UWB Radar for Non-contact Heart Rate Variability Monitoring and Mental State Classification

Yang Han[1], Timo Lauteslager[1] *Student Member, IEEE,* Tor S. Lande[2] *Fellow, IEEE,* and Timothy G. Constandinou[1] *Senior Member, IEEE*

***Abstract*— Heart rate variability (HRV), as measured by ultra-wideband (UWB) radar, enables contactless monitoring of physiological functioning in the human body. In the current study, we verified the reliability of HRV extraction from radar data, under limited transmitter power. In addition, we conducted a feasibility study of mental state classification from HRV data, measured using radar. Specifically, arctangent demodulation with calibration and low rank approximation have been used for radar signal pre-processing. An adaptive continuous wavelet filter and moving average filter were utilized for HRV extraction. For the mental state classification task, performance of support vector machine, k-nearest neighbors and random forest classifiers have been compared. The developed system has been validated on human participants, with 10 participants for HRV extraction, and three participants for the proof-of-concept mental state classification study. The results of HRV extraction demonstrate the reliability of time-domain parameter extraction from radar data. However, frequency-domain HRV parameters proved to be unreliable under low SNR. The best average overall mental state classification accuracy achieved was 82.34%, which has important implications for the feasibility of mental health monitoring using UWB radar.**

I. Introduction

Heart rate variability (HRV), defined as the variation in cardiac beat-to-beat intervals over time, is increasingly being recognized as a biomarker for cardiovascular fitness, as well as for mental stress. HRV is regulated by the autonomic nervous system (ANS), which controls the fight-or-flight response and various bodily functions. Because ANS activity is affected by psychological state, HRV is an effective indicator of ANS imbalance and the state of mental health. Importantly, it can be assessed non-invasively, which makes it interesting for both clinical and consumer applications. Conventional approaches for HRV measurement, such as electrocardiography (ECG) and photoplethysmography (PPG), require sensors to be placed in contact with the body. This increases user burden and limits the usability for long-term health monitoring. In contrast, radar can provide non-invasive, contactless vital sign detection. Specifically, coherent ultra-wideband (UWB) pulsed radar is suitable for vital sign monitoring: The high bandwidth provides relative immunity to multipath interference. In addition, the coherent pulses enable phase detection for sensitive movement tracking, but unlike continuous wave Doppler radar, time-gating can be applied to distinguish between targets in space. UWB radar employs the same working principle as other radar systems: Electromagnetic pulses are transmitted using antennas, and time-of-flight analysis of reflected pulses allow for determining the distance of reflectors. This principle can be applied to detect human heart rate (HR) and respiration rate (RR) due to the fact that both respiration and the heartbeat cause a displacement of the chest wall (sub-mm in the case of the heartbeat).

In literature, whilst many different approaches have been proposed for HR and RR estimation using contactless measurements, there have been few empirical investigations into accurate monitoring of HRV using radar. In 2007, feasibility studies of measuring HRV with radar were presented, both using single-channel Doppler radar [1], and quadrature Doppler radar [2]. In both studies however, HRV parameters extracted from radar in the time domain showed large differences with parameters extracted from PPG reference. More recently, a template matching approach was proven to be successful for inter-beat interval estimation using UWB radar [3] and continuous wave radar [4]. Although high accuracy was demonstrated on HRV monitoring in both studies, the first study was performed such that the subjects held their breath, and the proposed method in the second study was only validated on a single subject. Additionally, performance evaluation of both proposed methods was limited to a comparison of the trend of HRV, rather than comparing statistical HRV parameters. An approach based on employing the continuous wavelet transform was presented in 2013, for HRV estimation using quadrature Doppler radar [5]. Good performance was shown on 10 human subjects. However, the high power on the transmitter side of the radar (exceeding radiation limits as set forth by the federal communications commission; FCC), does raise the question whether similar performance can be achieved using a lower power radar design, which would be a necessity for long-term monitoring in many applications. In 2018, an approach for HR and HRV parameter estimation with body movement compensation using IR-UWB radar was proposed [6]. The study demonstrated that the instantaneous heartbeat signal can be recovered even under body movement conditions, albeit large errors were present for some subjects.

