2022 44th Annual International Conference of
the IEEE Engineering in Medicine & Biology Society (EMBC)
Scottish Event Campus, Glasgow, UK, July 11-15, 2022

2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC) | 978-1-7281-2782-8/22/$31.00 ©2022 IEEE | DOI: 10.1109/EMBC48229.2022.9871416

Unobtrusive Heart Rate Monitoring using Near-Infrared Imaging During Driving

Vinothini Selvaraju[1,2], Student Member, IEEE, Nicolai Spicher[1], Member, IEEE, Ramakrishnan Swaminathan[2], Member, IEEE, and Thomas M. Deserno[1], Senior Member, IEEE

Abstract— **In-vehicle health monitoring allows for continuous vital sign measurement in everyday life. Eventually, this could lead to early detection of cardiovascular diseases. In this work, we propose non-contact heart rate (HR) monitoring utilizing near-infrared (NIR) camera technology. Ten healthy volunteers are monitored in a realistic driving simulator during resting (5 min) and driving (10 min). We synchronously acquire videos using an out-of-the-shelf, low-cost NIR camera and 3-lead electrocardiography (ECG) serves as ground truth. The MediaPipe face detector delivers the region of interest (ROI) and we determine the HR from the peak with maximum amplitude within the power spectrum of skin color changes. We compare video-based with ECG-based HR, resulting in a mean absolute error (MAE) of 7.8 bpm and 13.0 bpm in resting and driving condition, respectively. As we apply only a simple signal processing pipeline without sophisticated filtering, we conclude that NIR camera-based HR measurements enables unobtrusive and non-contact monitoring to a certain extent, but artifacts from subject movement pose a challenge. If these issues can be addressed, continuous vital sign measurement in everyday life could become reality.**

I. Introduction

The heart rate (HR) is an important measure of physiological activity and allows to assess the health status [1]. Thereby, it is one of the five most important vital signs to monitor cardiovascular activity [2] and is affected by physical activity, stress, or medication. Consequently, it is used in a wide range of applications namely, medical diagnosis, emotion analysis, or fitness measurement [3].

According to the World Health Organization (WHO), cardiovascular diseases cause approximately 32% of all deaths worldwide [4]. Continuous health monitoring is essential to detect early signs, provide prior treatment and prevention, improve patient's outcomes and to lower death rates [5].

Traditional methods for HR measurement such as, electrocardiography (ECG), pulse oximetry and photoplethysmography (PPG) are widely used in clinical practice [6]. However, they obtrusively require skin contact which may cause irritation or patient discomfort, expensive hardware, and medical staff for its application [3].

In the last years, imaging PPG (iPPG) gained research interest and shows promising results for non-contact HR measurements [2],[6],[7]. Image- or video-based iPPG measures subtle color changes in the skin due to the cyclic blood flow in the capillaries [8-11]. Several works demonstrate its potential for continuous and unobtrusive health monitoring in day-to-day life [8], [9], [12].

The majority of studies use red-green-blue (RGB) cameras [9], [13]–[18], although this approach has a low signal-to-noise ratio (SNR) in low-light conditions and is strongly affected from changes in the ambient light [19]. To overcome this issue, near infrared (NIR) cameras can be used. They are especially useful for sleep [20], hospital, fitness [3], in-vehicle [7], [21], [22] and in-home monitoring at day and night [23] for all age groups. Additionally, these cameras are inexpensive [20]. However, NIR cameras have an even lower SNR compared to RGB cameras [8], [10].

In this work, we investigate on the accuracy of HR measurement using NIR cameras in a driving scenario.

II. Methods

In this preliminary study, we conduct experiments in an indoor environment using a realistic driving simulator with subjects undergoing two kinds of activities. The estimated HR is compared with the ground truth HR from synchronously acquired ECG signal. Our research questions are:

- Can NIR cameras reliable measure the HR in the driving environment?
- In how far does the driver's movement impact the accuracy of HR estimation?

