HandRate: Heart Rate Monitoring While Simply Holding a Smartphone

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***Abstract*—We present HandRate, the first smartphone-based system using a standard sensor (accelerometer) for opportunistically computing heart rate while a user holds their phone. Fundamentally, HandRate revisits ballistocardiography (BCG), a century-old technique for monitoring heart activity by measuring the body movement caused by the cardiac cycle. Traditionally performed using custom hardware, attached to a subject's body, revisiting BCG for the smartphone, held in hand, faces several challenges. The hand is an external organ furthest from the aorta and subject to motion artifacts, leading to a weak and noisy signal, while the position the phone is held in can impact which accelerometer axis best captures BCG. HandRate addresses these challenges by introducing a design involving two modules operating in tandem: the first aimed at transforming the accelerometer readings into a single-dimensional signal oblivious to how the phone is held, while the second module making heartbeat predictions based on this signal. Results from testing HandRate using data collected from 18 subjects show that it can estimate heart rate with accuracy similar to or better than systems requiring special sensors and/active user participation.**

I. Introduction

Essential to human life, healthcare remains costly, administered by a complex and insular apparatus, and often out of reach for many. Omnipresent and with advanced sensing and computing capabilities, smartphones can place, for the first time, advanced diagnosing and health monitoring capacities in people's hands, significantly democratizing healthcare [1]. With cardiovascular diseases (CVD) claiming more lives every year than cancer and chronic lung diseases combined [2], heart activity monitoring attracted some of the first works in the area [3]. Initially, researchers proposed adding custom hardware to smartphones, such as photoplethysmogram (PPG) [4] or electrocardiogram (ECG) [5] sensors. While important in demonstrating the potential of smartphone-based solutions, requiring custom hardware places a significant barrier to wide adoption. Sensing an opportunity, major smartphone manufacturers have introduced special sensors for heart activity monitoring in some of their high-end models, e.g. Samsung Galaxy S7. However, such models are accessible only to a limited number of users. To relax the requirement for custom hardware or high-end phones with special sensors, [6], [7] introduced solutions that use a standard smartphone camera to measure heart rate using the PPG technique. However, users are required to place the finger on the camera, with the accuracy tightly coupled to the precise placement [7]. To remove the requirement for physical contact, [8] introduced a solution for computing heart rate variability using a video of the user's face captured by the smartphone front camera. Nevertheless, it requires active user participation in the form of taking a video in good lighting conditions, making it unsuitable for continuous heart monitoring. Relying on seismocardiography (SCG), the technique of measuring and interpreting the acceleration in the chest wall in response to the heartbeat, [9] introduced a smartphone-based solution for estimating heart rate using the gyroscope. If an elegant and practical solution and relying on a common smartphone sensor it needs the phone placed on the chest, thus requiring active user participation.

Whether it is custom hardware or special sensors, relying on the photoplethysmogram or seismocardiography, the underlying assumption of the current smartphone-based solutions is that a user makes a conscious effort to measure their vitals. While marking a significant progress in democratizing healthcare, continues monitoring of heart activity needs a solution that requires no active user participation.

In this paper, we introduce HandRate, the first smartphone-based system relying on a standard phone sensor (accelerometer) that can estimate heart rate opportunistically while a user is simply holding their phone in hand. HandRate paves the way for continuous – as in as often as users manipulate their phones in their daily lives – heart monitoring. It relies on Ballistocardiography (BCG), a non-invasive technique for studying heart activity by measuring the body movement caused by the recoil forces rising during the cardiac cycle. Introduced in the 19^{th} century [10], the BCG signal is traditionally measured using a force sensor placed on a weighing scale or under the seat of a chair [11]. Recently, researchers have proposed leveraging standard smartphone accelerometers for acquiring the BCG signal and computing heart rate [12]. Since most of the force related to the BCG signal is believed to be generated on the aorta and transferred to the entire body through its connection to the spine, [12] proposes to place the smartphone on the navel with the user in the supine position. While demonstrating the feasibility of acquiring BCG with a commodity smartphone, the solution is not suitable for opportunistic heart monitoring. Therefore, HandRate aims at being the first system to acquire the BCG signal from the hand using a smartphone accelerometer. Realizing this ambitious objective, however, faces several challenges. The very first question arising is whether acquiring BCG from the hand, an external organ furthest from the aorta and subject to motion artifacts, is feasible at all. Assuming the answer is affirmative, a system whose complexity will depend on the nuance of the answer needs to be designed to automatically detect heartbeats in real-time and within the computing capabilities of commodity smartphones.

To answer the feasibility question, we carry an investigation that includes a survey of the accelerometers on commodity smartphones and an empirical study of their capability to sense BCG on hand. Our investigation paints a picture of opportunities and challenges: BCG can be acquired from the hand but the signal can be of poor quality and exhibit no clear peaks. What is more, the accelerometer axis with the strongest expression of BCG depends on how a user holds their phone, creating additional uncertainty.

In short, we address these challenges by introducing a design that combines two modules operating in tandem: Signal Processing and Heartbeat Identification. The first module leverages the PCA algorithm to transform the accelerometer readings into a phone position oblivious basis, reduces it to a single dimension by using a measurement-driven approach and performs a time-frequency analysis customized for poor signals to uncover peaks indicating possible heartbeats. The result is fed into the second module, which leverages neural networks for predicting heartbeats. While there is no dispute neural networks are trending, HandRate needs a solution that can run efficiently on commodity smartphones. Our answer is a light-weight design combining convolutional and recurrent neural networks and that takes into account the particularities of the signal generated by the Signal Processing module.

Throughout this work we make the following contributions:

- We demonstrate for the first time the feasibility of acquiring BCG from the hand using commodity smartphone accelerometers (§ III).
- We design HandRate, the first smartphone-based system using a standard sensor to calculate heart rate opportunistically while the user is simply holding their phone (§ IV).
- We introduce a multi-step approach that transforms the accelerometer readings into a single-dimensional signal oblivious to how a phone is held (§ V).
- We design a light-weight neural network architecture combining convolutional and recurrent neural networks that can detect heartbeats with high accuracy (§ VI).
- We implement HandRate as a standalone Android application (§ VII) and evaluate it with data collected from 18 participants in varying conditions. The results show that HandRate can estimate heart rate effectively, with performance similar to or better than systems requiring special sensors and/or active user participation – hence, achieving its stated goal (§ VIII).

