Influence of Sensor Position and Body Movements on Radar-Based Heart Rate Monitoring

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***Abstract*—Cardiac parameters are important indicators for health assessment. Radar-based monitoring with microwave interferometric sensors (MIS) is a promising alternative to conventional measurement methods, as it enables completely contactless cardiac function diagnostics. In this study, we evaluated the effects of sensor positioning and movement on the accuracy of radar-based heart rate measurements with MIS. For this purpose, we recruited 29 participants which performed semi-standardized movements, a reading task, and a standardized laboratory stress test in a seated position. Furthermore, we compared three different sensor positions (*dorsal*, *upper pectoral*, and *lower pectoral*) to a gold standard 1-channel wearable ECG sensor node. The *dorsal* positioning achieved the best results with a mean error (ME) of 0.2 ± 5.4 bpm and a mean absolute error (MAE) of 3.5 ± 4.1 bpm for no movement and also turned out to be most robust against motion artifacts with an overall ME of 0.1 ± 14.1 bpm (MAE: 9.5 ± 10.4 bpm). No correlation was found between movement intensity and measurement error. Instead, movement type and direction were identified as primary impact factors. This study provides a valuable contribution towards the applicability of radar-based vital sign monitoring with MIS in real-world scenarios. However, further research is needed to sufficiently prevent and compensate for movement artifacts.**

***Index Terms*—Heart rate monitoring, Medical radar, Remote sensing, Vital parameter measurement**

I. Introduction

Cardiovascular diseases are among the leading causes of death worldwide [1]. Monitoring cardiac parameters such as heart rate (HR) or heart rate variability (HRV) is an important measure to detect cardiac malfunctions at an early stage. Through long-term assessment, cardiac parameters can be an important predictor of neurodegenerative, chronic, and psychological conditions, such as Parkinson's disease [2], epilepsy [3], or depression [4]. However, the measurement principles of all established measurement modalities, such as electrocardiography (ECG), phonocardiography (PCG), and photoplethysmography (PPG), require direct skin contact, which limits the feasibility for long-term cardiac monitoring, even if the measurement is performed using lightweight, seemingly unobtrusive, wearable sensors [5], [6].

A novel and promising alternative to the existing methods is the radar-based assessment of cardiac parameters [5], [7]–[11]. The electromagnetic waves used in medical radar systems can penetrate clothing and light materials whilst being reflected at the body surface. Vibrations of the body surface modulate the reflected signal, enabling non-contact measurements. This makes radar-based vital sign monitoring applicable for numerous long-term scenarios, such as home care [6], sleep anomaly detection [7], or driver monitoring [12]. Several approaches exist to extract cardiac parameters, such as HR(V), from radar measurements. Various publications utilize Fast-Fourier Transform to extract low-frequency pulse wave components that correspond to the HR from the data [8]–[10]. To calculate HRV, beat-to-beat intervals, which can be derived from heart sounds, are required. For that purpose, Will et al. introduced a microwave interferometric sensor (MIS), that can extract heart sounds by measuring micro-displacements of the skin due to cardiac activity [5]. This approach has previously been validated for individuals lying at rest [5], [11], [13], [14]. Thus, it is well suited for hospital settings with bedridden patients [11], [13]. However, for long-term monitoring, a static position cannot be ensured. Hence, the severity of motion artifacts must be minimized which can, e.g., be achieved by finding an optimal sensor position where motion artifacts have a minimal impact on the HR measurement. This is a crucial step towards long-term monitoring with MIS in real-life scenarios. The first comparison of different measurement positions was carried out by Vinci et al. [7]. However, they only examined one single participant. Shi et al. [15] published a dataset with various positions of the radar sensor relative to the position of the body tested on upright sitting or standing participants. However, no comprehensive evaluation of the measurement accuracy was conducted. Thus, a systematic assessment of the optimal measurement position and the occurrence of motion artifacts, during daily-life activities, such as speaking or upper body movements, has not yet been performed.

Therefore, the main objective of our study is to determine the most suitable sensor position for radar-based cardiac monitoring, specifically heart rate, using MIS in an upright posture and to quantify the influence of different movements on the accuracy of the extracted parameters. To the best of our knowledge, our study is the first to systematically validate radar-based HR measurements for different positioning and movement scenarios.

