{1}
$$

The feature coordinate point is calculated using optical flow to extract the user's head sway (Fig 2 (b)). The first feature point $f_1(x_1, y_1)$ is determined from the first frame in the recorded video. The feature point $f_n(x_n, y_n)$ each frame is calculated by tracking the feature point $f_1(x_1, y_1)$ using optical flow, and the time change of the feature coordinate point in x-coordinate (Fig 2 (c)) and y-coorfinate (Fig 2 (d)) are extracted. The x-coordinate time change is analyzed in this paper.

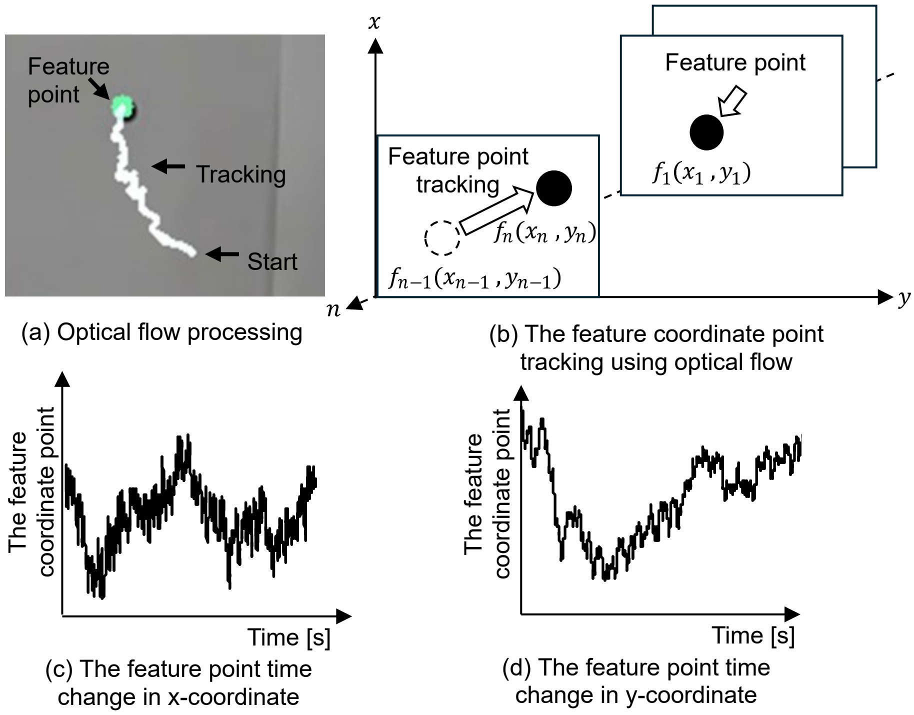

Figure 2: The feature coordinate point calculation using optical flow

2.2. Pulse rate estimation using frequency analysis

Figure 3 shows the pulse rate estimation using frequency analysis for the time change of the feature coordinate point. The time change of the feature coordinate point in x-coordinate Fig 3 (a) is extracted and detrended to remove linear components using a high-pass filter with a cutoff frequency of 0.2 Hz (Fig 3 (b)). The detrended time change is extracted 2,048 frames and the power for each frequency is calculated by applying the Fast Fourier Transform (FFT) to the detrended time change. The peak frequency (f_{max}) is calculated with $1 \sim 2$ band-pass filter (Fig 3 (c)). This frequency range ($1 \sim 2$ Hz) is chosen because the typical human pulse rate is between $60 \sim 120$ bpm. Then, the estimated pulse rate (PR_{est}) is calculated using equation (2).

$$PR_{est} = f_{max} \times 60 \tag{2}$$

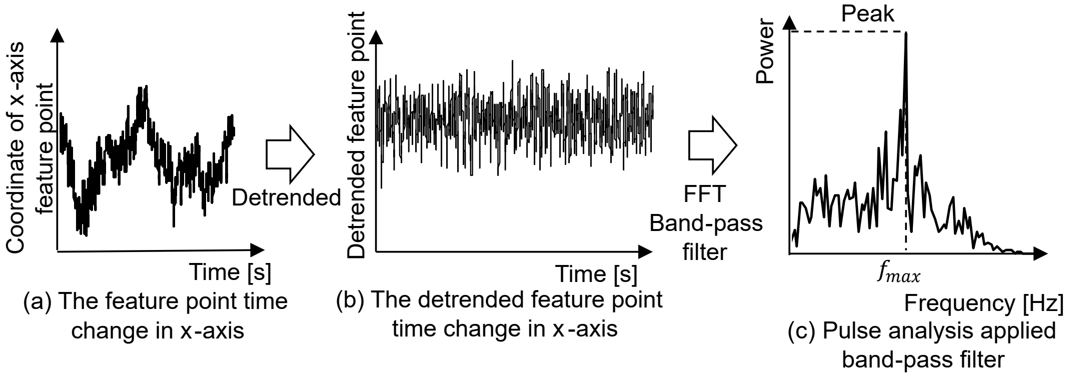

Figure 3: Pulse rate estimation using frequency analysis

3. Experiment procedure

3.1. Pulse rate estimation using human-recorder

In this experiment, a video is recorded by the human-recorder and analyzed to confirm that real-time pulse rate estimation is possible. Figure 4 shows the overview of pulse rate estimation using human-recorder. Raspberry Pi Zero 2W controls camera module 3 at 50 fps in this prototype. Three participants put on this prototype and record a video for 120 seconds in a sitting position. Then, the estimated pulse rate is calculated by analyzing the video recorded using the human-recorder. Additionally, the actual pulse rate of the participants is measured using a pulse sensor while they record a video to compare with the estimated pulse rate.

