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# Non-Contact Heart Rate and Respiration Rate Monitoring for Elderly Care

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**Abstract:** As the nursing shortage in Germany continues to intensify, the necessity for user-friendly assistance systems is becoming increasingly important. This paper describes an approach for the automatic and regular recording of vital signs using consumer-grade cameras. The effects of varying environmental conditions and behavioral changes on the accuracy of heart rate and respiration rate measurements are analyzed. The results demonstrate accurate monitoring in controlled settings with varying distances. However, lighting conditions and behavior highly impact accuracy, highlighting the need to tailor algorithms specifically for the respective real-world application.

**Keywords:** Contactless, heart rate, respiration rate, optical, remote photoplethysmography

## 1 Introduction

By the end of 2035, the number of people in need of care in Germany is projected to reach 5.6 million solely due to demographic aging, assuming a constant care rate, according to calculations by the German Federal Statistical Office [1]. Assuming that the care rate will also increase, the number of people in need of care by the end of 2035 will rise to 6.3 million. The increasing shortage of healthcare professionals extends beyond Germany and poses a global challenge. In this context, the development of intelligent systems to support nursing staff and relieve them of routine tasks has become increasingly essential. One approach is the

use of autonomous, non-invasive, and contactless vital signs monitoring solutions that do not require the attachment of measurement devices to the body. This is particularly advantageous for elderly individuals with sensitive skin. A cost-effective option is an optical vital sign monitoring using RGB cameras.

The ability to measure heart rate using consumer level cameras was first demonstrated by Verkruysse et al. [2] using remote photoplethysmography (rPPG). RPPG detects variations in ambient light reflection on the surface of the skin caused by blood volume fluctuations during each cardiac cycle. Research on various rPPG methods for remote patient monitoring has expanded quickly, exploiting both conventional signal processing techniques and deep learning-based approaches [3]. Respiration rate can be estimated from heart rate signal modulations [4, 5] or by analyzing chest motion. For instance, Tan et al. [6] detect movement through frame differencing and edge analysis, while Bartula et al. [7] transform regions of interest (ROIs) into one-dimensional vectors and compute the differences between consecutive frames through cross-correlation. Other methods, such as those by Lukac et al. [8], utilize feature tracking and optical flow.

While automated contactless vital sign monitoring with conventional cameras offers many benefits, its performance remains sensitive to changes in measurement conditions. For now, no method is superior across all applications, and most models lack extensive testing in real-world scenarios. This means that methods must be tailored to specific use cases. Public datasets have helped refine methods and improve accuracy, but gaps remain, particularly in diversity of appearance, behavior, and environment [9].

In this work, the impact of various scenarios on the accuracy of two algorithms is examined, one for extracting heart rate and one for extracting respiration rate. The focus is particularly on scenarios associated with naturalistic settings in nursing homes or home care applications. The accuracy is compared based on the mean absolute error (MAE) and root mean square error (RMSE) relative to the ground truth. From this, approaches are derived that must be considered for real-world deployment. In the future, the camera system will be integrated onto a care robot to facilitate automatic and regular

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non-contact vital sign monitoring. As the robot moves through various environments, each measurement will occur under different conditions. Therefore, it is essential to specifically adapt the algorithms to address these challenges. Regular monitoring of heart rate and respiration rate is crucial for early identification of health risks and changes. For instance, an elevated resting heart rate can serve as a predictor of cardiovascular and overall mortality [10]. The respiration rate has been demonstrated to be a predictor of serious adverse events, acting as an early warning sign for conditions including sepsis, shock, cardiac arrest, and respiratory failure [11, 12]. This underscores the importance of accurate monitoring.

## 2 Methods

### 2.1 Data Acquisition

In the study, eleven people between the ages of 20 years and 69 years were included, with an average age of 39 years. The subjects were recorded in a seated position facing the camera. Recordings were captured using an Allied Vision Mako G223C. To achieve a frame rate of 50 fps, only a subsection of the camera image with a resolution of 960 pixels by 1348 pixels was used. The measurement duration was 90 seconds. Simultaneously, conventional contact-based reference measurements were taken using a NeXus-10 MKII device. This included the acquisition of a single-channel electrocardiogram (ECG) with a sampling rate of 256 samples per second and the recording of a respiratory signal using a chest belt with a sampling rate of 32 samples per second.