A. Study population

$S_{tot} = 10$ healthy subjects (5 male, 5 female) with an age of 29.5 ± 4.7 (mean ± standard deviation) years and all being licensed driver were included in this study. The subjects had different ethnic origins (Central and Eastern Europe, Southern and Eastern Asia) and partly wore eye glasses ($S_{glas} = 5$) and beard ($S_{beard} = 3$). All participants gave written consent.

B. Data acquisition

We record the data with a desktop-mounted NIR camera (Raspberry NoIR Camera Module V2 (Raspberry Pi Foundation, Cambridge, UK) delivering 1280 x 720 pixels at 10 frames per seconds (FPS) connected to single-board computer (Raspberry Pi 4 Model B, Raspberry Pi Foundation, Cambridge, UK) with 8 GB RAM. In addition to fluorescent

[1]Peter L. Reichertz Institute for Medical Informatics, TU Braunschweig and Hannover Medical School, Braunschweig, Germany (corresponding author e-mail: vinothini.selvaraju@plri.de).

[2]Biomedical Engineering, Department of Applied Mechanics, Indian Institute of Technology Madras, Chennai, India.

ceiling light, external day light through the windows and computer screen illumination, we provide infrared (IR) illumination (JC IR illuminator, Jcheng security, Shenzhen, China). The subjects sat in a driving simulator (RaceRoom simulator RR3055, KW automotive, Fichtenberg, Germany). The distance between camera and subjects' faces was approximately 1 m (Fig. 1).

According to Taamneh et al. [24], we perform two experiments. First, we instruct the subjects to rest, i.e., to sit normally without any intentional movements (5 min). Then, they performed the real-time driving game using the steering wheels and pedals of the simulator (10 min). We store the videos in the h264 file format for offline analysis. As ground truth, we synchronously record an electrocardiography (ECG) lead II (BiosignalPlux Explorer, Plux Wireless Biosignals, Lisboa, Portugal).

Fig. 1. Driving simulator used within this study.

C. Data processing

We extract individual frames from the video and feed them into the MediaPipe face detector providing 468 face landmarks [25]. We only use a landmark outlining the facial contour (Fig. 2).

Subsequently, we obtain the raw iPPG signal by spatial averaging of all the channels of each pixel in the ROI. We apply a de-trending filter to eliminate the signal trend and a Butterworth band-pass filter to restrict the data to a sensitive range between 45 bpm and 120 bpm (0.75 Hz to 2 Hz), which is regular for healthy subjects at rest or moderate physical activity [26]. Before transforming into the frequency domain, we window with 60 s and 10 s step size. Then, we compute the power spectrum (PS) for each window, detect the maximum, and multiply the corresponding frequency by 60 to obtain the HR in the unit of bpm.

D. Statistical analysis and performance evaluation

We calculate the HR from the reference ECG signals utilizing the simultaneous truth and performance level estimation (STAPLE) peak detector [27]. For evaluation, we compute mean absolute error (MAE) and root mean square error (RMSE) as performance metrics:

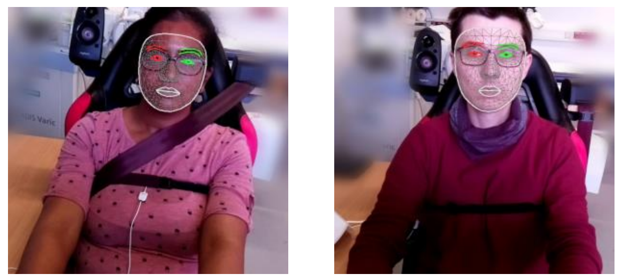
$$\mathrm{MAE} = \frac{\sum_{i=1}^{I} |\mathrm{HR}_{\mathrm{ECG}}(i) - \mathrm{HR}_{\mathrm{NIR}}(i)|}{I} \tag{1}$$

$$\mathrm{RMSE} = \sqrt{\sum_{i=1}^{I} \frac{(\mathrm{HR}_{\mathrm{ECG}}(i) - \mathrm{HR}_{\mathrm{NIR}}(i))^2}{I}} \tag{2}$$

where N denotes the number of frames in the video with 10 FPS, I = (N-window length/step size) +1 is the number of windows, and $\mathrm{HR}_{\mathrm{ECG}}$ and $\mathrm{HR}_{\mathrm{NIR}}$ denote the reference (ECG-based) and the measured (NIR-based) HR, respectively. In addition, we conducted statistical analysis by means of computing mean and standard deviation.