II. A primer on BCG

Ballistocardiography (BCG), first introduced in the 19th century [10], is a non-invasive technique for studying heart activity. It involves measuring the body movement caused by the recoil forces rising during the cardiac cycle. In particular, during systole, the heart contracts, propelling blood inside the arteries – the blood movement throughout the body evokes it to react to conserve momentum. The body movement caused by the reaction can be measured as a displacement, velocity or acceleration and is inherently a 3-D signal [11].

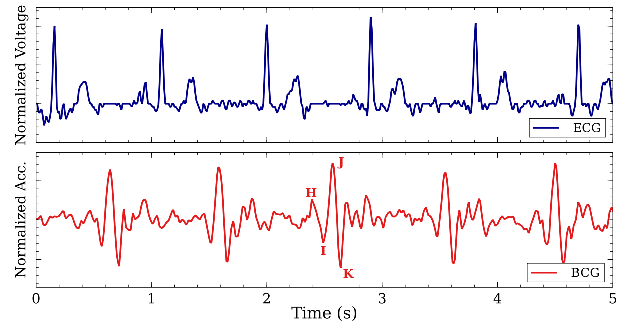


Fig. 1: BCG waveform example

To elucidate, consider the BCG signal depicted in Fig. 1 acquired by the accelerometer of a smartphone placed on the navel of a volunteer lying in the supine position. The gold-standard electrocardiogram (ECG) signal is added as reference (see § III for the details of how these signals are acquired). The ballistocardiogram consists of different waves occurring at different phases of the systole and described using capital letters from H to K [13]. Figure 1 illustrates, for example, how BCG is capable of providing the same heartbeat information as the ECG.

Since its discovery BCG has been used extensively for diagnosis [14], [15] and prognosis of cardiovascular diseases [16]. With the advent of smart devices and wearables, equipped with inertial sensors and capable of running sophisticated signal processing algorithms, BCG has gained new momentum as an enabler of everyday heart activity monitoring [3], [17], [18].

III. Can BCG be acquired from the hand using a smartphone?

Most of the force related to BCG's J-wave is believed to be generated on the aorta [23]. It is transferred to the entire body through its connection to the spine, explaining why the only smartphone-based systems for acquiring BCG rely on placing the phone on the navel [12]. In this section, we carry out an investigation on whether BCG can be acquired from the hand, an external organ furthest from the spine and subject to motion artifacts, using smartphone accelerometers.

A. Accelerometer sensitivity

Most people are probably not aware their hands move due to the recoil forces rising during the cardiac cycle. A survey of the accelerometers on commodity smartphones, however, shows they are highly sensitive, and highly likely capable of sensing such motions. For instance, in its default configuration (full scale acceleration range of $\pm 16\,\mathrm{g}$), the STMicroelectronics LSM6DSM accelerometer found in Google Pixel 2 phones has a sensitivity of $0.488\,\mathrm{mg}$ and a RMS (Root Mean Square) noise level of $3\,\mathrm{mg}$ [21]. As a result, it is able to sense very small motions, barely stronger than the noise level. This corresponds to signals with an amplitude as low as $2.94 \times 10^{-2}\,\mathrm{m\,s^{-2}}$. Such a high sensitivity is very common in commodity mobile phones (see Table I).

TABLE I: Sensitivity and noise level of accelerometers found in different commercial mobile phones

Phone	Accelerometer sensor	Full-scale range	Sensitivity	Noise level (RMS)
Samsung Galaxy S10 (2019)	STMicroelectronics LSM6DS0 [19]	$\pm 4\,\mathrm{g}$	$1.19 \times 10^{-3}\,\mathrm{m\,s^{-2}}$	$1.96 \times 10^{-2}\,\mathrm{m\,s^{-2}}$
Iphone 8 (2018)	Bosch BMI160 [20]	$\pm 8\,\mathrm{g}$	$2.39 \times 10^{-3}\,\mathrm{m\,s^{-2}}$	$1.76 \times 10^{-2}\,\mathrm{m\,s^{-2}}$
Google Pixel 2 (2017)	STMicroelectronics LSM6DSM [21]	$\pm 16\,\mathrm{g}$	$4.78 \times 10^{-3}\,\mathrm{m\,s^{-2}}$	$2.94 \times 10^{-2}\,\mathrm{m\,s^{-2}}$
Iphone 6 (2015)	InvenSense MPU-6500 [22]	$\pm 2\,\mathrm{g}$	$5.98 \times 10^{-4}\,\mathrm{m\,s^{-2}}$	$6.17 \times 10^{-2}\,\mathrm{m\,s^{-2}}$
LG Google Nexus 5 (2013)	InvenSense MPU-6500 [22]	$\pm 2\,\mathrm{g}$	$5.98 \times 10^{-4}\,\mathrm{m\,s^{-2}}$	$6.17 \times 10^{-2}\,\mathrm{m\,s^{-2}}$

Fig. 2: Experimental Setup

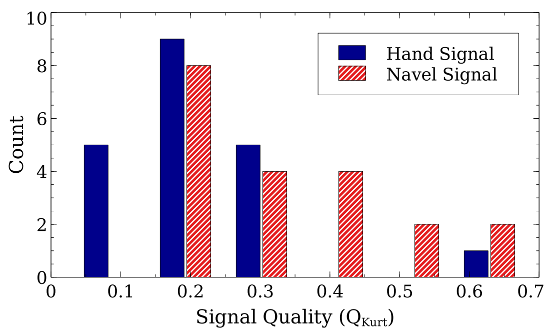
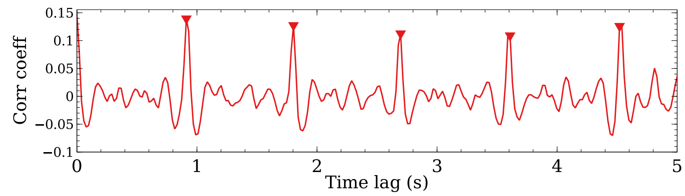
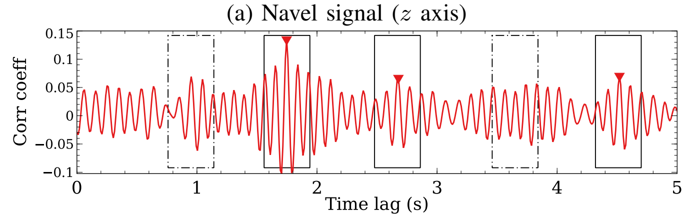


Fig. 3: Hand and navel signal quality.