Because HRV is known to be an indicator of ANS imbalance and mental state, several studies before have investigated whether mental state can be predicted from HRV data. Reasonable accuracy was found, but most studies

This work was supported by an EPSRC DTA scholarship

[1]Yang Han, Timo Lauteslager and Timothy G. Constandinou are with the Centre for Bio-Inspired Technology, Department of Electrical and Electronic Engineering, Imperial College London, UK. Email: {yang.han17, t.lauteslager14, t.constandinou}@imperial.ac.uk

[2]Tor S. Lande is with the Department of Informatics, University of Oslo, Norway. Email: bassen@ifi.uio.no

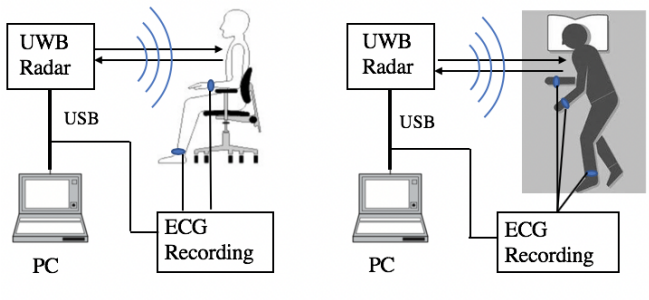


Fig. 1. Experimental setup when subject is seated (left) and sleeping (right).

used contact-based measurements [7], [8]. Although it has been demonstrated that mental stress can be monitored using contactless thermal imaging [9], this modality involves much more complex and costly hardware than UWB radar.

In the current work, we use a low power UWB radar-on-chip to monitor HRV and mental state. HRV estimation mainly follows the previously proposed continuous wavelet approach [5], combined with low rank approximation for further noise elimination. HRV parameter extraction accuracy is validated on 10 subjects. Furthermore, we demonstrate mental state classification from HRV features on three subjects, using four mental states: normal, fatigue, stress, and sleep. Successful mental state classification further verifies the effectiveness of contactless HRV parameter estimation, and acts as a first proof of concept that mental state can be monitored using radar.

II. Methods

A. Experimental setup

The Xethru X4M200 respiration sensor (Novelda AS, Kviteseid, Norway), was used to stream raw radar data. The sensor makes use of Noveldas X4 UWB radar chip, which is a coherent impulse radar transceiver system with a sampling rate of 23.3 GS/s, and a center frequency of 7.29 GHz. The sensor is CE and FCC certified, which indicates compliance with European and US emission limits. The radar operates under the noise floor of -41 dBm/MHz and the radiation exposure by the device is far lower than radiation exposure due to WiFi, Bluetooth and mobile phone use. This ensures that the radar will not cause damage to health during long-term recordings. The frame rate in slow-time is configured to 80 Hz and data were transmitted to PC via USB.

A schematic of the experimental setup, both in seated and lying position (sleeping condition), is shown in Fig. 1. For optimal radar positioning and orientation, a stethoscope was used to identify the exact location of the participant's heart, and a laser pen attached to the radar module was used to assist in radar orientation. The sensor was set up 10 cm from the chest wall. The chosen approach was found to consistently provide sufficient SNR of the recorded HR signal component. ECG data were recorded for HRV validation (Arduino and Olimex EKG shield, sampling rate 250 Hz).