III. RESULTS

The ROI is tracked accurately during rest as well as motion (Fig. 2). The raw signals show a regular pattern and a drift in both resting and driving positions (Figs. 3a and 3b) respectively. The preprocessing removes the drift (Figs. 3c, 3d and 4). In the exemplary data, the highest peak in the PS is located at 1.30 Hz (78.5bpm) and 0.99 Hz (59.8 bpm) during rest and motion (Figs. 3e and 3f), respectively. The reference ECG delivers a high-quality signal (Figs. 3g and 3h).



(a) resting (b) driving

Fig. 2. Example NIR frames after ROI detection

Subject S7 and S3 showed lowest (3.3 and 6.6) and highest (18.6 and 25.8) MAE in rest and driving respectively (Tab. I). For most subjects, the reference HR is increased during driving, which may reflect the physical activity of moving arms and legs. Also, the MAE increases in the second experiment for almost all the subjects (Fig. 4). Over all the subjects, our method achieves an average MAE of 7.8±5.0 and 13.0±6.5 bpm during resting and driving, respectively. In total, this technique reaches the average MAE of 10.4±5.2 bpm. Subjects without and with glasses yield an average MAE of 8.1±2.1 and 12.7±6.7 bpm, respectively. Furthermore, the female subsects yield a higher MAE compared to the male participants.

IV. DISCUSSION

The preliminary results of this study demonstrate that the proposed technique has promising potential for in-car HR measurement using NIR cameras. We observe the MAE of 7.8 bpm and 13.0 bpm in rest and driving condition, respectively. Our results clearly evident an increase in error as a result of increased physical activity that might be associated with the motion. Apparently, glasses have a significant impact on performance which might be reflected in the iPPG signal obtained from their faces. From this, we answer the research question as follows:

- RQ-A: NIR based techniques show a potential for HR estimation (Fig. 3). However, we observe a high intra-subject variability with five volunteers showing less than 5 bpm MAE but also five volunteers showing more than 5 bpm MAE during resting (Tbl. I).