(a) Navel signal (z axis)



(b) Hand signal (x axis)

Fig. 4: Cross-correlation of the signal with a $1\,\mathrm{s}$-long slice centered at the maximum amplitude. Ground truth heart rate: $65\,\mathrm{bpm}$ ($\sim$5.4 pulses in $5\,\mathrm{s}$ window)

B. Empirical study

To investigate the capability of commodity mobile phones to acquire the BCG from the hand, we conduct the experiment shown in Fig. 2. A user (female, 26 years old) holds a smartphone (Google Pixel 2) in hand while seated and the hand placed on a table for reducing motion artifacts. A GIMA PM10 Portable ECG Monitor [24] is used on the same hand to collect ground truth. As a reference, we also carry an experiment similar to [12]. The user is asked to lie horizontally in the supine position with the same phone placed on the navel. The phone runs an Android application which records the 3-axis accelerometer readings. Each measurement lasts a minute. We analyze the signal in the frequency and time domains.

1) Frequency domain analysis: We collect a total of 20 accelerometer signals from the hand and navel, respectively, and use the Q_{Kurt} metric [9] to quantify their purity:

$$Q_{Kurt}(s) = \frac{kurtosis\big(FFT(s)\big)}{kurtosis(P_s)}$$

where FFT is the Fast Fourier Transform and P_s, the perfect sine wave with frequency corresponding to the estimated heart rate. Informally, Q_{Kurt}, considers a signal with a single frequency component purer than one with multiple frequency components. For each signal, we compute the Q_{Kurt} value of each axis and report the axis with the best (highest) value. In § V we introduce an approach for computing the best signal dimension.

Figure 3 shows that the accelerometer signal collected with the phone on the navel, in close proximity to the aorta, is of superior quality. It explains why BCG can be reliably acquired from the navel using only signal processing [12]. The results for the signals collected on the hand are mixed. A significant proportion have quality comparable to the navel, giving credence to the possibility of acquiring BCG from the hand. At the same time, a non-negligible number of signals present poor quality, a source of errors – making such a goal far more challenging when compared to acquiring BCG from the navel.

2) Time domain analysis: For each signal, we select as template a $1\,\mathrm{s}$-long signal centered at its maximum amplitude and compute the cross-correlation of the entire signal with that template. As an illustration, Fig. 4 shows the results of the best axis of each signal, for one of the measurement sessions. The data paints a similar picture to what was observed in the frequency domain. The navel signal presents clear and sharp peaks where a heart beat occurs (per ground truth), meaning the beginning end of each heart cycle can be easily identified.

The results for the hand signal are mixed. Part of the signal exhibit clear peaks (solid line rectangles), similar to the navel signal, showing BCG can be acquired from the hand. Other parts, however, exhibit no clear pattern even if a heart beat occurs (dotted line rectangles), underlining the difficulty of acquiring a clear BCG signal from the hand.

C. Summary

Our investigation paints a picture of opportunities and challenges. A survey of commodity smartphones shows they are equipped with highly sensitive accelerometers, capable of sensing signals barely stronger than noise. Our empirical study, shows that the body movement caused by the recoil forces rising during the cardiac cycle can be sensed on the hand. It gives credence to the possibility of acquiring the BCG signal and, thus, compute the heart rate while simply holding a commodity smartphone. Nevertheless, the signal, measured on an external organ the furthest form the aorta, and subject to motion artifacts, can be of poor quality. It makes the reliable computation of heart rate particularly challenging, especially when relying only on signal processing approaches. In the next section, we introduce HandRate, a system that combines signal processing with neural networks for addressing this challenge.

IV. HandRate System Overview

Figure 5 shows a high-level depiction of HandRate's architecture. To compute heart rate, HandRate takes as input the accelerometer signals of a smartphone held in hand and process them using two modules:

1) Signal Processing: The 3-axis accelerometer readings are first preprocessed to remove all hardware-specific features and fed into the Signal Recomposition module. Its objective is to transform the signal to make it oblivious to how the phone is held and reduce to a single dimension. The resulting signal is passed on to the Signal Analysis module which performs a time-frequency transformation to uncover heartbeats events as clearly as possible.
2) Heartbeat Identification: It uses a light-weight design combing state-of-the-art convolutional and recurrent neural networks to identify heart beats based on the scalogram produced by the Signal Processing module.

In the following, we describe in detail every element of HandRate along with the thinking behind the design choices.

V. Signal processing

A. Preprocessing

The purpose of the preprocessing module is to remove all hardware specific features (sampling frequency, noise) and focus only on the shape of the input signals. It consists of four stages: filtering, resampling, normalization and denoising

1) Filtering: The first step of the preprocessing module consists of filtering out very weak signals, resulting from the phone having been placed on solid surfaces for example. HandRate computes the average amplitude level of the signal and ignores it if its value is below a given threshold.

2) Resampling: Since different phones have accelerometers with different sampling frequencies, the input signal is resampled to a fixed sampling frequency. It allows HandRate to run on any commodity phone without modifications. In our implementation, we use $F_s = 100\,\mathrm{Hz}$ as the target sampling frequency since it is sufficient for heart activity monitoring [25], [26] and it is in the common range of sampling frequencies of smartphone accelerometers.

3) Normalization: The objective of the normalization is to focus on the shape of the signal, rather than on the values. The signal is first detrended by removing the interpolated order-two polynomial trend to center it to zero mean. It is then normalized by dividing it by the maximum of its absolute value, resulting in values in the [-1, 1] range.

4) Denoising: We apply wavelet-based denoising as wavelets are very suitable for denoising a signal while preserving its peaks [27]. In HandRate, we perform a 7-level Bayes denoising using *sym4* wavelet, with median threshold rule on a level-independent noise estimation basis. Note that, this denoising process is applied on each of the 3 axes separately.