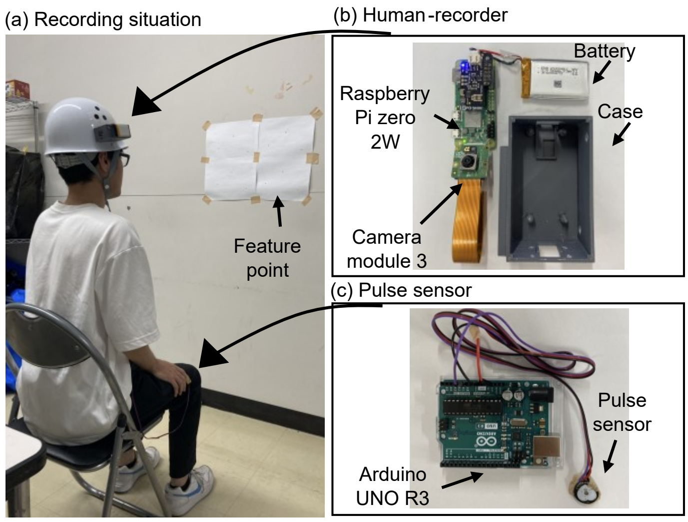

Figure 4: Pulse rate estimation using human-recorder

3.2. Verification pulse rate estimation accuracy by fps

In this experiment, the effect on the accuracy of the pulse rate estimation is verified by setting the fps values to 30, 40, 50, and 60 in the same situation as in Section 3.1. The Root Mean Square Error (RMSE) is used to evaluate the accuracy of predictions by calculating the square root of the mean of the squared differences between predicted and actual values. It is defined by equation 3 provides a single value that summarizes how close the estimated values are to the true values. Smaller RMSE values indicate higher accuracy and better model performance.

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{3}$$

4. Experiment result

4.1. Result of pulse rate estimation using human-recorder

Figure 5 shows the result of the estimated pulse rate calculated using the human-recorder and the actual pulse rate measured using pulse sensor for each participants. The solid line is the time change of the estimated pulse rate and the dashed line is the time change of the actual pulse rate. Table 1 shows RSME of each result between the estimated pulse rate and the actual pulse rate. The estimated pulse rates for participants 1, 2, and 3 were estimated to be approximately $93 \sim 98$ bpm, $70 \sim 73$ bpm, and $64 \sim 67$ bpm, respectively. In Fig 5, the estimated the pulse rate consistently tracks the actual pulse rate with high fidelity. Therefore, it is verified that pulse rate can be estimated using the human-recorder.

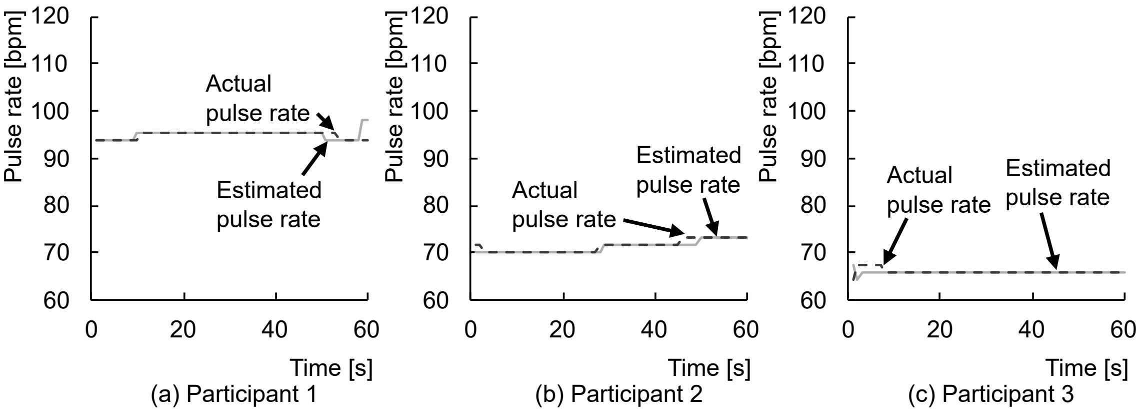

Figure 5: Result of pulse rate estimation

4.2. Verification of pulse rate estimation by fps

Figure 6 shows the results of the estimated pulse rate of one participant by 30, 40, 50 and 60 fps and the actual pulse rate. These fps values are selected because the pulse rate generally range from 1 $\sim$ 2, indicating that 30 fps is sufficient for estimation. The solid line is the time change of the estimated pulse rate and the dashed line is the time change of the actual pulse rate. Also, Table 3 shows the RSME for the results at each fps. In Fig 6, the estimated pulse rate generally tracks the actual pulse rate by 30, 40, 50 and 60 fps. From Table 3, the estimated pulse matched actual pulse rate at 50 fps, showing 0 Hz. For both 60 fps and 30 fps, the error was 0.0146 Hz, while 40 fps had the largest error at 0.0416 Hz. This indicates that the pulse rate estimation error due to fps is small. It is likely that main reason for errors is body movement during recording.