II. Methods

A. Data Acquisition

Data were collected from $n = 29$ healthy participants aged 23.5 ± 6.9 years (16 male, 12 female, 1 other). All participants

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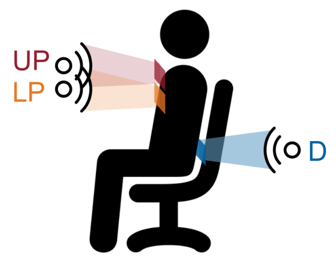

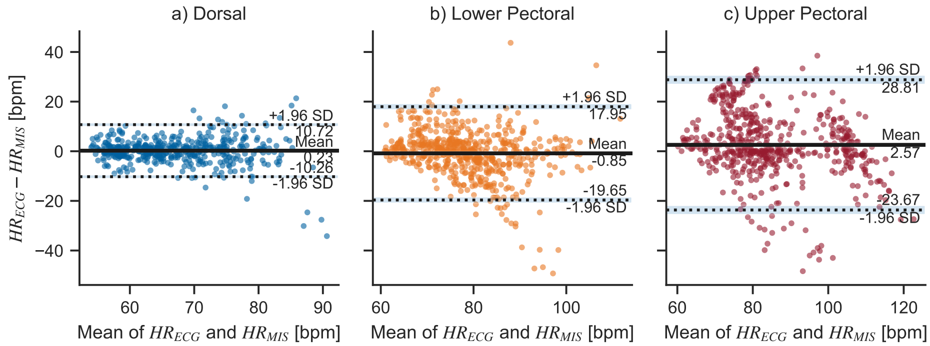

Fig. 1. Upper Pectoral (UP), Lower Pectoral (LP) and Dorsal (D) sensor position.

Fig. 2. Bland-Altman plot showing measurement differences between ECG and MIS during baseline phase, evaluated for each sensor position.

provided written informed consent before the study. The study was approved by the Ethics Committee of Friedrich-Alexander-Universität Erlangen-Nürnberg (number 493_20B).

HR of the participants was measured using an MIS operating at 24 GHz as initially proposed by Michler et al. [11]. The In-Phase and Quadrature components of the radar signal were recorded with a sampling rate of 2000 Hz. Simultaneously, each participant was equipped with a wearable device (Portabiles GmbH, Erlangen, Germany) consisting of a 6-axis inertial measurement unit (IMU) and an ECG unit that acquires a 1-channel ECG from a chest strap according to Lead I of Einthoven's Triangle. An additional IMU sensor was worn on the left wrist. Sensor data were logged onto the internal sensor's storage with a sampling rate of 256 Hz and transmitted to a computer for further processing. The ECG data served as ground truth for HR, whereas the IMU data were used to quantify movement intensity.

The participants were seated on a chair with a mesh backrest. To capture the different sensor positions, the radar sensor was either placed behind the participant pointing at the lower back (*dorsal*), in front of the participant aiming at the lower chest region (*lower pectoral*), or in an elevated position aiming at the upper chest region (*upper pectoral*), as shown in Fig. 1. The distance between the participant's skin and the radar source was approximately 25 cm for each measurement position. Each participant was randomly assigned to one of the measurement positions (*dorsal*: n = 10, *lower pectoral*: n = 10, *upper pectoral*: n = 9).

In our study protocol, different daily-life activities were simulated consisting of a baseline measurement (60 s), reading (to simulate speech artifacts, 30 s), 8 different semi-standardized movements (15–30 s), and a standardized laboratory stress test to induce more HR variations (180 s). Movements were performed moderately once and then again more intensely, distinguishing between head movements, rectangular arm movements, medial-lateral torso movements (ML), and posterior-anterior torso movements (PA). As stress test, we used the social evaluative cold pressor test (SECPT) [16] to assess the reliability of MIS measurements for biopsychological research. The complete recording phase was video-captured for control purposes. Two participants (measurement position *dorsal*) were excluded from further analysis due to corrupted ECG or MIS data.

B. Data Processing

1) ECG Data: From the acquired ECG data, we extracted RR intervals after filtering and applying a QRS detection algorithm provided by the *Neurokit2* library [17]. Artifacts in RR intervals were reduced as in previous work [18].

2) MIS Data: The radar sensor derives cardiac parameters from micro-displacements of the skin surface due to heart contractions. A displacement of the skin translates into a relative phase shift between transmit and receive signal [13]. The displacement is calculated by arctangent demodulation of complex baseband data after ellipse fitting, as described by Will et al. [5].

The measurement quality was assessed using an automatic signal quality index (SQI) as proposed by Shi et al. [19]. To segment heartbeats from the resulting displacement data, a hidden semi-Markov model (HSMM) detecting the first heart sound of every heartbeat [20] was applied to MIS data [11]. Based on the inter-beat-intervals, the instantaneous HR was calculated. Finally, HR outliers from radar data were removed analogously to the ECG processing pipeline.

