Estimating Heart Rate Variability in Challenging Low SNR Regimes using Wearable Magnetocardiography Sensors

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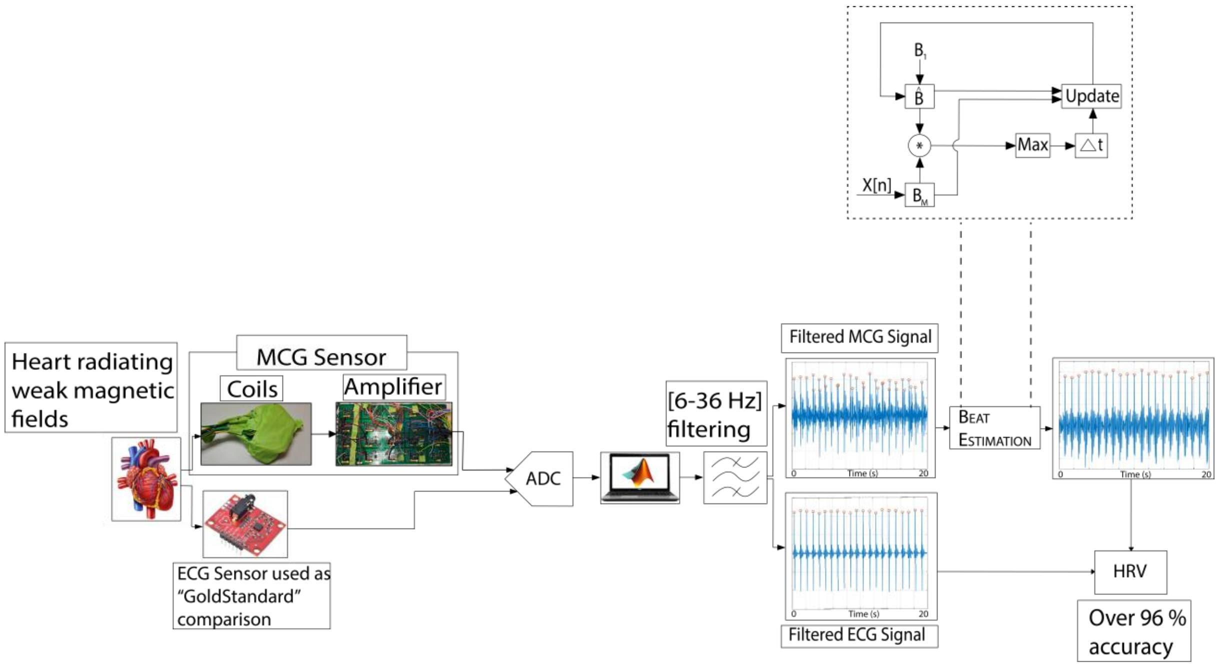

A novel signal processing approach to estimate Heart Rate Variability (HRV) from wearable magnetocardiography (MCG) sensors in high noise environments.

Take-Home Messages

- We report a novel signal processing approach, namely BEAT ESTIMATION, that is capable of pinpointing a patient's heart beats and estimating heart rate variability (HRV) using in-house wearable magnetocardiography (MCG) sensors that detect the extremely weak magnetic fields of the heart.
- BEAT ESTIMATION is the first to render wearable MCG sensors capable of accurately estimating HRV metrics, despite the low signal to noise ratio (SNR) levels associated with sensor operation.
- Seamless and non-contact acquisition of HRV metrics using the magnetic field of the heart can be game-changing in assessing heart health, cardiovascular fitness, stress levels, cognitive workload, and more.
- BEAT ESTIMATION relies on correlation of a single heartbeat with the remainder signal to identify the beat locations of MCG signals having SNR as low as -7 dB and to estimate HRV metrics using the resulting beat locations as opposed to traditional R-peak-based approaches.
- Ultimately, BEAT ESTIMATION can be applied to other periodic, low-SNR signals, besides MCG.

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Abstract*—We report BEAT ESTIMATION, a novel method used to calculate Heart Rate Variability (HRV) from low Signal to Noise Ratio (SNR) data (-7 dB to -4 dB in this work) acquired via wearable magnetocardiography (MCG). MCG activity is first collected using an in-house wearable sensor and filtered to remove noise outside the band of interest. BEAT ESTIMATION extracts a single heart beat from the filtered recording and correlates it with a small number of beats individually to average out the remaining noise. The de-noised beat is then correlated with the full recording to identify the location of each of the heart beats. Using these locations, HRV parameters are, finally, calculated. Results show ∼99.9% accuracy in estimating HRV metrics using beat-to-beat intervals as opposed to traditional R-to-R-peak intervals. The average accuracy of detecting the true location of beats is shown to increase to 96.43% using BEAT ESTIMATION as opposed to 59.98% using our previous method that relied on R-peak detection. In summary, BEAT ESTIMATION renders wearable MCG sensors capable of accurately estimating HRV, despite the low SNR levels associated with sensor operation. The approach can be game-changing in assessing heart health, cardiovascular fitness, stress levels, cognitive workload, and more.