B. Signal Recomposition

With the accelerometer generating a 3-D signal, a central question for HandRate is how to acquire a one-dimensional BCG signal to calculate a single heart rate. One naive solution would be to use a measurement-based study for identifying the accelerometer axis that best captures the BCG signal. However, the best accelerometer dimension may depend on how a user holds the phone. An alternative approach introduced in [9] for fusing the gyroscope readings would be to calculate a different heart rate for every raw accelerometer signal and then fuse the results. However, this approach would involve running essentially every heart rate calculation step three times.

Our solution to this challenge is to a) transform the accelerometer readings into a new basis, removing the dependence on how a user holds the phone, and b) combining an approach for quantifying information in accelerometer readings with large-scale measurements to generate a single-dimension signal. Towards this, we leverage the principal component analysis (PCA) algorithm [28]. PCA converts a set of observations of variables into a new coordinate system, such that the greatest variance lies on the first coordinate (the first principal component), the second greatest variance on the second coordinate, and so forth.

To transform the readings into a new basis, HandRate applies PCA on the accelerometer signal. The result is still a multi-dimensional (component) signal but that is oblivious to how a user holds the phone. To reduce the signal to a single dimension, allowing HandRate to compute a single, and precise, heart rate value, we adopt a measurement-based approach. We perform experiments using a very large number of participants – a 105. Every participant is asked to simply hold a smartphone (Google Pixel 2) for 30 s, as they see fit, while an application collects accelerometer readings. Figure 6 depicts the retained variance of the first 3 principal components for all 105 participants. The data shows that an average of 92.1% of the variance is

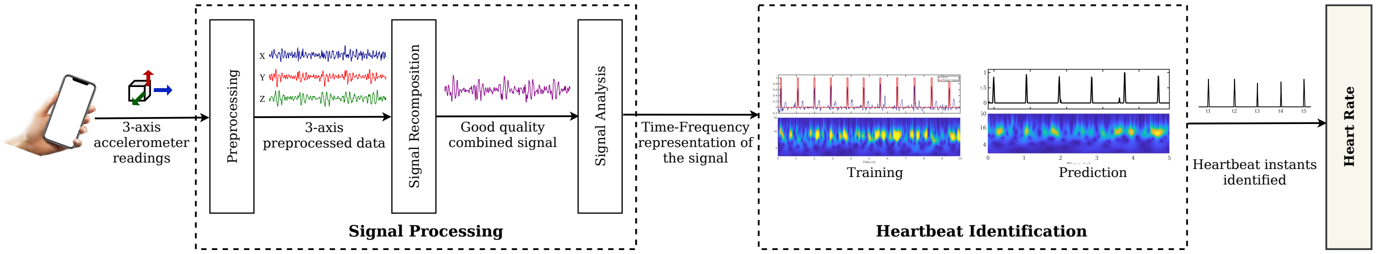


Fig. 5: HandRate System Architecture

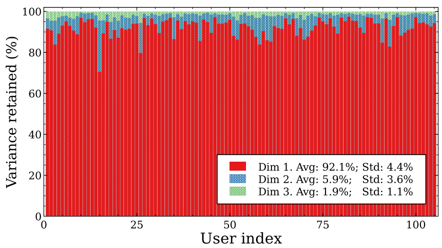


Fig. 6: Amount of variance retained after Principal Component Analysis

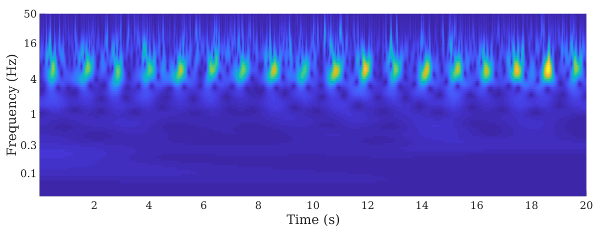
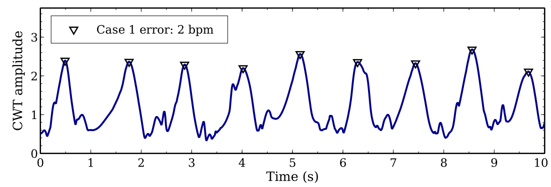
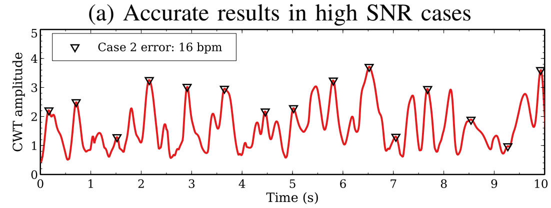


Fig. 7: Scalogram (CWT): Time-Frequency Analysis of the Signal



(a) Accurate results in high SNR cases



(b) Inaccurate results in low SNR cases

Fig. 8: CWT-based heart rate computation produces mixed results

retained on the first principal component. As a result, the Signal Recomposition module maintains only the first PCA component, producing a single-dimension signal oblivious to how the phone is held.

C. Signal Analysis

While phone position independent and one dimensional, the result of the Signal Recomposition module is still a raw time domain signal. One common approach for analyzing such a signal, to extract useful information like the heart rate, is to perform an analysis of the Fourier frequency spectrum [9], [29] and selecting the most dominant bin in a given range. However, as the hand-acquired signal suffers from low quality (see § III), a false and distant FFT bin can be identified as corresponding to the heart rate, leading to a significant error. What is more, our signals do not exhibit clear peaks, making pure time-domain peak detection methods inadequate.

To address the challenge raised by the hand-measured BCG signal, HandRate performs a time-frequency analysis of the signal, retaining both, time and frequency domain information. The two common approaches of time-frequency analysis are spectrogram and scalogram, obtained by applying Short Time Fourier Transform (STFT) [30] and Continuous Wavelet Transform (CWT) [31], respectively. However, wavelet analysis is more suitable for non stationary signals whose frequency can vary rapidly. It can capture both slow variations and abrupt changes in the signal, which is not the case for STFT [31], [32]. Figure 7 shows an example of such a resulting scalogram, generated while the ECG indicated a $56\,\mathrm{bpm}$ heart rate. The CWT (details of its computation in § VII-A) has a time resolution equal to that of the input signal, $20000/2000 = 10\,\mathrm{ms}$.