3) IMU Data: To objectively quantify movement intensity, the power of the accelerometer signal was computed as mean signal energy over each study phase after removing the gravity component. For the upper body and head movements, the chest-mounted IMU sensor was utilized for the power calculation, whereas the wrist-mounted IMU sensor was used for arm movements.

C. Evaluation

For a direct comparison between ECG- and MIS-derived HR (HR_{ECG} and HR_{MIS}), both signals were synchronized via the internal clocks of the measurement devices. Next, HR_{MIS}, HR_{ECG}, and the MIS data SQI were resampled at 1 Hz and cut into the study part intervals. Afterwards, we computed the sample-wise (absolute) error between both HR

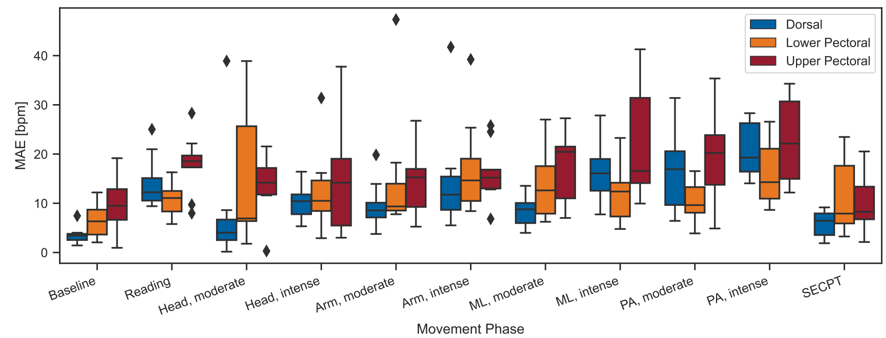

Fig. 3. Mean absolute errors (MAE) of HR_{MIS} measurements per participant grouped by MIS position and movement phase.

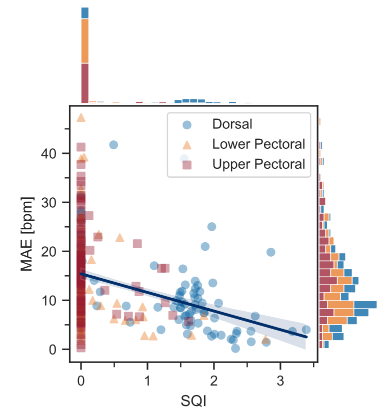

Fig. 4. MAE per phase depending on the SQI. The frequency of occurrence of different SQIs and MAE, respectively, is depicted as a histogram on the corresponding axis.

measurements and computed the mean error (ME) as well as the mean absolute error (MAE) by error-averaging over each phase, respectively. All processing steps were performed using *BioPsyKit*, our open-source package for the analysis of biopsychological data [21].

III. Results

A. Position Evaluation

Fig. 2 shows the measurement differences between ECG and MIS during the baseline phase for each evaluated sensor position. For *dorsal* positioning, a bias of 0.2 ± 5.4 bpm was observed, 95% CI [−10.26 bpm, 10.27 bpm]. The *lower pectoral* MIS position yielded a bias of −0.8 ± 9.4 bpm. The errors are distributed broader than for the *dorsal* position, 95% CI [−19.65 bpm, 17.95 bpm]. For the *upper pectoral* position, a bias of 2.6 ± 13.4 bpm between HR_{MIS} and ground truth was observed, 95% CI [−23.67 bpm, 28.81 bpm]. Considering data over all movement phases, *dorsal* yields the lowest MAE (9.5 ± 10.4 bpm) and ME (0.1 ± 14.1 bpm), followed by *lower pectoral* (MAE of 11.9 ± 12.1 bpm, ME of −1.3 ± 17.0 bpm) and *upper pectoral* (MAE of 14.2 ± 12.6 bpm, ME of 2.0 ± 18.9 bpm).

The MAE in relation to the SQI for each position is shown in Fig. 4. An SQI > 0 was observed 70.54% of the time for the *dorsal* position, whereas the SQI for *lower pectoral* and *upper pectoral* was above zero only 10.95% and 14.14% of the time, respectively. Mean SQIs over all phases were at 1.49 for *dorsal*, 0.21 for *lower pectoral*, and 0.23 for *upper pectoral*. Spearman's correlation coefficient (CC) yielded a tendency towards negative correlation between SQI and MAE, $r = -0.35, p < 0.001$, that increases when only measurements with SQI > 0 are considered, $r = -0.51, p < 0.001$.