B. Experimental protocol

The experimental procedures involving human subjects described in this paper were approved by the institutional ethics review board. The experiment for HRV extraction was conducted on 10 healthy participants (age range 23 to 28; four males and six females), who reported no history of cardiovascular disease. Participants were asked to remain seated statically in a chair with their back against the chair backrest, and to minimize movement during the recording. The recording for each participant lasted for two minutes. Three subjects participated in the mental state classification experiment, which involved the following states: normal, fatigue, stress and sleep. For each state, five segments of each 5 minutes were recorded, resulting in a total recording time of 25 minutes for each state. More details on the individual states:

- Normal state: To guarantee that participants were not in a fatigued state, the recording of the normal state was performed in the morning after a restful night of sleep. Participants were instructed to take a rest for 5 minutes before the recording to ensure that they were fully relaxed.
- Fatigue state: The recording was conducted in the evening, after a full day of work (8 hours on average) and half an hour of exercise. After exercise, subjects were instructed to take a rest for 10 minutes and then fill out the Chalder fatigue scale questionnaire to measure the degree of mental tiredness.
- Stress state: It was reported in past research that a mental arithmetic task (MAT) can be an effective stimulus to induce stress. A MAT was designed, consisting of an addition and subtraction task. The MAT was presented automatically on a computer monitor. The interval between each question was sufficiently short to induce stress. To avoid body movement, participants were asked not to respond verbally to the task. However, due to the small number of highly motivated participants, we were confident of participant compliance.
- Sleep state: Recordings were performed at participants' homes. Participants were required to sleep on one side during the recording. The duration of the recording was 1 hour, initiated at bed time (lights out), to ensure that the sleep stage would be covered. It is known that HR drops during sleep, therefore low HR was used as a rudimentary sleep classifier. The 1-hour recording was truncated into 5-minute segments, from which 5 segments with low HR and high SNR were selected.

C. Data Processing

Raw radar data were converted to baseband using digital down conversion. Phase data were obtained from the imaginary and real part using arctangent demodulation. The DC offset and imbalance errors were corrected using a previously proposed calibration method [10]. After arctangent demodulation, unwanted clutter and noise were eliminated using a low rank approximation technique: The singular values of

the noise space, which were found to be significantly smaller than those of the signal subspace, were set to zero before signal reconstruction.

As an initial estimate, average RR and HR were estimated using Fast Fourier Transform (FFT). To successfully extract the instantaneous HR components, respiration components should be removed from the signal by band-pass filtering. Rather than using conventional filters, which often suffer from problems such as signal leakage and phase-shift, continuous wavelet filters were employed. Better estimates of instantaneous HR and heartbeat interval were then obtained by adjusting the band-pass cutoff frequencies adaptively. The lower and higher cutoff frequencies were chosen as the average HR frequency minus 0.3 Hz and plus 0.3 Hz, respectively. This range was chosen due to the fact that HR variation generally does not exceed 10 beats per minute for healthy adults.

As an indicator of HR signal quality, SNR was defined as the detected power of the heartbeat component over the average power of non-HR frequency components. For data segments with relatively low SNR, heartbeat peak detection was complicated by noise, even after adaptive wavelet filtering. Consequently, a moving average filter was applied after the wavelet band-pass filter for further signal smoothing. It was found that a 50-point moving average filter, equivalent to a low-pass FIR filter with a 0.7 Hz cutoff frequency (-3 dB), resulted in the best heartbeat peak estimation. After smoothing, heartbeat peaks were detected and heartbeat intervals were calculated. Several standard HRV parameters in time-domain and frequency-domain were extracted, including average inter-beat interval (IBI), standard deviation of NN-intervals (SDNN), root mean square of successive beat interval differences (RMSSD), percentage of successive beat intervals that differ by more than 50 ms (pNN50) as well as power in the low-frequency band (0.05-0.15 Hz; LF) and high-frequency band (0.15-0.5 Hz; HF).

The mental state data were analyzed and classified as follows: Firstly, radar and ECG recordings of the four mental states were segmented into 30 s windows with 15 s window overlap. HRV features in time domain (IBI, SNDD, RMSSD and pNN50) were extracted from each 30 s window, and used for classification. Apart from within-subject mental state classification, an inter-subject classification experiment was attempted to test the generalizability of the classifier. Therefore, a normalization step was included in the feature preparation stage to eliminate cross-individual factors. As HRV features are likely to show inter-feature correlation, a feature dimension reduction step using principle component analysis (PCA) was performed. The final step employed three different approaches, k-nearest neighbors (k-NN), random forest (RF) and support vector machine (SVM), to perform classification on the low-dimensional features obtained using PCA. The classification performance was validated using leave-one-recording-out cross validation (LOROCV) as well as leave-one-subject-out cross validation (LOSOCV). In the former, a single 30 s segment was left out as test data, whereas in the latter, all data from a single participant were left out (inter-subject classification only).