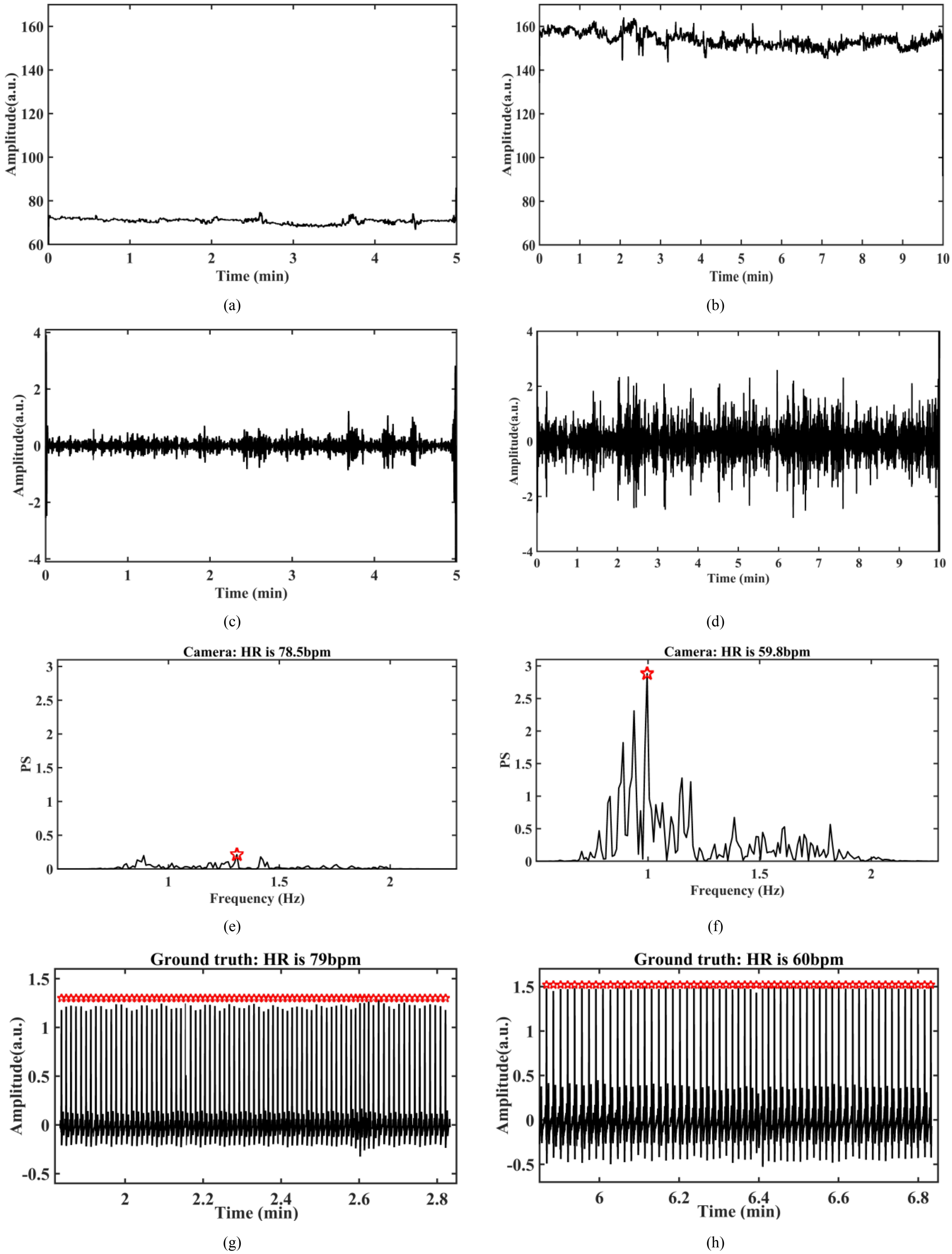


Fig. 3. Representative image of a-b) raw signal, c-d) preprocessed signal, e-f) frequency domain and g-h) ECG ground truth signal in rest condition (1st column) and driving condition (2nd column). Red stars denote maximum peak in PS (e-f) and QRS complexes (g-h).

Table I. Quantitative results of each subject

Subject	Gender	Glasses	Rest			Driving			Total		
ID	M/F	yes / no	ECG mean	NIR mean	MAE (bpm)	ECG mean	NIR mean	MAE (bpm)	ECG mean	NIR mean	MAE (bpm)
S1	F	No	66.6	66.3	4.3	70.4	63.5	8.0	68.5	64.9	6.2
S2	F	Yes	70.8	60.6	11.5	77.6	68.0	11.1	74.2	64.3	11.3
S3	F	Yes	80.6	62.9	18.6	86.4	61.0	25.8	83.5	62.0	22.2
S4	F	No	69.8	63.8	8.3	70.1	64.1	8.1	70.0	64.0	8.2
S5	F	Yes	80.6	70.0	11.2	82.4	61.4	21.8	81.5	65.7	16.5
S6	M	No	68.4	66.9	10.0	68.9	69.3	8.7	68.6	68.1	9.4
S7	M	Yes	60.4	61.4	3.3	60.1	61.1	6.6	60.2	61.3	4.9
S8	M	No	76.7	72.4	4.7	80.5	64.6	17.2	78.6	68.5	11.0
S9	M	No	65.3	62.0	3.3	68.7	63.2	8.7	67.0	62.6	6.0
S10	M	Yes	78.1	75.1	3.5	76.7	63.3	14.5	77.4	69.2	9.0
Mean (SD)	-	-	71.7 (6.9)	66.1 (4.9)	7.8 (5.0)	74.1 (7.9)	63.9 (2.7)	13.0 (6.5)	72.9 (7.3)	65.0 (2.7)	10.4 (5.2)