B. Impact of Movements

The MAE over all participants is shown in Fig. 3 for each sensor position and phase, respectively. The baseline phase yielded the lowest MAE for all measurement positions. The *dorsal* position yielded the lowest MAE for the phases *arm and head movement*, moderate ML torso movement, and SECPT, whereas *lower pectoral* showed the best results for reading, intense ML torso movement, and moderate PA torso movement. *Upper pectoral* showed the highest MAE values for all movement phases. Furthermore, no meaningful correlations were found between the MAE and the mean accelerometer power for each position and phase.

IV. Discussion

As many application scenarios of radar-based cardiac monitoring involve moving individuals, it is important to assess the performance in dynamic scenarios. Therefore, the main objective of our study was to quantify the impact of different movement types and intensities, as well as sensor positions on the HR measurement accuracy.

Our results show that the *dorsal* sensor position proved to be the most robust against all minor movement artifacts. All movements induced errors in HR estimation, however, the intensity of the movement did not determine the magnitude of the error, as no correlation between movement intensity and MAE was found. The *dorsal* sensor position seemed to have weaknesses especially during PA movements which could be due to the movement being performed along the same axis as the skin displacement caused by the heart sounds.

Similarly to our study, Vinci et al. [7] also found a dorsal sensor positioning to yield the most robust signal for HR detection but stated excellent performance for pectoral positioning as well. However, due to only one participant, their results are hardly generalizable. Shi et al. also recorded cardiac parameters in the upright or seated position with a similarly constructed MIS [15]. They reported a bias of −0.03 bpm for *pectoral* baseline measurements, 95% CI [−10.2 bpm, 10.1 bpm], which is in a comparable range to our *dorsal* baseline results. It has to be noted that Shi et al. used an ECG device that was hardware-synchronized with an MIS device, and the sensor orientation was individually adjusted to the anatomy of every individual [15], which might be responsible for the more precise *pectoral* measurements. In comparison, we synchronized radar and reference ECG signal during post-processing, which yields less precise results than hardware synchronization and, thus, requires improvement in the future.

Another source of error is the HSMM, which has been trained on data that were free of motion artifacts and, thus, might yield several seconds of incorrect measurements as soon as one heart sound is not detected. This problem could be approached by using an LSTM network instead of the HSMM, as previously introduced by Shi et al. [14].

Major parts of our measurements were rated with an SQI of zero, although MAE was not necessarily above average (see Fig. 4). These low SQI scores also originate from the fact, that the ensemble classifier for SQI determination was trained on motion artifact-free data from lying individuals [19]. The SQI determination classifier would need to be retrained on real-world data to accurately identify signal parts with an appropriate quality for physiological evaluations.

Finally, it needs to be mentioned that the semi-standardized periodic movement scenarios performed in our study, do not accurately represent real-life movements. The movements were chosen to increase inter-participant comparability and to systematically reveal weaknesses of MIS measurements. Whereas the MIS is currently not suitable for instantaneous HR and HRV measurements because of the relatively high MAE, the low MEs suggest good applicability for long-term monitoring of average HR. Based on the findings of this study, algorithms for heart sound extraction from MIS can be improved and applied to real-life scenarios in future work.

V. Conclusion and Outlook

In this publication, we assessed the feasibility of contactless, radar-based cardiac parameter monitoring with MIS. One aim was to find a measurement position that is as robust as possible against motion artifacts and does not require individual position adjustments by experts. Our findings suggest that a *dorsal* placement of the radar sensor meets these criteria best. Furthermore, the impact of different movements on the measurement accuracy was analyzed. Our results confirm that HR measurements using MIS can accurately be estimated by averaging over a time period. However, they are susceptible to large-body movements and speaking, thus limiting their validity for instantaneous HR or HRV acquisition. Future studies should investigate compensation for these artifacts and thus improve the robustness of the sensor outputs. With the recorded data, we provide a solid basis for further improvement of HR extraction algorithms and thus make radar-based vital sign monitoring using MIS applicable for long-term monitoring in daily-life situations.

Acknowledgements

We would like to thank Rebecca Seidl, Katharina Murner, Corinna Thoni, and Luca Abel for their support in data collection. This work was funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) – SFB 1483 – Project-ID 442419336, EmpkinS. Further, Bjoern M. Eskofier gratefully acknowledges the support of the German Research Foundation (DFG) within the framework of the Heisenberg professorship programme (grant number ES 434/8-1).

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