A total of seven scenarios were recorded. Out of the 77 measurements, 69 were ultimately included in the analysis. The individual measurements were excluded based on the following criteria:  $N = 5$  for speaking in the incorrect scenario,  $N = 2$  for circulatory issues and  $N = 1$  for occlusion of the face. In the baseline measurements, the distance between the camera and the subject was 1 meter, and the lighting in the room was provided by ceiling lamps, with no speaking from the subject. In addition to the baseline, recordings were made with an increased distance of 1.5 meters, under various lighting conditions, i.e. lateral light, frontal light and backlight, as well as with different behavior, i.e. after exercise, and while speaking. The speaking scenario was excluded from the respiration rate measurements, as it can severely alter the breathing pattern, compromising a reliable respiration rate measurement even for reference measurements.

### 2.2 Heart rate extraction

The video recordings are divided into sliding windows of 20 seconds with a step size of 1 second, for each of which the heart rate is estimated. For each frame, ROIs for rPPG extraction are localized. First, the face and its outlines are detected by combining an SSD (Single Shot Detector) face detector with a face landmark detector from OpenCV, which extracts 68 facial landmarks [13]. Subsequently, the landmarks are tracked over time using a MOSSE Tracker. Relative to these landmarks, two ROIs are defined, the forehead region and the nose region. Additionally, to improve robustness, face detection is repeated every 3 seconds to assess the overlap between the newly detected and the previously used face region. If the deviation exceeds 60 %, the newly detected facial region is used. The average red, green and blue values for each frame and window from both ROIs are calculated. The resulting signals for each color channel are filtered using an FIR bandpass filter to remove low-frequency noise below 0.75 Hz (e.g., breathing noise) and high-frequency noise above 3 Hz. To obtain the rPPG signal, the POS transformation by Wang et al. [14] is applied. POS transformation effectively extracts pulsatile features and has demonstrated high accuracy in heart rate measurements in preliminary studies [15]. Subsequently, Welch's method is used to determine the heart rate within the specified frequency range by assigning the fundamental frequency, considering all frequencies between 0.75 Hz and 3 Hz.

For the reference measurements, the heart rate is determined in the time domain. The same temporal windows used for the video recordings are applied. RR intervals are calculated using NeuroKit2 [16] R-peak detection, which is used to calculate the heart rate according to Equation 1.

$$HR = \frac{60}{\overline{T}_{RR}} \quad (1)$$

where  $HR$  is the heart rate and  $\overline{T}_{RR}$  is the mean of the RR intervals.

### 2.3 Respiration rate extraction

The breathing rate is determined in sliding windows of 30 seconds with a step size of 1 second. Relative to the detected facial region, the chest region is localized. In the latter, prominent feature points are identified and tracked over time using Sparse Optical Flow. For each window, the mean trajectory of all feature points representing the up and down movement of the chest is calculated. The resulting respiratory signal is mean adjusted and bandpass filtered with cut-off frequencies of 0.1 Hz and 1.2 Hz. Welch's method is applied

to convert the time domain data into the frequency domain data, with the fundamental frequency assigned as the respiration rate, considering all frequencies between 0.1 Hz and 0.6 Hz.

For the reference respiratory signal, the same temporal windows used for the video recordings are applied. The respiration rate is determined using a bandpass filter and Welch's method with the same settings and frequency ranges as for the motion signal of the video recordings.

### 3 Study Results

Table 1 presents the MAE and RMSE for heart rate measurements across the respective scenarios. The highest accuracy is obtained in the baseline scenario and under increased distance. A distance change of 0.5 meters has only a minor effect on the detection of the subtle skin color variations. Contrary to expectations, increased distance yields slightly higher accuracy for heart rate measurement. Possible reasons for this could include small changes in lighting conditions due to ceiling lamps. For the larger distance, the subject was positioned slightly differently in the room. Another factor might simply be the amount of data collected. Changing the lighting conditions highly impact the accuracy, leading to increased error values, with the lowest accuracy observed under backlight conditions. Lateral and frontal lighting often caused overexposure, leading to saturation in certain pixel areas, preventing the detection of color intensity variations. In addition, lateral lighting caused shadowing on parts of the face, obstructing the detection of strong rPPG signals. In direct backlighting, the measured subject is poorly illuminated, which does not allow for robust ROI tracking or detection of the pulsatile color changes.