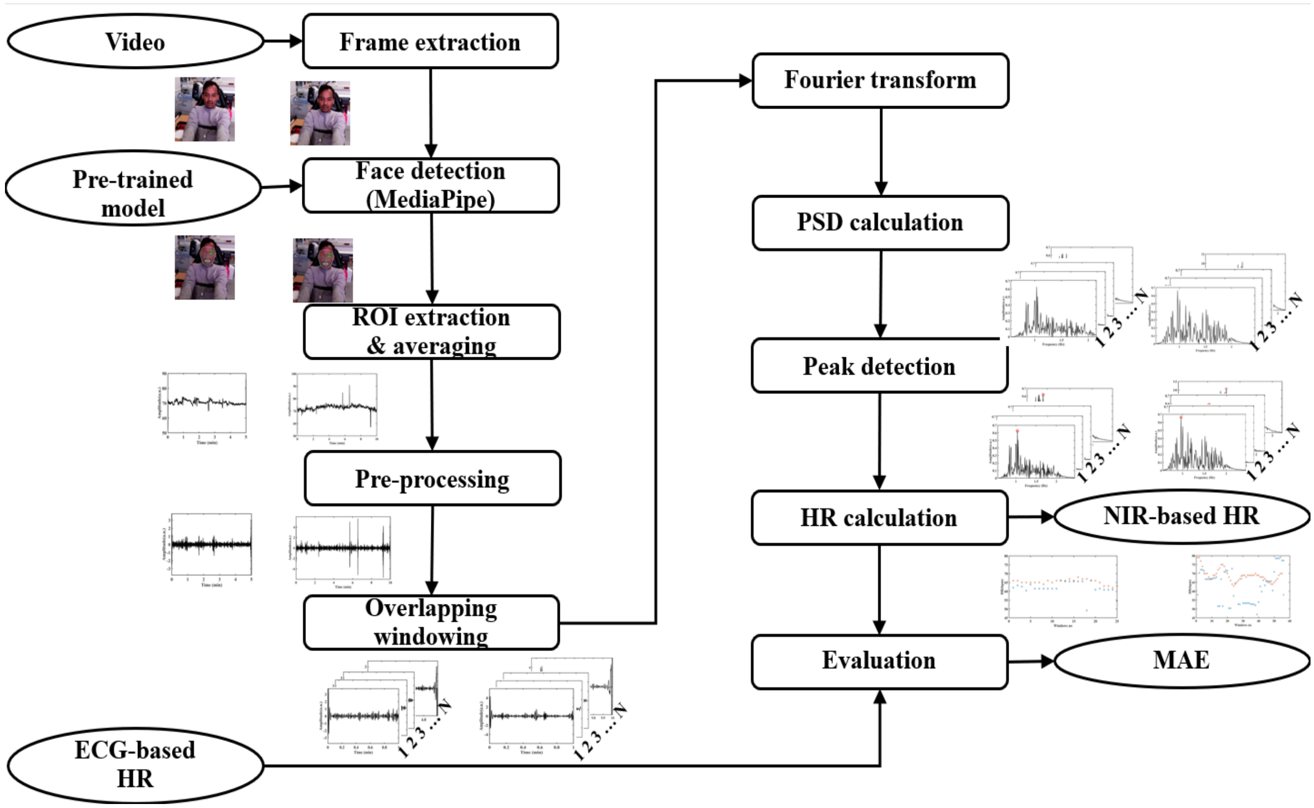


Fig. 4. The pipeline of our approach

- RQ-B: Physical movement has a high impact on the reliability of the NIR-based HR measurement (Tbl. I and Fig. 4). However, we used only simple signal processing and our results probably improve with more comprehensive processing.

We observed that the performance of all studies yielded more than 10 bpm RMSE due to large motion associated with driving environment (Tbl. II). Nowara et al., achieved lowest error utilizing RGB (9.6 bpm) and NIR (11.6 bpm) compared to other studies. Our study achieves an RMSE of 13.6 bpm by utilizing simple signal processing technique. Future study will be carried out to handle the motion by employing more advanced signal processing techniques.