***Keywords*—Heart rate variability, magnetic fields, magnetocardiography, sensors, signal to noise ratio.**

I. INTRODUCTION

MAGNETOCARDIOGRAPHY (MCG) is a non-invasive sensing technique that detects the weak magnetic field generated by the electrical activity of the heart [1]. Compared to electrocardiography (ECG), MCG can provide three-dimensional mapping of the heart, is highly sensitive to tangential and vortex currents, and is robust to the presence of biological tissues that are inherently non-magnetic [2]. In turn, MCG has major clinical applications that include detection of myocardial ischemia and viability, arrhythmogenic risk assessment, cardiac source localization, and more [3].

More recently, we demonstrated the use of MCG to measure Heart Rate Variability (HRV) [4]. Traditionally, HRV has been measured using ECG, photoplethysmography (PPG), and radar sensing, among others [5], [6], [7]. ECG is viewed as the "gold standard" but requires electrodes in contact with the skin that make it obtrusive. PPG and radar-based approaches are contactless, but lack accuracy and reliability [8], [9], [10]. Hence, MCG was brought forward as a non-contact (and, therefore, much more seamless) alternative to conventional ECG, as well as a more reliable alternative to PPG and radar-based approaches. In this case, focus has been on the R-peak detection of the MCG signal, with applications including, but not limited to, cardiovascular diseases [11], [12], sleep disorders [13], assessing heart health, stress levels, cognitive workload, and more [14], [15].

Unfortunately, capturing MCG activity is challenging as attributed to the low value of the heart's magnetic fields (50-100 pT). An overview of technologies used to sense MCG signals is available in [16], [17]. In brief, superconductive quantum interference devices (SQUIDs) are the most used and accurate magnetometers [18]. Their operation is based on the expulsion of magnetic fields when cooled to very low temperatures (as close as absolute zero) [19], allowing superconducting materials to conduct electrical current for long periods while avoiding energy losses [20]. However, SQUIDs suffer from drawbacks that limit their clinical usage, including bulkiness, high cost [21], [22], and sophisticated fabrication [17]. Atomic magnetometers (AMs) capture MCG signals with sensitivity similar to that of SQUIDs while being smaller and avoiding the need of cryogenics [23]. However, they are required to be heated to a high temperature (150 °C), and because of the presence of alkali atoms, they can be dangerous [24].

To overcome these limitations, we recently reported a passive, compact (in the order of centimeters), lightweight (in the order of grams), and sensitive (as low as pT/$\sqrt{Hz}$) sensor capable of detecting MCG signals in unshielded settings, without needing any heated alkali atoms nor cryogenics [25], [26]. The sensor is envisioned to be wearable and operates based on Faraday's law where voltage is induced on coils placed upon the chest as the varying magnetic flux from the heart is incident upon them. Its compactness and lightweight are directly related to the sensing coils used. These coils have been designed based on the model of a tightly winded air core induction coil. Contrary to previous designs [27], our coils do not require an iron core, hence resulting in significant weight savings. In addition, optimization of the coil length to outer diameter ratio as well as the outer diameter to inner diameter ratio, as explained in detail in [25], result in

Manuscript received December, 2023. This research was supported by The Ohio State University Chronic Brain Injury (CBI) Discovery Theme, the National Science Foundation (NSF) under grant no. 2320490, and The Ohio State University Center for Medical and Engineering Innovation (CMEI).

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TABLE I
COMPARISON TO ALTERNATIVE QRS DETECTION METHODS

Reference	Signal	Type of Equipment	Patients?	No. of Patients	SNR level (if reported) (dB)
[14]	ECG	Online Datasets	No	-	25.21
[32]	ECG	Online Datasets	No	-	-
[33]	ECG/MCG	SQUID	Yes	1	High
[34]	MCG	SQUID	Yes	1	-
[35]	MCG	SQUID	Yes	2	-
[36]	ECG	Online Datasets	No	-	-
[37]	ECG	Online Datasets	No	-	12.69
This work	ECG/MCG	Wearable Sensor	Yes	6	-4dB

significant improvements in sensitivity. Recently, this sensor was used to detect the QRS complex of the heart by averaging the coil measurements over time, as well as to calculate HRV by locating R-peaks in real-time [2].