The data shows that CWT yields identifiable peaks in time and frequency. Furthermore, we observed on all our data that the interesting features lie in the frequency range between 4-50 Hz. Therefore HandRate computes the CWT only in that frequency range. This has the effect of speeding up the computation and also the Heartbeat identification process (§ VI) as it considerably reduces the size of the scalogram from $174 \times num\_timesteps$ to $59 \times num\_timesteps$ (the CWT frequency spectrum is on a logarithmic scale).

VI. Heart Rate Computation with Neural Networks

The scalogram acquired in § V is a good time-frequency representation of the BCG signal. The challenge, however, is identifying peak events with high reliability in order to accurately compute the heart rate. The straightforward approach to address this challenge would be to identify the time instants having the highest magnitude in the scalogram. Figure 8a shows a best-case scenario of such an approach – a simple peak detection leads to a very good heart rate (HR) estimation error of $2\,\text{bpm}$ (ground truth HR is $56\,\text{bpm}$). However, this method is very sensitive to the SNR of the input signals and motion artifacts, leading to highly inaccurate results – HR estimation error of $16\,\text{bpm}$ – when the SNR is low, as shown in Figure 8b (large-scale results in § VIII-C).

With the hand-measured BCG signal having low SNR, a different approach is needed. HandRate addresses this challenge by designing a solution based on state-of-the-art neural networks.

A. Neural network architecture for heartbeat identification

The architecture of HandRate's Neural Network model is shown in Figure 9. It is designed to meet two key requirements: a) taking into account the particularities of the hand-acquired BCG signal represented as a scalogram, and b) being light-weight enough to run on a commodity smartphone.

To meet the first requirement, our design makes use of the encoder-decoder architecture. The encoder is aimed at identifying the best way to extract and represent useful and pertinent features from the input scalogram – the best encoding for this data. The objective of the decoder, on the other hand, is identifying the most likely output corresponding to the encoded data. In our implementation, the scalogram is processed in 3-second slices. Considering its size (§ V-C) and the sampling frequency of $100\,\text{Hz}$, the input to our model is a 300×59, 2-D matrix.

To meet the requirement for a light-weight solution while taking into account the particularities of our signal, the HandRate design uses only two main stacked layers for both the encoder and decoder. The encoder starts with a convolutional layer which learns the specific filters for extracting low level (spatial) features from the input scalogram, a 2D image. It is composed of 128 filters performing same padding convolutions (to conserve the input time resolution), with a stride of 1; with each filter having a width of 5 units. The convolutional layer is complemented by two auxiliary layers: a dropout [33] layer, with a dropout rate of 20%, to prevent overfitting, and a batch normalization [34] layer to speed up training. Stacked over the convolutional layer, the objective of the Recurrent layer is to identify a good representation of the inherent temporal nature of this information. The recurrent layer is implemented as a Long Short-Term Memory (LSTM) [35] layer with 128 cells.

In the decoder, an LSTM layer is followed by a time-distributed fully connected layer. The LSTM layer is composed of 128 memory cells. To generate its output, it does not take the encoder's LSTM outputs but only its final states and a start-of-sequence number (always zero in our implementation). The last layer is a fully connected layer with sigmoid activation. It outputs, for each time step, a value between 0 and 1, the probability of there being a heartbeat. Thus, the output of the model is a 300×1 time series. In terms of complexity, the total number of parameters of the model is 236,673.

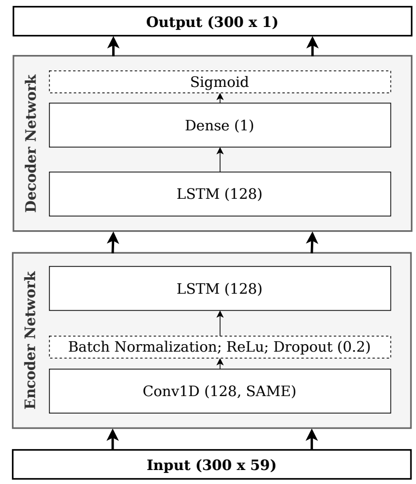


Fig. 9: HandRate's Neural Network Architecture.

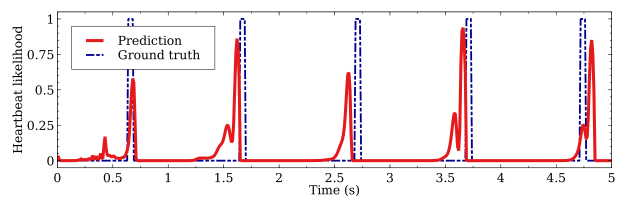


Fig. 10: HandRate example output

B. Heart rate computation

Figure 10 depicts 5 seconds of a typical heartbeat probability signal produced by our neural network model. As a final step, we apply a $0.5\,\text{s}$ spacing constraint to eliminate false peaks, since we are targeting heart rates of up to $120\,\text{bpm}$. The heart rate is derived after computing the average Inter-beat Interval.

VII. Implementation and Dataset

A. Implementation

We implemented HandRate as a standalone Android application. The machine learning part is implemented in TensorFlow with Keras interface and ported to the mobile as a *tflite* [36] model with float32 precision. The signal processing part is implemented in standard Java and makes use of *Apache Commons Maths* library [37]. The CWT is computed with the Morse wavelet and the following parameters: 16 voices per octave and a time-bandwidth product of 10.

B. Data acquisition protocol

To acquire our dataset, we follow the protocol depicted in Figure 2 (§ III). A user holds a a Google Pixel 2 phone in their hand while sitting down[1] as well as a portable ECG, a GIMA PM10 ECG monitor [24], for acquiring the ground truth. Both the accelerometer signal from the phone (originally at $50\,\text{Hz}$) and the ECG from the portable ECG monitor (originally at $250\,\text{Hz}$) are resampled to the same sampling frequency of $Fs = 100\,\text{Hz}$ (§ V-A).

[1]We evaluate HandRate under different holding patterns, and with the user standing, in § VIII-E.