In addition, this study has some limitations that can also be addressed in future work. First, the camera specifications (e.g., FPS) are inferior in comparison to other works, which satisfies the Nyquist sampling theorem but may impact performance in moving subjects. Second, our experiment was conducted in a laboratory with adequate illumination and a controlled temperature, which needs to be more variable in future experiments.

`Third, the experiments were conducted with a rather small number of participants (S_{tot} = 10). In future work, we will address these issues by conducting a large-scale study using a vehicle that is in real traffic.

Table II. Comparison of performance with previous driving studies on HR estimation

Author, year	Camera	RMSE (bpm)
Nowara et al., 2018 [28]	NIR	13.6
Nowara et al., 2020 [22]	NIR	11.6
Nowara et al., 2018 [28]	RGB	9.6
Huang et al., 2021 [6]	RGB	13.0
Lee et al., 2018 [29]	RGB	15.8
Ours	NIR	13.6

V. Conclusion

In this paper, we demonstrated non-contact HR monitoring in healthy volunteers utilizing a NIR camera. The results show that the MediaPipe face detection algorithm is capable of extracting the face area accurately and rather simple signal processing results in a MAE of 7.8 bpm and 13.0 bpm in resting and driving conditions, respectively. In future, NIR-based HR measures may allow unobtrusive and more continuous health monitoring in vehicles, while travelling, and at home to prevent adverse events such as strokes.

Acknowledgment

We want to thank all volunteers who supported the data acquisition.

References

[1] Sörnmo L, Laguna P. Bioelectrical signal processing in cardiac and neurological applications. Academic Press; 2005.

[2] Antink CH, Lyra S, Paul M, Yu X, Leonhardt S. A Broader Look: Camera-Based Vital Sign Estimation across the Spectrum. Yearb. Med. Inform. 2019 Aug;28(1):102–114.

[3] Wang C, Pun T, Chanel G. A Comparative Survey of Methods for Remote Heart Rate Detection From Frontal Face Videos. Front. Bioeng. Biotechnol. 2018 May;6:33.

[4] Yahaya L, David Oye N, Joshua Garba E. A Comprehensive Review on Heart Disease Prediction Using Data Mining and Machine Learning Techniques. Am. J. Artif. Intell. 2020 Apr;4(1):20-29.

[5] Mahajan A, Pottie G, Kaiser W. Transformation in Healthcare by Wearable Devices for Diagnostics and Guidance of Treatment. ACM Trans. Comput. Healthc. 2020 Mar;1(1):1–12.

[6] Leonhardt S, Leicht L, Teichmann D. Unobtrusive Vital Sign Monitoring in Automotive Environments—A Review. Sensors. 2018 Sep;18(9):3080.

[7] Huang PW, Wu BJ, Wu BF. A Heart Rate Monitoring Framework for Real-World Drivers Using Remote Photoplethysmography. IEEE J. Biomed. Health Inform. 2021 Sep;25(5):1397–1408.

[8] Zaunseder S, Trumpp A, Wedekind D, Malberg H. Cardiovascular assessment by imaging photoplethysmography – a review. Biomed. Eng. Biomed. Tech. 2018 Oct;63(5):617–634.

[9] Hassan MA, Malik AS, Fofi D, Saad N, Karasfi B, Ali YS, Meriaudeau F. Heart rate estimation using facial video: A review. Biomed. Signal Process. Control. 2017 Sep;38:346–360.

[10] Yu X, Laurentius T, Bollheimer C, Leonhardt S, Antink CH. Noncontact Monitoring of Heart Rate and Heart Rate Variability in Geriatric Patients Using Photoplethysmography Imaging. IEEE J. Biomed. Health Inform. 2021 Aug;25(5):1781–1792.

[11] Spicher N, Kukuk M, Maderwald S, Ladd ME. Initial evaluation of prospective cardiac triggering using photoplethysmography signals recorded with a video camera compared to pulse oximetry and electrocardiography at 7T MRI. Biomed. Eng. OnLine. 2016 Dec;15(1):1-28.

[12] Selvaraju V, Spicher N, Swaminathan R, Deserno TM. Face detection from in-car video for continuous health monitoring. in Medical Imaging 2022: Imaging Informatics for Healthcare, Research, and Applications, San Diego, 2022 Apr;12037:49-56.