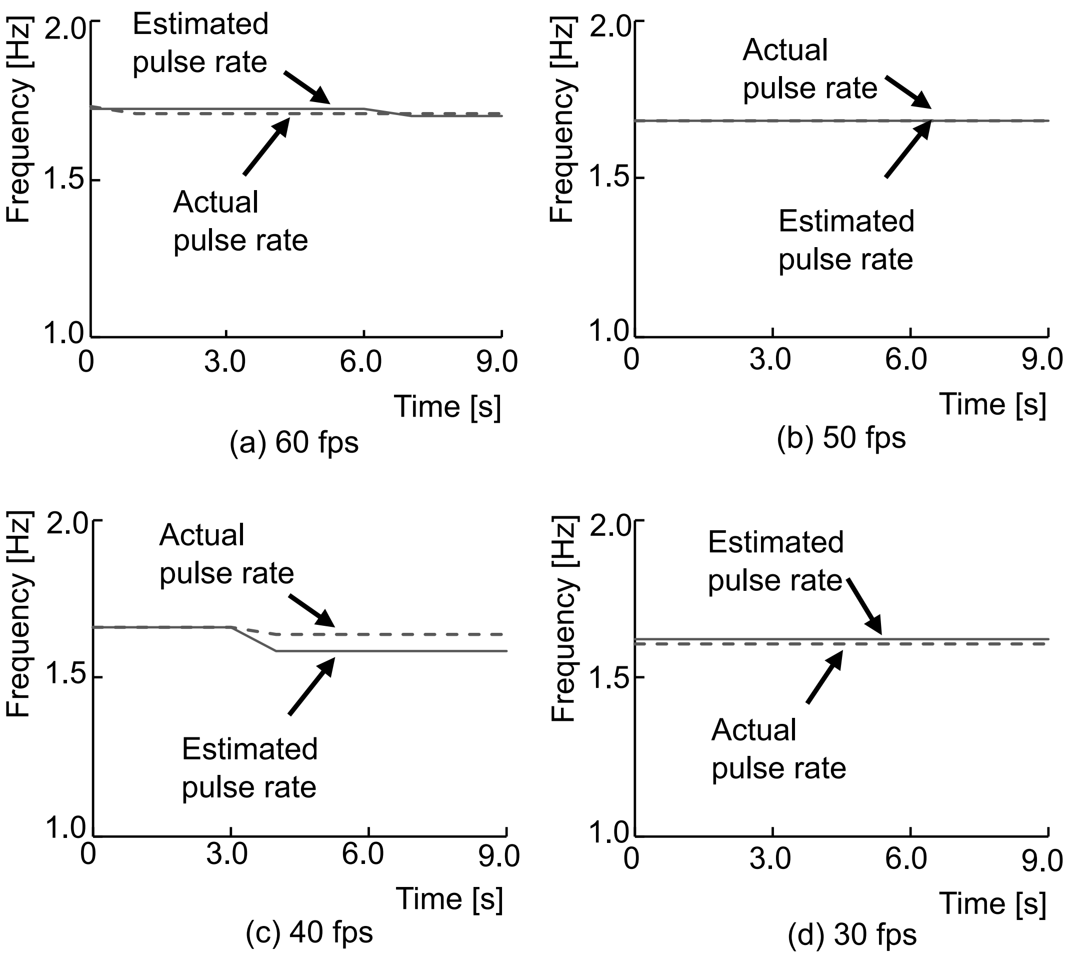

Figure 6: Result of pulse rate estimation by fps

Table 1
RMSE of pulse rate estimation results

	60 fps	50 fps	40 fps	30 fps
RMSE [Hz]	0.0146	0.0000	0.0416	0.0146

4.3. Conclusion

In this paper, the estimated pulse rate was calculated using the human-recorder to confirm that pulse rate can be estimated in real time. Furthermore, the effect of the camera's frame rate on the accuracy of pulse rate estimation was evaluated. The results demonstrated that the pulse rate measured by the human-recorder was in close agreement with the actual pulse rate. In other words, the human-recorder enables pulse rate estimation. Based on the RMSE results, it can also be confirmed that the difference in fps has little effect on the accuracy of pulse rate estimation. However, it was observed that the number of reliable feature coordinate points decreases as the fps decreases, which may negatively affect estimation accuracy. To address this issue, future work will focus on developing methods to interpolate missing or sparse feature point data, especially under low-fps conditions, in order to maintain stable performance.

Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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