REVISIMO – Contactless Monitoring of Beat-to-beat Heart Rate and other Vital Parameters via Cameras

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With the advent of smartwatches and other wearables, the continuous optical monitoring of vital signs using photoplethysmography (PPG) has become broadly available. At CSEM, we have developed an advanced solution that adapts this capability to consumer grade cameras, removing the need for dedicated wearable devices. Our approach integrates a specialized deep learning model to extract remote PPG (rPPG) signals from camera videos. These rPPG signals are then processed with CSEM's clinically validated PPG algorithms for the continuous estimation of various vital signs. We successfully showed the feasibility for remotely monitoring beat-to-beat heart rate via cameras under controlled conditions, including scenarios with motion. If validated in real-life settings and specific patient populations, this solution has the potential to enable convenient and widespread telemonitoring through commonly available cameras, increasing accessibility for personal health monitoring.

Contactless monitoring of vital signs via cameras has been studied for several years [1], with much of the focus on monitoring the breathing rate and heart rate, as these parameters are the easiest to measure reliably in a contactless manner. Consequently, most medically certified solutions available on the market are limited to monitoring heart rate and breathing rate.

The aim of the present work was to investigate the potential of expanding the contactless monitoring via cameras by reconstructing the remote photoplethysmography (rPPG) signals and evaluating their feasibility for more advanced measurements, such as beat-to-beat heart rate estimation.

A total of 101 volunteers participated in a protocol that involved simultaneous acquisition of facial videos and biosignals, including ECG and upper arm PPG. During the protocol, the participants were exposed to controlled artificial illumination and underwent different short (2-3 minutes) controlled scenarios in standing and sitting positions (including orchestrated breathing, head movements and leg extension) as well as a 10-minute free working scenario sitting in front of a computer and performing usual office work. This study was approved by the local ethics committee (CER-VD Project-ID 2023-00324).

A pretrained YOLO-based deep learning algorithm was used to detect and extract the faces from the video data along with some facial landmarks needed for motion tracking. A spatiotemporal autoencoder-based 3D convolutional neural network (CNN) was then trained on the preprocessed and windowed facial videos. The 3D CNN is designed to predict the rPPG from a given sequence of frames by leveraging both spatial and temporal information simultaneously.

Out of the 101 subjects, 10 had to be rejected due to technical issues. The remaining 91 subjects were separated in 86 for model training and 5 for testing.

The resulting rPPG signals were then processed with CSEM's algorithms for optical monitoring, which were originally developed for contact-based PPG and have been extensively validated in previous studies [2]. To evaluate the beat-to-beat heart rate measurement, reference heartbeats were extracted from the ECG and compared to heartbeats from both contact-based PPG and rPPG. Beat-to-beat detection performance was evaluated by classifying the number of correctly detected heartbeats (F1 score) and the mean absolute error (MAE) of subsequent heartbeats, i.e., the inter-beat-intervals.

Table 1 shows the heartbeat detection performance comparing contact-based PPG to contactless rPPG for different scenarios. Even for scenarios with high motion ("Head Movements") most of the heartbeats are correctly detected (i.e., high F1 score). However, the higher the motion, the higher the error (MAE) for the contactless rPPG approach. Even for very controlled scenarios with low motion ("Breathing") the MAE of rPPG remains more than three times higher than for PPG. This can be explained by rPPG signals showing lower signal quality (both in terms of signal-to-noise ratio as well as frequency content) than contact-based PPG signals.

Table 1: Heartbeat detection performance for remote (rPPG) and contact-based PPG (PPG) as median [1st and 3rd quartiles].

	Scenario	**F1 Score (%)**	**MAE (ms)**
rPPG	Breathing	99.4 [99.2, 99.6]	15.7 [12.8, 20.8]
	Leg Extension	99.7 [99.6, 99.8]	14.7 [12.6, 16.7]
	Head Movements	98.8 [95.9, 99.6]	25.0 [19.1, 38.7]
	Free Working	99.3 [99.2, 99.4]	27.9 [24.9, 30.7]
PPG	Breathing	99.5 [99.3, 99.6]	4.1 [3.3, 6.6]
	Leg Extension	99.8 [99.7, 99.8]	4.0 [2.6, 5.3]
	Head Movements	99.5 [97.0, 99.6]	3.6 [3.3, 17.4]
	Free Working	99.7 [99.5, 99.8]	5.8 [5.3, 7.1]

Nevertheless, the current performance remains promising for estimating vital parameters beyond beat-to-beat heart rate such as breathing rate, heart rate variability or the detection of cardiac arrhythmia [2]. Estimating blood pressure from rPPG remains particularly challenging and requires further investigation and adaptation to improve accuracy and reliability.

This approach shows significant potential but is currently limited in two areas. First, the recordings were performed in a very controlled environment and future work should explore more challenging scenarios, such as varying illumination and recordings via smartphones or webcams. Second, the study population should be extended to include the target population, such as patients with cardiac arrhythmia, in real-world settings like their home environment for telemonitoring.

In summary, we successfully showed the contactless monitoring of beat-to-beat heart rate via cameras under controlled conditions, including scenarios with motion. Further validation in real-life settings and specific patient populations is required to confirm its broader applicability.

[1] Wang, W., & Wang, X. (Eds.). (2021). Contactless vital signs monitoring. Academic Press.

[2] Lemay, M., *et al.* (2021). Applications of optical cardiovascular monitoring. In Wearable Sensors (pp. 487-517). Academic Press.