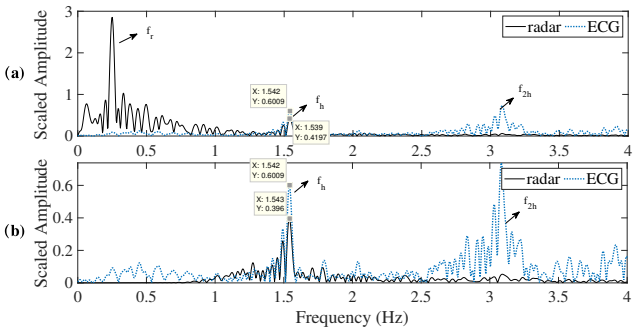


Fig. 2. Spectrum of radar and ECG signal (HR frequency is specified as label X, and Y is the corresponding power): before removing respiration component (a) and after removing the respiration component (b). The respiration frequency is labeled with f_r. The heart rate frequency and it's first harmonic is labeled by f_h and f_{2h}, respectively.

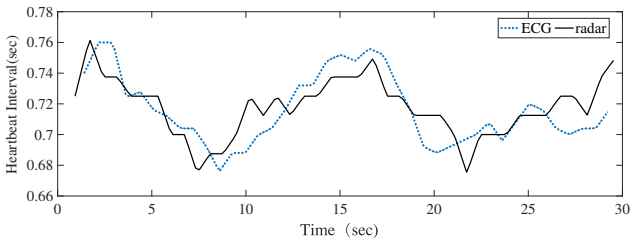


Fig. 3. Inter-beat intervals extracted from radar heartbeat peaks in time domain, in comparison to the peak-to-peak intervals extracted from ECG data.

III. Results

HR could precisely be estimated using FFT, with a mean error of 1.23% and standard deviation of 0.8%. Fig. 2 shows the spectrum of radar signal before and after removing the respiration component, with the spectrum of ECG as reference. Respiration component removal and noise reduction has little impact on the heartbeat component, which has been perfectly preserved by applying a continuous wavelet filter. An example HRV signal, as extracted from radar data, is shown in Fig. 3, with the HRV signal from ECG data shown for comparison. The two signals show a highly similar trend. It was observed that, under high SNR of the heartbeat component, the radar-derived HRV spectrum was consistent with the ECG-derived HRV spectrum. Under low SNR conditions however, the spectrum of the two HRV signals showed a large difference. Mean estimation error of individual HRV parameters across participants is shown in Fig. 4. Among the four parameters, the median IBI has the least bias from the ground truth, whereas the median of RMSSD has the largest deviation. The estimation error of both low and high frequency components are much higher than the errors in time domain, which renders them unreliable. Additionally, A clear inverse relationship was found between the estimation errors of HRV parameters in time domain, and SNR of the HR component (not shown).

For the mental state classification dataset, mean error of

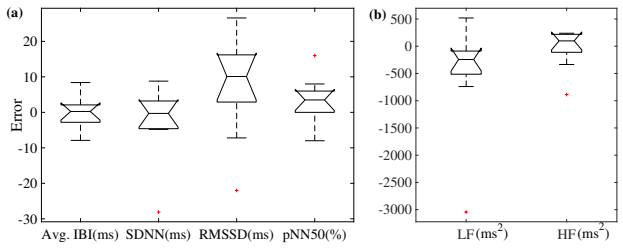


Fig. 4. Boxplot analysis of HRV parameter estimation error in time domain (a): Average inter-beat interval (IBI), standard deviation of NN-intervals (SDNN), root mean square of successive beat interval differences (RMSSD), and percentage of successive beat intervals that differ by more than 50 ms (pNN50). Estimation error of parameters in frequency domain (b): Power in low-frequency band (LF) and high-frequency band (HF). Units of absolute error per feature given in x-axis label.