C. Dataset statistics

We collected data from 18 participants, aged between 22 and 52 years old, including 6 female and 12 male subjects[2]. The subjects are faculty and students. Note that this data collection is different from the one described in § V-B as this one involves different volunteers participating in multiple measurement sessions. For each participant, we performed at least ten $30\,\mathrm{s}$ measurement sessions, for a dataset total of 242 measurement sessions. An analysis of the dataset reveals three key attributes:

Wide-range of heart rates: Figure 11a shows the distribution of the heart rates in the dataset, as reported by the portable ECG monitor. The measured values, 54-106 bpm, cover the entire range of the adult heart rate values, at rest[3], in the general population, which studies show varying between 60-100 beats per minute [39].

Weak signals: Figure 11b shows the 95th percentile of the signal amplitudes of every measurement in the dataset. We depict the 95th percentile because the rest are most likely outliers due to motion artifacts. We observe that the amplitude of the signals in the dataset is highly variable from one measurement to another and remains generally low, with an average of $0.09\,\mathrm{m\,s^{-2}}$. This is consistent with our findings in § III showing the challenges of acquiring BCG from the hand, in part due to the fact that the signal is weak.

Motion artifacts: Figure 11c shows the distribution of the maximum amplitudes observed in every measurement session of the dataset. The fact that a small percentage of the signals has a significantly higher amplitude strongly suggests that these are due to motion artifacts. This data supports the intuition that holding a phone in hand inevitably leads to high level of motion artifact, making acquiring BCG more challenging.

D. Data labelling

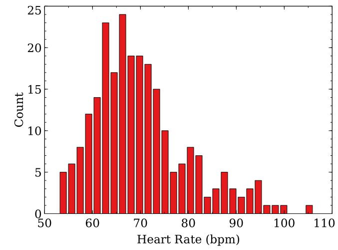
To label our data, we rely on the ECG monitor. We process the ECG data to produce a binary vector by marking the R peaks with ones and other (non-peaks) timesteps with zeros. Each acquired signal is processed in slices of $3\,\mathrm{s}$, which represents a good tradeoff between accuracy and processing time. A longer slice can lead to a better accuracy but also to a more complex network necessary to process an increasing quantity of information. What is more, processing the signal in small slices has the advantage of isolating the errors introduced by motion artifacts. Note that we include a $1\,\mathrm{s}$ overlap between consecutive signal slices in order to have enough context information for each timestep's prediction and therefore improve the system accuracy. For the overlapping region, we take as output the average of the predicted probabilities while processing the two neighboring slices.

E. Addressing sample imbalance

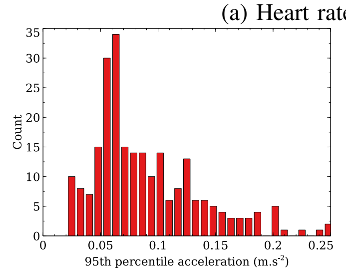
With HandRate using a sampling frequency of $100\,\mathrm{Hz}$ and the heart rate rarely exceeding $120\,\mathrm{bpm}$, the 0's (lack of a heart beat) will dominate the 1's (a heart beat), leading to an imbalanced dataset. Using such datasets for training can lead to difficulties, as the model will tend to produce the dominant class (0 in this case) [40].

[2]Our experiments are in agreement with the ethics defined in the Helsinki Declaration [38].

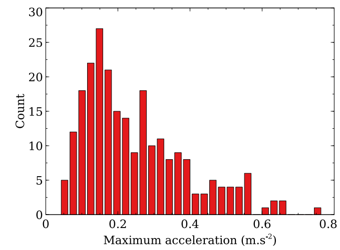
[3]We evaluate HandRate on higher heart rates after exercise in § VIII.



(a) Heart rate distribution



(b) 95th percentile peak distribution



(c) Maximum peak distribution

Fig. 11: Dataset statistics. Data collected from 18 participants, aged between 22 and 52 years old, including 6 female and 12 male subjects.

To address this challenge, we introduce an approach for over-sampling the rare class. In addition to marking with one the exact peak indices, we also mark the surrounding $n_{surroundings}$ time steps (centered at the actual peak). Our over-sampling strategy has the additional benefit of reducing the chances of missing an actual peak.

We set the default value of this parameter ($n_{surroundings}$) to 20, as in our cross validation experiments we found that it led to the best performance.

VIII. Evaluation

In this Section, we evaluate HandRate's ability to provide accurate heart activity monitoring while the user simply holds their phone in hand.

A. Training

During the training process, to furthermore account for the dataset imbalance, we penalize the model more when it misses a one (a heartbeat). For this, we use a weighted binary cross entropy as loss function. We use $w_1 = 0.75$ and $w_0 = 0.25$ as weights for ones and zeros, respectively.

We train the model with Adam optimizer [41] with learning rate decay until no more improvement is observed on the validation loss value. During the training phase we also employ the teacher forcing [42] approach by feeding the second LSTM layer with the ground truth target signal, in order to speed up the training process.

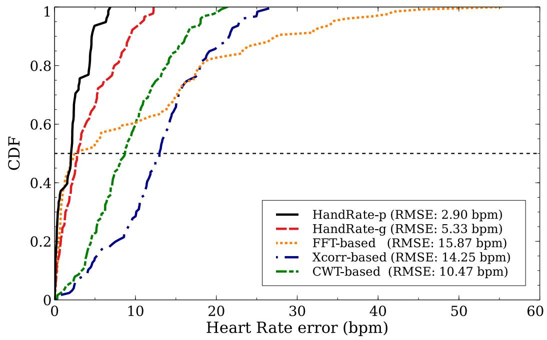


Fig. 12: CDF of HR computation error

TABLE III: Comparison between HandRate and other HR monitoring techniques: SCG, PPG and special sensor. *The last three columns as reported in [9].*

	HandRate-g	HandRate-p	HeartSense [9] (SCG)	Commercial App (camera: PPG) [43]	Commercial App (special HR sensor) [44]
25th p.	**1.21**	**0.32**	0.38	0.83	1
50th p.	**2.92**	**2.06**	1.03	3.85	2.55
75th p.	**6.65**	**3.10**	3.59	5.54	4.64
90th p.	**9.40**	**4.60**	-	-	-
RMSE	**5.33**	**2.90**	**4.98**	**5.2**	**4.07**

B. Setup

Training/Val/Test split: For this evaluation, we train the model using two types of data, creating two versions of HandRate: (1) *HandRate-g*, a general model with all the training data of the dataset (from multiple people), and (2) *HandRate-p*, a personalized model trained with a person's data. *HandRate-g* is evaluated using leave-one-out cross validation (with data from 12, 5 and 1 users for train, validation and test sets respectively); and for *HandRate-p* we apply a 60/20/20 splitting rule on the user's measurement sessions.)