However, a major limitation of our previous work [2] is that the digital signal processing (DSP) methods applied on the collected MCG signal cannot significantly reduce the noise level. Notably, noise has been estimated to be more than 5 times higher than the signal. This increases the difficulty of extracting features of interest that are buried in or distorted by noise. In the case of HRV detection, our previous approach leads to: (a) miss-detection of R-peaks and (b) classification of high-amplitude noise as R-peaks, resulting in wrong calculations. For example, only 3 mins out of the 5 mins MCG recordings were identified as usable in [4].

In the literature, several techniques have been developed to detect R-peaks as a goal of calculating HRV parameters from heart signals that are challenging in terms of abnormalities in the waveform. For example, the wavelet transform's ability to display spectral components of a signal as time elapses makes it a relevant means of analysis [28]. The approach has achieved good accuracy in detecting the QRS complex as well as wave peaks (such as the P and T) in the ECG signal [29]. Neural networks have also shown effectiveness in detecting ECG signal waveforms and their R-peaks [30], [31]. By contrast, referring to Table I, previous approaches for QRS detection rely on less noisy signals and/or known signal waveforms. Specifically, QRS detection based on wavelet transform has utilized ECG signals with SNR higher than 20 dB [14], [32], [33]. MCG has been considered, but only in the case of high temperature SQUIDs employed in a shielded room, which is known to provide signals with relatively high SNR [34], [35]. In other cases, QRS detection based on neural networks has been demonstrated [36], [37], but this requires training on large datasets that are currently only available for ECG and high SNR values. The approach is also computationally expensive and complex to implement.

To overcome these limitations in the state-of-the-art, we propose a method called BEAT ESTIMATION that relies on correlating a random heart beat with the full signal to point out the exact beat locations which are otherwise buried in or distorted by noise. The capitalization of the subject term is to emphasize on the name of the algorithm and to help distinguish it when utilized within the context of a sentence. The key novelty of this work lies in the detection of HRV parameters from wearable MCG signals that have: (a) very low SNR (-4 dB demonstrated in this work in measurements and as low as -14 dB in simulations), and (b) an unknown waveform for the signal itself. We demonstrate that BEAT ESTIMATION can effectively locate the heart beats even in environments with noise levels that are 5 times higher than the signal. We also demonstrate the ability of BEAT ESTIMATION to accurately capture HRV by validating it on both ECG and MCG data. To our knowledge, this is the first signal processing method to empower HRV detection from wearable MCG sensors that are inherently very noisy.

The rest of the paper is organized as follows: Section II describes BEAT ESTIMATION step by step. Section III confirms the ability of BEAT ESTIMATION's beat-to-beat intervals to estimate HRV metrics equivalent to those of traditional R-to-R intervals, as validated upon ECG signals. Section IV describes an experimental setup for the acquisition of MCG signals on human subjects, applies BEAT ESTIMATION on the collected MCG signals, reports HRV estimations, and compares these estimations to the ground truth. Section V includes a discussion of the findings. The paper concludes in Section VI.

II. BEAT ESTIMATION METHOD DESCRIPTION

A. Estimating the Average Duration of a Heart Beat

To apply BEAT ESTIMATION, an estimate of the average duration of a heart beat, denoted as T_{AVG}, must first be obtained. To do this, we need to refer to the auto-correlation profile of the signal. An example is shown in Fig. 1 that plots the auto-correlation profile of an MCG signal acquired on a human subject (red, dashed line). For comparison purposes, ECG activity is also recorded for the same individual and its auto-correlation profile is super-imposed in Fig. 1 (blue, solid line). Here, ECG and MCG signals were recorded simultaneously by using an off-the-shelf 3-lead ECG sensor and our in-house wearable MCG sensor [4], respectively, as described in detail in Section IV. The y-axis in Fig. 1 (namely, normalized power) is the normalized auto-correlation $\frac{R_{xx}(\tau)}{R_{xx}(0)}$ of a discrete-time signal $x(n)$ at time lag τ, with the auto-correlation $R_{xx}(\tau)$ being computed as:

$$R_{xx}(\tau) = \frac{1}{N-\tau} \sum_{n=0}^{N-\tau-1} x(n)x(n-\tau) \quad (1)$$

where N is the total number of samples.