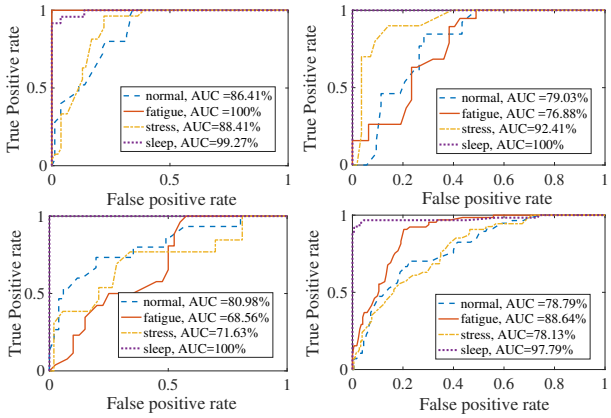


Fig. 5. ROC curve for each mental state for different participants, and for the inter-individual dataset (bottom-right).

HRV parameter estimation was analyzed. With the exception of the sleep state condition, which resulted in an average IBI error of 19 ms, the IBI error of all other recording conditions was below 10 ms, indicating accurate HRV extraction. In terms of classification accuracy, the highest performance was found using LOROCV on a single participant: 82.34%. Classification accuracy achieved on the inter-individual dataset was 71.37%. However, when validating using LOSOCV, the average overall accuracy was merely 52.88%. Amongst the three classification algorithms, k-NN showed better performance than RF and SVM, both across all subjects as well as on the inter-subject classification dataset. Classification performance on each mental state was measured using the area under curve (AUC) of the receiver operating characteristic (ROC), which is presented in Fig. 5. For all three participants, the AUC was found to be the highest for the sleep state, signifying the strong ability of the model to distinguish the sleep state from other mental states. Interestingly, there were clear differences in the classification performance of each mental state between different participants. For the first participant, the fatigue state shows higher AUC whilst for the second subject, the stress state presents better performance.

IV. Discussion

The HRV signal obtained from radar corresponded well to that extracted from ECG data, which demonstrates the feasibility of using UWB radar to estimate the trend of HR change. Estimation error was low for all four time-domain parameters, but increased with decreasing SNR. Errors of time-domain parameters were low also in comparison with past research [5], but estimation errors in frequency-domain parameters were found to be much higher and more disperse. Particularly low SNR conditions limited the reliability of frequency-domain HRV parameters. Further research is required to investigate approaches that can accurately extract HRV parameters in the frequency-domain, or alternatively to identify novel HRV parameters that prove to be more robust to low SNR but still carry clinically relevant data. When comparing HRV parameter extraction performance to past research, it should be noted that the Doppler radar sensor used in [5] transmitted significantly more power, with -30.1 dBm/MHz at the transmitter. This compared to -41.3 dBm/MHz in the current work. The SNR of the heartbeat component is related to the transmitted power of the radar system, as well as the distance between the radar and the participant. This has important implications for seeking a balance between the location of the radar and required parameter estimation accuracy. Estimation of time-domain HRV parameters using the proposed algorithm was robust even under limited transmitter power, but a rather low sensor distance was used in all measurements (10 cm). This implies that further signal processing developments are required for a higher sensor range, or alternatively higher transmitted power is needed. Unlike several published studies on HR tracking using radar, all recordings in the present study were done while participants were allowed to breathe freely. Due to the possible interference of respiration harmonics and the HR signal in the frequency domain, this poses an additional challenge. The proposed method of denoising and adaptive filtering proved successful in isolating the cardiac signal. Future research will involve extracting HRV in a more challenging environment: higher range and participant motion. As for the mental state prediction feasibility study, small errors were found between radar-estimated HRV parameters and ECG parameters, demonstrating again that accurate HRV tracking using radar is possible. The mental state classification on the small group of participants showed promising results. Besides a first proof-of-concept that contactless mental state classification using radar is possible, the results also demonstrate that HRV parameters measured using radar carry relevant information about a person's ANS activity.