**Table 1:** Mean absolute error (MAE) and root mean square error (RMSE) in beats per minute (bpm) of the heart rate measurements for different scenarios.

| Scenario           | MAE     | RMSE     |
|--------------------|---------|----------|
| Baseline           | 1.9 bpm | 2.9 bpm  |
| Increased distance | 1.6 bpm | 2.7 bpm  |
| Lateral light      | 4.4 bpm | 6.8 bpm  |
| Frontal light      | 2.8 bpm | 4.1 bpm  |
| Backlight          | 9.2 bpm | 12.6 bpm |
| After sport        | 8.1 bpm | 10.3 bpm |
| Speaking           | 8.1 bpm | 12.0 bpm |

Regarding behavior, measurements taken after exercise and while speaking show markedly lower accuracy compared to baseline. After exercise, the subject tends to sit less still, and during speaking, not only the mouth moves, but for most individuals, this is accompanied by intense head movement. This makes not only accurate ROI tracking difficult but also rPPG extraction due to altered light reflections caused by movement.

In Table 2, an overview of the MAE and RMSE for respiration rate measurements across the different recorded scenarios is presented. The baseline scenario and increased distance show approximately comparable error values. The detection and tracking of chest features function well even at a greater distance of 0.5 meters. Lateral and frontal lighting conditions lead to slightly higher accuracy compared to the baseline scenario, while the lowest accuracy is observed under backlight conditions. Feature recognition relies on identifying distinct regions that stand out from others, thus benefiting for instance from lateral shadowing. Conversely, when the entire chest area is poorly illuminated, feature detection and tracking perform worse due to minimal contrast differences. The accuracy for respiration rate is highest in the post-exercise scenario, which can be attributed to deeper breathing that enhances chest motion.

**Table 2:** Mean absolute error (MAE) and root mean square error (RMSE) in respirations per minute (rpm) of the respiration rate measurements for different scenarios.

| Scenario           | MAE     | RMSE    |
|--------------------|---------|---------|
| Baseline           | 1.1 rpm | 1.3 rpm |
| Increased distance | 1.2 rpm | 1.5 rpm |
| Lateral light      | 0.8 rpm | 1.1 rpm |
| Frontal light      | 0.8 rpm | 1.1 rpm |
| Backlight          | 1.7 rpm | 2.3 rpm |
| After sport        | 0.6 rpm | 0.9 rpm |

### 4 Discussion

The results of this study highlight the need for detailed examination of the impact of naturalistic settings. While heart rate and respiration rate can be measured with high accuracy under ideal conditions, further algorithmic improvements are required for reliable non-contact measurement in real-world scenarios, particularly regarding stability against lighting and motion variations. Lighting variations can severely affect the visibility of features, cause unwanted specular reflections and

further impair the underlying signals due to under- or overexposure. Motion artifacts in videos can hinder accurate ROI tracking and complicate the extraction of the rPPG signal due to motion-induced changes in light reflections. This is consistent with previous findings that identify lighting and movement as major challenges [3, 9]. For our intended use in care, this means that different lighting conditions must be automatically detected and optimized by adjusting the exposure time before each measurement begins. Backlighting should be avoided, which users should be informed about in advance. Additionally, an adjustable light source integrated into the robotic system could help minimize these issues. Speaking should be prohibited during measurement, and violations detected to ensure measurement reliability. In addition, the applied method used to detect the heart rate should be enhanced by techniques that increase robustness to strong movements.

For robust vital signs measurement, it is essential to identify the different scenarios and react with adapted approaches, depending on their characteristics and variations. These functionalities must be implemented and integrated into a process control system. Future studies should also include more participants and longer observation periods with individuals in need of care. Additionally, complete remote monitoring could be extended by integrating further vital signs such as blood pressure and SpO<sub>2</sub>.

## 5 Conclusion

In this work, a data collection study was conducted to evaluate an optical measurement approach for heart rate and respiration rate in different conditions for use in care settings. The results show that heart and respiration rate measurements are accurate for baseline and increased distance scenarios, but further work is needed on robustness regarding lighting and motion, with the need to recognize and adapt to specific conditions individually. Considering this, the presented non-contact vital sign monitoring system offers great benefit in both inpatient and outpatient settings. It has the potential to reduce nursing workload and enables the detection of emergencies and care changes, while promoting independent living.

### Author Statement

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