Referring to Fig. 1, the average duration of a heart beat, T_{AVG}, can be estimated by taking the difference of the timing between the peak in the middle (i.e., the peak which represents the highest correlation between the signal and itself and that of the noise) and the following peak (estimated to represent the correlation of the signal with itself solely, without noise).As

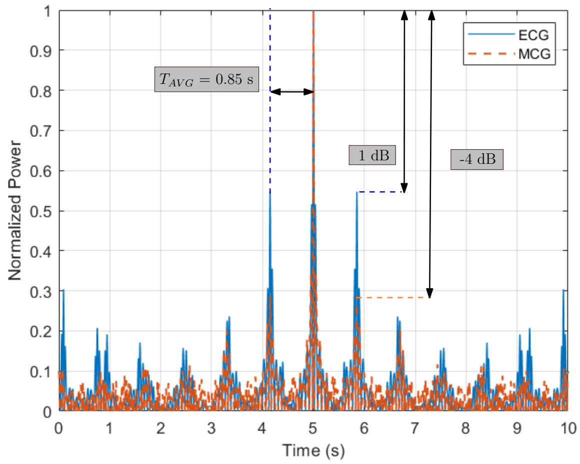

Fig. 1: Auto-correlation profile of ECG (blue) and MCG (red) signals from an example human subject recording.

would be expected, for the example of Fig. 1, both ECG and MCG result in a secondary peak at the same location. They achieve $T_{AVG} = 0.85s$ (approximately 67 bpm), which is a reasonable number for a healthy individual. Since patients were sitting during the MCG recordings, the obtained T_{AVG} is assumed constant throughout the recording. That is, T_{AVG} does not vary significantly from its calculated value and there is no need to re-calculate it periodically. Accordingly, due to the patient sitting and associated lack of motion, there are no rapid changes in the heart rate; the latter is relatively constant throughout the recording.

We note that the reason why the other peaks in the MCG auto-correlation profile of Fig. 1 decay over time is the noise level overcoming the level of the signal which is inherently not perfectly periodic (the time interval between adjacent heart beats varies over time). If the signal was perfectly periodic, multiple sub-peaks would be visible at every heart beat location. Indeed, Eq. 1 shows that as N increases, the value of $R_{xx}(\tau)$ decreases for a signal x that is not perfectly periodic. That is, the obtained value of T_{AVG} is an approximation of the actual value. We also note that a higher Signal-to-Noise Ratio (SNR) is expected to yield better auto-correlation profiles. Per the well-known Eq. 2, an increasing SNR is the result of an increase in the signal level compared to that of the noise. Indeed, for the ECG auto-correlation profile, the sub-peaks do not decay as fast as those of MCG because its SNR (SNR_{ECG} = 1 dB) is higher than that of MCG (SNR_{MCG} = -4 dB) for this specific recording. Note that this SNR for the ECG signal is still relatively low compared to other ECG signals captured by more advanced sensors. We also note that the MCG signal has negative SNR as obtained from the autocorrelation profile, indicating that the noise power is stronger than that of the signal. Specifically, the MCG signal can me modeled as $x[n] = s[n] + n[n]$ where $s[n]$ denotes the signal part and $n[n]$ denotes the noise. Given the independence assumption of noise, the MCG signal's autocorrelation can be written as $R_x[t] = R_s[t] + R_n[t]$, where $R_s[t]$ and $R_n[t]$ are the signal's and the noise's autocorrelation, respectively. Assuming white gaussian noise, we have $R_n[t] = P_n$ if t=0 and 0 for all other t. Also, since $s[n]$ is periodic with period equal to L samples, we have that $R_s[kL] = P_s$ for every integer k. Then, $R_x[0] = P_s + P_n$ and $R_x[L] = P_s + 0 = P_s$ (i.e., first period). Therefore, to calculate the signal's SNR, we can obtain the amplitude of the middle peak and the next available peak in Fig. 1 and plug those values in Eq. 2. In this work, the SNR range is -4 dB to -7dB for the MCG signals, which is the same as that in [2].

$$SNR_{dB} = 10 \log_{10} \left(\frac{SignalPower}{NoisePower} \right) \quad (2)$$

B. Detecting Heart Beats and Generating Peaks at the Corresponding Locations

Algorithm 1 describes the proposed approach of detecting heart beats in the noisy signal and generating peaks at the corresponding locations. We note that, prior to applying Algorithm 1, the MCG signal (also applicable to ECG) is band-pass filtered in the range [6-36 Hz] to eliminate unnecessary noise outside the band of interest [25], [38]. Once the recording is filtered and an approximate of T_{AVG} is obtained (per Section II-A), BEAT ESTIMATION can be applied.

Referring to Algorithm 1, let S be the recording of interest and define B_1 to be the first beat of this recording with length (duration) L_B. First, the initial beat is taken as a reference signal. Second, this reference signal is correlated with the next available beat, i.e., B_N, in search for the best estimate of the relative shift that maximizes the correlation, Z, between the beat estimate and the current available beat, where the beat estimate is the initial extracted beat that is being updated after every correlation.