Naturally, evoking and quantifying mental states in a research setting is challenging and the used protocol has its limitations. The lack of control over the actual mental state is likely to cause differences in classification performance on different mental states between individuals. Despite the fact that the experimental protocol was identical for each of the participants, the effects of the experimental conditions on

the participant's ANS activity may vary considerably. It is hypothesized that particularly the level of mental stress and the level of mental fatigue as a result of the experimental protocol will vary strongly between participants. The sleep state is likely to suffer less from inter-individual differences in response to the experimental condition, which might help explain the high performance in classifying sleep.

Differences between individuals' physiology and their mental response to the protocol may explain why inter-individual classification using a leave-one-subject-out validation approach showed reduced performance. This implies a lack of generalizability of the developed classification models, but a larger dataset is required to validate that. Although the mental state classification study suffers from a low number of participants, to our knowledge this is the first proof-of-concept that mental state classification using contactless radar monitoring is possible. Future work should involve a higher number of participants and more robust stimuli design. For instance, an improvement on the fatigue state could involve a baseline fatigue survey at the start of the working day.

V. Conclusion

Based on the methods proposed in [5], in combination with a noise elimination technique, the present study has further confirmed that UWB radar can be used to accurately extract HRV, while discriminating against respiration components and noise. The negative trend identified between the estimation errors of HRV parameters and increased SNR provides a clear opportunity for enhancing estimation accuracy for studies in the future. By evoking different mental states in a small number of participants, we have also shown that the HRV parameters measured by UWB radar are sufficiently accurate to classify between four mental states (normal, fatigue, stress, sleep) within subjects. This may serve as a base for future studies regarding predicting mental states using UWB radar, which could lead to a cost-effective way to monitor mental health non-invasively.

Acknowledgment

The authors would like to thank Novelda for providing radar hardware.

References

[1] W. Massagram *et al.*, "Feasibility of hrv measurement from single-channel doppler radar," *IEEE AP-S Int Symp*, pp. 269–272, 2007.

[2] W. Massagram *et al.*, "Feasibility of heart rate variability measurement from quadrature doppler radar using arctangent demodulation with dc offset compensation," *IEEE EMBC*, p. 1643, 2007.

[3] T. Sakamoto *et al.*, "Feature-based correlation and topological similarity for interbeat interval estimation using ultra-wideband radar." *IEEE Trans Biomed Eng*, vol. 63, no. 4, pp. 747–757, 2016.

[4] C. Will *et al.*, "Advanced template matching algorithm for instantaneous heartbeat detection using continuous wave radar systems," *IEEE IMBIOC*, pp. 1–4, 2017.

[5] H. Wei *et al.*, "Noncontact accurate measurement of cardiopulmonary activity using a compact quadrature doppler radar sensor," *IEEE Trans Biomed Eng*, vol. 61, no. 3, pp. 725–735, 2014.

[6] W. Yin *et al.*, "Hear: Approach for heartbeat monitoring with body movement compensation by ir-uwb radar," *Sensors*, vol. 18, no. 9, p. 3077, 2018.

[7] G. Tanev *et al.*, "Classification of acute stress using linear and non-linear heart rate variability analysis derived from sternal ecg." *IEEE EMBC*, p. 3386, 2014.

[8] H. Al-Libawy *et al.*, "Hrv-based operator fatigue analysis and classification using wearable sensors," *IEEE SSD*, pp. 268–273, 2016.

[9] M. N. H. Mohd *et al.*, "A non-invasive facial visual-infrared stereo vision based measurement as an alternative for physiological measurement," *ACCV*, 2014.

[10] B. K. Park *et al.*, "Arctangent demodulation with dc offset compensation in quadrature doppler radar receiver systems," *IEEE Trans Microw Theory Tech*, vol. 55, no. 5, pp. 1073–1079, 2007.