Comparison: We compare HandRate with three approaches for BCG-based heart rate computation:

- **FFT-based**: It involves computing the Fourier spectrum of the signal and taking the most active frequency in the range [0.8 Hz - 2 Hz]. This frequency is multiplied by 60 to have the result expressed in beats per minute.
- **Xcorr-based**: Used in [12], it involves computing the cross correlation between the signal and a template, and taking the peaks as heartbeats. The template is obtained by taking a 1 s long signal centered at the signal's highest peak. As we do for HandRate (§ VI-B), we impose a 0.5 s distance between consecutive peaks.
- **CWT-based**: It involves downsampling the scalogram obtained by CWT by taking the maximum value for each time step and considering the peaks as heartbeats. We impose a 0.5 s distance between consecutive peaks.

TABLE II: Comparison between HandRate and other methods for processing Hand-BCG.

	HandRate-g	HandRate-p	FFT-based	Xcorr-based	CWT-based
25th p.	**1.21**	**0.32**	0.70	9.24	5.25
50th p.	**2.92**	**2.06**	2.67	13.00	8.72
75th p.	**6.65**	**3.10**	17.02	16.69	12.70
90th p.	**9.40**	**4.60**	27.46	21.59	16.31
RMSE	**5.33**	**2.90**	**15.87**	**14.25**	**10.47**

C. Heart Rate Detection

In this section, we evaluate the accuracy of HandRate and compare it to the baseline solutions. Figure 12 shows the heart rate computation errors, in bpm, relative to the ground truth for all methods under consideration. Table II shows summary statistics, including the Root Mean Squared Error (RMSE).

The data shows that HandRate can estimate heart rate effectively, with median errors of 2.92 and 2.06 bpm for HandRate-g and HandRate-p, respectively, and clearly outperforms the other approaches. FFT-based is shown to have to most competitive performance among them in terms of median error, 2.67 bpm but its error explodes when considering the 75th and 90th percentile. This is because, as shown in Section § III-B, the dominant FFT bin may be far away from the good one. In contrast, HandRate maintains a reasonable error in all cases.

D. Hand BCG vs. SCG vs. PPG. vs. Special hardware

In this section, we aim at contextualizing the performance of HandRate by comparing it with established systems. We compare HandRate with a recent approach [9] that uses SCG (Seismocardiography), acquired by placing the phone directly on the chest, and two popular commercial mobile applications: Instant Heart Rate Monitor [43] (downloaded more than 10 millions times) and Samsung Health [44] (downloaded over a 1 billion times). The first application relies on PPG (photoplethysmogram) while the second relies on a special HR sensor found on high-end Samsung devices.

Table III shows that HandRate is very effective at detecting heart rate. The performance of HandRate-g is very similar to that of [9][4], which requires direct chest contact, and of Samsung Health, which relies on special hardware. HandRate-p ourperforms them all.

E. Varying Experimental Conditions

In this section, we evaluate the robustness of HandRate under different real-life scenarios. We focus on two key aspects: 1) HandRate's robustness to changes in signal quality, in particular due to how a user holds the phone; 2) HandRate's robustness to changes in heart rate, due to a user's physical state.

For this part of the evaluation we run a new set of experiments with the same participants and use HandRate-g, the most general version of our solution and providing a lower bound on its performance.

1) Phone holding patterns: We consider different ways of holding the phone, horizontally/vertically, and different hand

[4]Its performance as reported in [9] on experiments with 11 subjects.

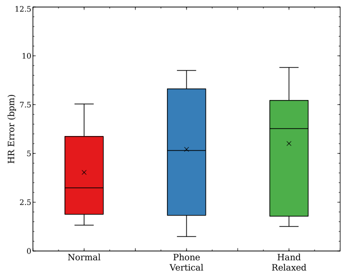
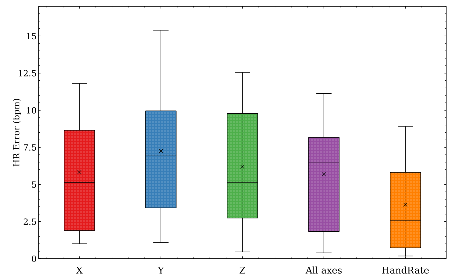
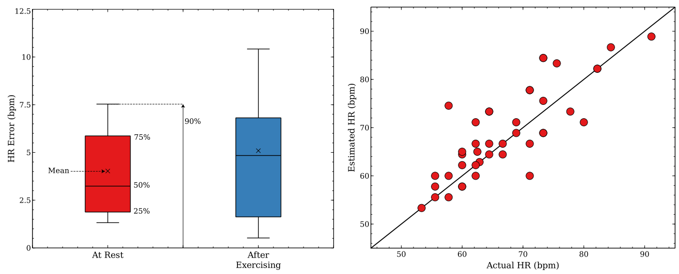


Fig. 13: Performance with different holding patterns



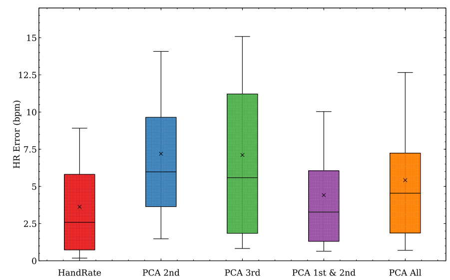
(a) Raw accelerometer axes vs PCA-based fusion



(a) Performance at rest and after exercising

(b) Performance at different heart rates

Fig. 14: HandRate's Performance at different HR



(b) Different PCA-based approaches

Fig. 15: Comparison of different strategies of using the accelerometer signal.

positions, hand forward (as when one checks the phone)/hand relaxed along the body. In the following, we refer to a phone held horizontally with the hand forward, as when one uses their phone, as the *normal* holding pattern. Although the best results are obtained in the *normal* condition, Figure 13 shows that HandRate is robust against different ways of holding the phone. With a phone held vertically, HandRate achieves a median error of $5.15\,\mathrm{bpm}$ and a 90th-percentile error of $9.19\,\mathrm{bpm}$ in that setting. With a hand relaxed (along the body), HandRate achieves a median error of $6.27\,\mathrm{bpm}$ and a 90th-percentile error of $9.36\,\mathrm{bpm}$.