Algorithm 1 Beat Finding Algorithm

$B_1 \leftarrow S(1 : T_{AVG})$
$L_B \leftarrow numel(B1)$
for $i = 2$ **to** M **do**
  $B_M = S(T_{AVG} * (i-1) + 1 : T_{AVG} * i)$
  $Z = ifft(conj(fft(B_1)). * (fft(B_M)))$
  $[Val_P, Loc_P] = max(abs(Z))$
  if $Loc_P > L_B/2$ **then**
    $Loc_p = Loc_P - L_B - 1$
  end if
  $B_1 = (\frac{i-1}{i}) * B_1 + (\frac{1}{i}) * circshift(B_M, -Loc_P)$
end for
$Beat\_Estimate = ifft(conj(fft(B_1)). * (fft(S)))$

Note that this method works under the assumption that the variations in the estimated value of T_{AVG} are small. The process is repeated until M beats are used, where M denotes a small number of beats. The chosen value of M is a trade-off between reducing the time needed for the correlation process to finish and getting the best estimate for the heart beat. The obtained estimate is, finally, correlated with the full recording to generate peaks whenever a heart beat is detected. The correlation is performed as multiplication in the frequency domain for computational efficiency purposes. The block diagram in Fig. 2 provides a visualization of the algorithm's operating principle.

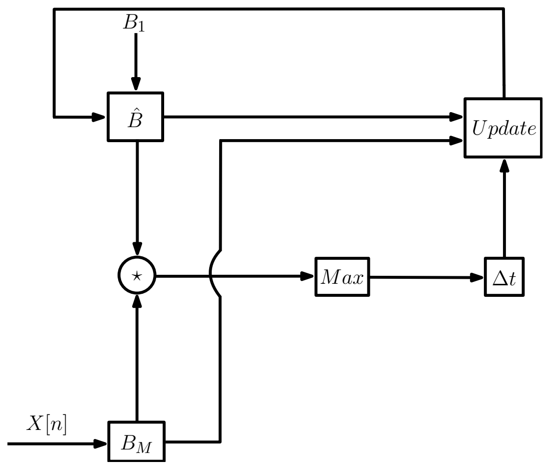

Fig. 2: Block diagram of BEAT ESTIMATION

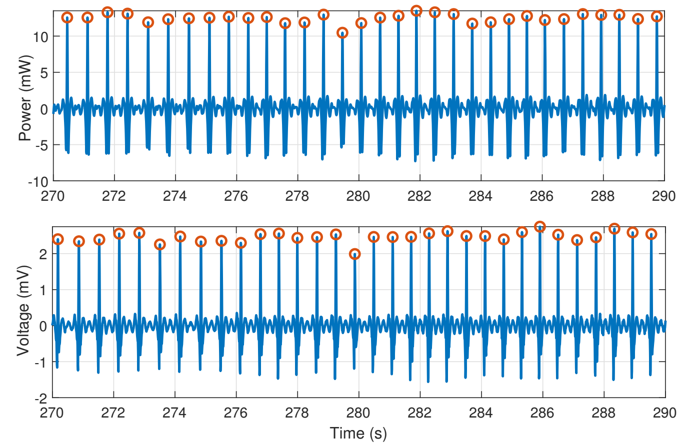

Fig. 3: Example ECG signal from the MIT-BIH Database with circles representing R-peaks (bottom) and beats estimated through the proposed BEAT ESTIMATION method (top).

III. ESTIMATING HRV USING BEAT ESTIMATION: PROOF-OF-CONCEPT VALIDATION FOR ECG SIGNALS

A. Method

We first apply BEAT ESTIMATION on a a publicly available database of ECG signals as a low-risk approach to validate its accuracy in calculating HRV as compared to traditional methods that rely on R-peak (i.e., instead of beat) detection. The term ”traditional R-peak methods” refers to the methods that rely on R-peaks to acquire HRV, as opposed to our work where heartbeats are used to calculate HRV. The metrics of interest are: (a) the average duration of the difference in distance between consecutive R-peaks (a metric known as mean values of adjacent R-peaks, or MeanRR, in traditional HRV calculation on ECG signals), and (b) their standard deviation (a metric known as standard deviation of RR intervals, or SDRR, in traditional HRV calcuation on ECG signals). To this end, we utilize the MIT-BIH Arrhythmia Database [39] which is known for its quality of a substantial number of annotated ECG recordings collected under controlled conditions. The database has been used for basic research of cardiac dynamics at about 500 sites worldwide since 1980 [40].