[13] Poh MZ, McDuff DJ, Picard RW. Advancements in Noncontact, Multiparameter Physiological Measurements Using a Webcam. IEEE Trans. Biomed. Eng. 2011 Oct;58(1):7–11.

[14] Alonso-Cuevas JL, Sanchez-Yanez RE. Simplified Heart Rate Measurement from Video. International Workshop on Interactive and Spatial Computing. 2018 Apr;2018:23–28.

[15] Benedetto S, Caldato C, Greenwood DC, Bartoli N, Pensabene V, Actis P. Remote heart rate monitoring-Assessment of the Facereader rPPg by Noldus. PloS one. 2019 Nov;14(11):e0225592.

[16] Gupta P, Bhowmick B, Pal A. MOMBAT: Heart rate monitoring from face video using pulse modeling and Bayesian tracking. Computers in biology and medicine. 2020 Jun;121:103813.

[17] Rapczynski M, Werner P, Al-Hamadi A. Effects of video encoding on camera-based heart rate estimation. IEEE Trans. Biomed. Eng. 2019 Mar 13;66(12):3360-70.

[18] Hassan MA, Malik AS, Fofi D, Karasfi B, Meriaudeau F. Towards health monitoring using remote heart rate measurement using digital camera: A feasibility study. Measurement. 2020 Jan;149:106804.

[19] Cheng J, Wang P, Song R, Liu Y, Li C, Liu Y, Chen X. Remote heart rate measurement from near-infrared videos based on joint blind source separation with delay-coordinate transformation. IEEE Trans. Instrum. Meas. 2020 Nov;70:1-13.

[20] Zhu K, Li M, Akbarian S, Hafezi M, Yadollahi A, Taati B. Vision-based heart and respiratory rate monitoring during sleep–a validation study for the population at risk of sleep apnea. IEEE J. Transl. Eng. Health Med. 2019 Oct 14;7:1-8.

[21] Warnecke JM, Boeker N, Spicher N, Wang J, Flormann M, Deserno TM. Sensor Fusion for Robust Heartbeat Detection during Driving. Annu Int Conf IEEE Eng Med Biol Soc. 2021 Nov; 2021:447-450.

[22] Nowara EM, Marks TK, Mansour H, Veeraraghavan A. Near-Infrared Imaging Photoplethysmography During Driving. IEEE Trans. Intell. Transp. Syst. 2020 Dec:1-12.

[23] Wang J, Spicher N, Warnecke JM, Haghi M, Schwartze J, Deserno TM. Unobtrusive health monitoring in private spaces: The smart home. Sensors. 2021 Jan;21(3):864.

[24] Taamneh S, Tsiamyrtzis P, Dcosta M, Buddharaju P, Khatri A, Manser M, Ferris T, Wunderlich R, Pavlidis I. A multimodal dataset for various forms of distracted driving. Scientific data. 2017 Aug;4(1):1-21.

[25] Kartynnik Y, Ablavatski A, Grishchenko I, Grundmann M. Real-time facial surface geometry from monocular video on mobile GPUs. ArXiv190706724. 2019 Jul:1-4.

[26] Favilla R, Zuccala VC, Coppini G. Heart rate and heart rate variability from single-channel video and ICA integration of multiple signals. IEEE J. Biomed. Health Inform. 2018 Nov;23(6):2398-408.

[27] Kashif M, Jonas SM, Deserno TM. Deterioration of R-wave detection in pathology and noise: a comprehensive analysis using simultaneous truth and performance level estimation. IEEE Trans. Biomed. Eng. 2016 Dec;64(9):2163-75.

[28] Nowara EM, Marks TK, Mansour H, Veeraraghavan A. SparsePPG: Towards Driver Monitoring Using Camera-Based Vital Signs Estimation in Near-Infrared. IEEE/CVF CVPRW. 2018 Jun;2018: 1353–1362.

[29] Lee K, Park D, Cho C, Ko H. Robust remote heart rate estimation in car driving environment. IEEE Int Conf Consum Electron. 2018 Jan; 2018: 1–2