2) Changes in heart rate: To evaluate its performance under varying heart rate levels, we run HandRate when users are at rest and after exercising. Figure 14a shows that HandRate maintains an interesting accuracy even after exercising, with a median error of $4.84\,\mathrm{bpm}$ and a 90th-percentile error of $10.03\,\mathrm{bpm}$ in that setting. Figure 14b also shows that HandRate's accuracy does not depend on the actual value of the HR. A perfect estimate would lie on the oblique line with slope 1. Here, we have a correlation coefficient between the estimated heart rates and the actual ones as high as 0.81.

F. Signal Recomposition

In this section, we evaluate the accelerometer signal recomposition approach (§ V-B), a cornerstone of HandRate. We organize the evaluation into two parts. First, we compare HandRate to different approaches of using the accelerometer axes. In the second part, we compare it to different strategies of applying PCA (Principal Component Analysis).

1) Using the accelerometer axes: We compare HandRate's signal recomposition approach to using each of the raw accelerometer axis individually as well as an approach combing them all. The latter involves applying HandRate on every axis separately and then combining the heart rate results using a weighted average. The weights are computed according to the respective signal's quality, quantified using the Q_{Kurt} value [9].

Figure 15a shows that HandRate's signal fusion approach leads to the best result – the error in heart rate computation is divided by two when compared to the next best approach. This result also shows that our approach of combining the signal axes before processing them instead of processing before combining as in [9], [29] leads to the best performance.

2) Applying PCA: HandRate's signal fusion approach involves using only the first principal component. We evaluate this choice by comparing to approaches using different principal components and/or a combination of them. To combine the different PCA components, we apply the same Q_{Kurt}-based strategy as above.

Figure 15b, show's that HandRate's approach of relying only on the first principal component leads to the best performance. While one intuitive hypothesis might be that adding more principal components, thus more useful information, could improve accuracy, the results show that the benefit of additional information is outweighed by the additional noise.

G. Processing time

In this section, we evaluate the execution time of the HandRate's Android implementation (§ VII-A) on different devices including a Google Pixel 2 (2017), a Samsung Galaxy S8 (2017), a OnePlus 7T (2019).

TABLE IV: Operation latency of HandRate

	Avg. Processing time (ms)			
Device	Signal process.	Encoder	Decoder	Total
Google Pixel 2	76.7	70	33.9	180.6
Samsung Galaxy S8	146.8	81.4	50.9	279.1
OnePlus 7T	40.2	41.8	14.8	96.8

Table IV shows that HandRate can run in real time, with an average execution time between 96.8 and $279.1\,\mathrm{ms}$, depending on the phone model. Recall that this processing is done once every $2\,\mathrm{s}$. What is more, the data shows that our Neural Network model also has a small prediction time (only the offline training phase requires a significant time), meeting a key requirement of our design.

Note that, in this implementation of HandRate, we use the default *tflite* settings. The execution time can, therefore, be further improved by leveraging optimizations like using *tflite*'s GPU delegate or NNAPI delegate [45], or by optimizing the model through pruning or quantization [46].

IX. Related Work

Identifying them as highly capable sensing and computing devices, always on us, several works have proposed to use smartphones for monitoring heart activity. Some works propose to perform opportunistic monitoring by adding to the phone some custom sensing hardware: Photoplestymogram (PPG) sensors in [4] or ECG sensors [5]. Furthermore, major manufacturers, like Samsung, have included special sensors for heart activity monitoring in some of their high end models. While these methods may offer reliable results, they are not accessible to a wide range of users. Using the phones cameras as a PPG sensors has also been thoroughly investigated in the literature. A popular approach leverages the PPG technique to monitor heart activity when a user places the finger on the smartphone camera [6], [7], [47]–[53], similar to the principle of oximeters. However, such approaches require active user participation and their accuracy depends on multiple factors, including precise finger placement with respect to the camera [7]. In order to relax the constraint of finger contact with the camera, another family of approaches proposes to obtain a remote PPG signal by capturing a video of the user's face, identifying regions of interest or points of interest, and tracking the variation of their color intensity within the different frames of the video [8], [54]–[56]. However, their accuracy may vary with the lighting conditions and may simply not work depending on user's skin tone or makeup. Researchers have also explored the usage of mobile phones motion sensors (accelerometers and gyroscopes) for heart activity monitoring. They propose to use these sensors to capture body movement in response to heartbeats events, therefore performing Seismocardiography (SCG) when the phone is placed on the chest [9], [57] or Ballistocardiogr态 (BCG) when it is placed anywhere else, on the navel for example [12]. These methods however still require the user to place the phone on specific areas of their bodies, necessitating active user participation. To the best of our knowledge, HandRate is the only smartphone-based solution using standard phone sensor for computing heart rate without requiring active user participation.

X. Conclusion and Future Work

We presented HandRate, the first smartphone-based system using a standard sensor, an accelerometer, for heart rate monitoring while a user holds their phone. HandRate addressed the unique challenges arising from acquiring the BCG signal from the hand by introducing a design using two modules – Signal Processing and Heartbeat Identification – working in tandem. The Signal Processing model addressed the challenge of transforming the accelerometer readings into a single-dimensional signal oblivious to how the user holds their phone. The resulting signal serves as input to the Heartbeat Identification module, which uses a light-weight design combining convolutional and recurrent neural networks to predict the heartbeats. We implemented HandRate as a standalone Android application and evaluated its performance using data from 18 subjects. The results showed that HandRate computes the heartbeat with accuracy similar to or better than systems requiring special sensors and/or active user participation.

This work is not the last chapter on HandRate. A more diverse data collection and evaluation is necessary before a potential large-scale adoption of HandRate in real life. This diversity spans across multiple dimensions, including, but not limited to, testing on a large range of phone models with different sensor characteristics, testing for large periods of times as users go about their daily lives and expanding the set of volunteers beyond healthy subjects.

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