A zoom-in on an example ECG recording from the MIT-BIH Database is shown in Fig. 3. To calculate HRV, two methods are applied: (a) BEAT ESTIMATION (with beats detected being marked as circles in the top figure) and (b) traditional R-peak detection (with R-peaks detected using Matlab's findpeaks function being marked as circles in the bottom figure).

First, the average R-R interval for the ECG signal is calculated using the location of the R-peaks identified in the bottom plot of Fig. 3:

$$E[X] = \frac{1}{N-1} \sum_{i=1}^{N-1} X_{i+1} - X_i \tag{3}$$

where X_i is the index of an R-peak.

Then, the standard deviation of the difference between R-peaks is calculated according to:

$$\sigma_X = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N-1} (X_{i+1} - X_i - \boldsymbol{E}[X_{i+1} - X_i])^2} \tag{4}$$

where $\boldsymbol{E}[.]$ represents the mean of the R-R interval. The abovementioned $E[X]$ and σ_X are the same as MeanRR and SDRR, which are standard HRV metrics and similar to those calculated in [4].

In the same fashion, we calculate the average Beat-Beat interval ($E[B-B]$) and its standard deviation (σ_{B-B}) by changing the index of an R-peak (X) to the index of a heart beat in Eq. 3 and Eq. 4 for the corresponding top plot of Fig. 3 that uses BEAT ESTIMATION.

B. Results

Six (6) ECG recordings, each of 512 sec in duration, were randomly selected from the MIT-BIH Arrhythima Database to validate the ability of BEAT ESTIMATION to accurately estimate HRV. Table II shows a summary of the calculated results. Here, ECG_{B-B} refers to the use of BEAT ESTIMATION on the ECG signal, while ECG_{R-R} refers to the use of the traditional R-peak detection method on the ECG signal.

The HRV % error was calculated according to the following formula:

$$\%\text{error} = \frac{ECG_{R-R} - ECG_{B-B}}{ECG_{R-R}} \tag{5}$$

Using Eq. (5), the % error of using the beats to calculate the indirect HRV metrics of Eq. (3) and Eq. (4) is negligible compared to obtaining the same metrics using R-peaks. This proves that once BEAT ESTIMATION is applied on the signal to identify the beats, HRV parameters can then be accurately calculated as a next step.

TABLE II
COMPARISON OF BEAT ESTIMATION VS. TRADITIONAL R-PEAK DETECTION IN CALCULATING HRV PARAMETERS FOR ECG RECORDINGS

Parameters	Recording No.	ECG_{R-R} (ms)	ECG_{B-B} (ms)	Percentage Error (%)
$E[x\_x]$	1	583.81	583.81	0
	2	560.65	560.65	0
	3	685.36	684.45	0.13
	4	664.30	665.16	0.12
	5	741.61	741.61	0
	6	615.99	616.62	0.1
σ	1	54.76	54.72	0.07
	2	70.32	70.22	0.14
	3	98.48	96.27	0.02
	4	59.93	56.44	0.05
	5	106.65	106.68	0.02
	6	54.76	51.41	6.11

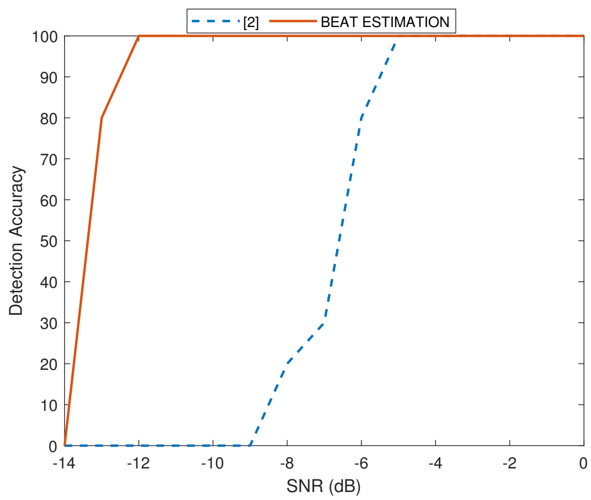

Fig. 4: Performance comparison of BEAT ESTIMATION vs. traditional R-peak detection at varying SNR levels.

IV. VALIDATION FOR MCG SIGNALS

A. Simulation Results

We carried out a simulation study with an MCG signal at varying noise levels and calculated the detection accuracy per Eq. 6 using: (a) the proposed BEAT ESTIMATION method and (b) the method reported in [2]. Results are summarized in Fig. 4 showing that BEAT ESTIMATION was capable of detecting heart beats at 100% detection accuracy for SNR as low as -14 dB whereas the method reported in [2] failed at around -10 dB. The accuracy was calculated according to the following formula:

$$\text{Detection Accuracy} = \frac{\text{\# of detected peaks}}{\text{\# of true peaks}} \times 100 \quad (6)$$

where the ECG signal was used as reference to determine the true location of R-peaks.

B. Experimental Setup

The experimental setup used to collect MCG activity on human subjects is shown in Fig. 5. It comprises of: (a) an array of seven (7) coils placed upon the chest to sense the magnetic field of the heart, followed by an amplifier array to amplify the collected signals (as described in [4], (b) a 3-lead off-the-shelf ECG sensor used to produce a reference signal to compare with, (c) an Analog to Digital Converter (ADC) used to digitize the signals, and (d) a laptop used for signal processing.

For the purposes of this study, MCG (and concurrent ECG) data were collected on six (6) different subjects. The protocol was approved by The Ohio State University Institutional Review Board (protocol # 2019H0259). There were no restrictions on the sex of the subjects. The MCG sensor was secured on the chest without any gap. It was fixed in place using tape, yet it can be seamlessly embedded in a garment in the future. Though exact measurements of the heart-to-coil distance are not possible to acquire, all subjects had a healthy body mass index (BMI$< 30kg/m^2$) to ensure the MCG signal gets picked up. In the future, advances in the MCG sensor design will overcome this limitation. Data collection for each subject lasted 5 min. Throughout this duration, the subjects were sitting still on a chair.

C. Challenges with Previously Reported Methods

In our previous work [25], denoising of the MCG signal consisted of two steps. First, the signals of each coil were band-passed in the interval [6-36 Hz] to remove noise outside the band of interest. Next, the outputs of the 7 coils were averaged together to strengthen the amplitude of the obtained signal. Averaging was done as:

$$M_{AVG} = \frac{1}{7}\sum_{i=1}^{7} M_i \quad (7)$$

where M_i is the output of a single coil.

Fig. 6 shows the resulting MCG signal (i.e., after filtering and averaging) for one of the subjects (blue, solid line). For comparison, the collected ECG signal is super-imposed (red, dashed line). The equivalent MCG and ECG signals for other subjects look similar, as are the recordings throughout the 5 min for each subject.

The sensor in hand operates based on Faraday's law, where the changing magnetic flux of the heart results in a time-varying voltage across the coils. Therefore, there exists a derivative relationship between MCG and ECG (which directly measures the electrical activity of the heart). Per [2], even though in a given period there will be the same number of

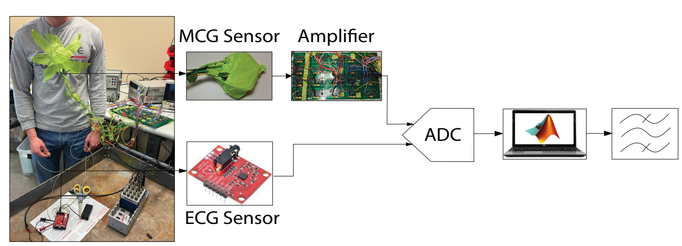

Fig. 5: Experimental setup used to collect MCG and ECG activity on human subjects.

cardiac cycles, perfect alignment of R-peaks between ECG and MCG is not expected due to the derivative relationship. Indeed, in Fig. 6, where we are looking directly at the R-peaks between ECG and MCG, we do not see alignment due to the derivative relationship.

It is evident that locating R-peaks in the averaged MCG signal is highly problematic because of the high noise level. That is, multiple fake peaks show up in the vicinity of the true R-peak. Thus, calculating HRV parameters from this recording is expected to result in a high percentage of error. Indeed, as shown in Table III, the accuracy of detecting R-peaks for the six (6) human subjects using this method (namely MCG_{R-R} in Table III) ranges from 28.4% to 94.8% with an average of 59.98 %. The wide range of accuracies is directly related to the recording and how noisy it is. The variation in the SNR of the signal varies the detection accuracy as well.

To have an intuition on the noise power, the SNR is calculated by using Eq. 2 where the values of the signal power and noise power can be estimated from the auto-correlation profile in Fig. 1. Here, the peak in the middle represents the normalized power of the signal plus noise, whereas the second largest peak represents the normalized signal power only. Even though the noise is assumed to be White Gaussian Noise, its auto-correlation profile is not represented by a single peak at τ=0, but might show some smoothing effects or tapering towards the edges due to the finite duration. Using Eq. 2, the SNR for the averaged MCG signal was estimated to range between -7 dB and -4 dB across all experimental trials.

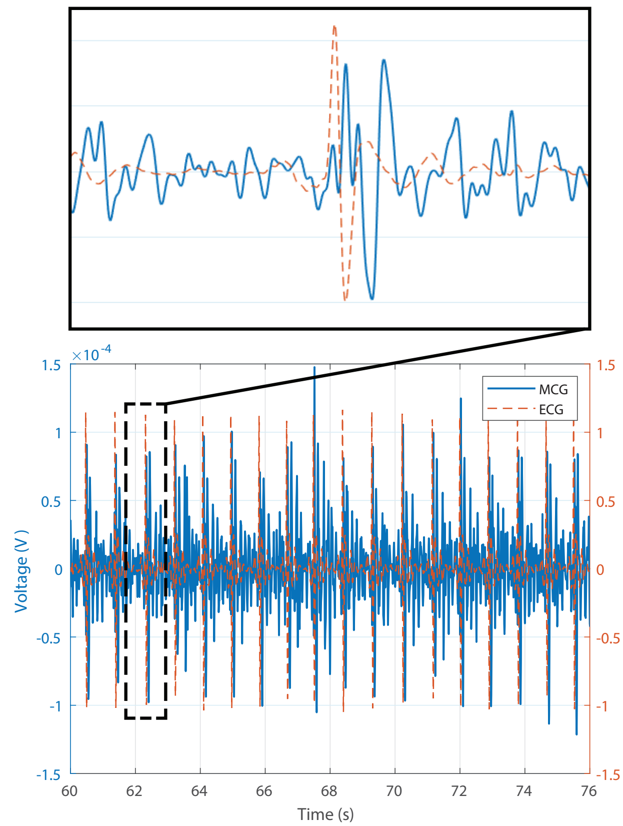

Fig. 6: Performance of previously reported method [2] for HRV calculation from MCG signals: comparison of MCG vs. gold-standard ECG for subject 3.

D. Beat Estimation *Performance*

To overcome the low SNR and achieve our ultimate goal of accurately calculating HRV parameters from wearable MCG sensors, Beat Estimation was applied on the filtered and averaged MCG signal. Fig. 7 shows the resultant MCG signal following Beat Estimation (blue, solid line) as well as the ECG signal for comparison (red, dashed line). As seen, beat locations on the MCG signal (marked with a blue cross) can be clearly identified despite the noise level being 3 to 5 times stronger than the signal level. By inspecting the zoomed-in plot of the third beat, one can realize that only a single peak is present, unlike the one in Fig. 6 where multiple fake peaks are present.

We remark that the peaks in Fig. 7 represent heart beats (not R-peaks, by contrast to Fig. 6), as they are the resultant of correlating a single heartbeat with the full recording. Such correlation projects the MCG recording into a new domain, the signal domain, where peaks appear whenever similarity occurs between the extracted heartbeat and the recording. Hence, no delay is expected between MCG and ECG in Fig. 7.

The process was repeated for all six (6) human subjects and achieved 84.6%, 96.24%, 99%, 99.9%, 99%, and 99.9% beat detection accuracy, where the accuracy was calculated according to Eq.(6). By comparing the aforementioned accuracies to those in Sec. IV-B, one can see the improvement achieved in detecting the true location of beats with a noticeable improvement in the average accuracy that increased from 59.98% to 96.43%.

Once the beat locations are identified, HRV parameters can be calculated. Table III shows a summary of the obtained results, where ECG_{R_R} refers to the traditional calculation of HRV metrics using R-peak detection on an ECG signal, MCG_{R_R} refers to our previously reported approach [4] of calculating HRV metrics using R-peak detection on an MCG signal, and MCG_{B_B} refers to the proposed Beat Estimation method used to estimate HRV metrics from beats detected on an MCG signal.

As seen, the HRV percentage error for MCG_{B_B} ranges from 0.03% to 0.63% with an average of 0.25%, where the percentage error was calculated according to Eq. (5). The % error for the standard deviation witnesses higher values as it is highly sensitive to miss-detected beats; it, thus, results in higher error values even when the beat detection accuracy is high but not equal to 100%. As for the HRV percentage errors for MCG_{R_R}, they range from 4.04% to 38.95% with an average of 20.61%, which is 32.2 times higher than that obtained in MCG_{B_B}

V. Discussion

Accurate acquisition of HRV using wearable, non-contact, and seamless sensing solutions, such as the MCG sensor of Fig. 5, brings forward unprecedented clinical opportunities for monitoring heart health, cardiovascular fitness, stress levels, cognitive workload, and more, in the individual's real-world

TABLE III
BEAT ESTIMATION ON MCG VS. ECG

		Gold Standard	Previous Method			Proposed BEAT ESTIMATION Method		
Parameters	Recording No.	ECG_{R-R} (ms)	MCG_{R-R} (ms)	R-peak Detection Accuracy (%)	HRV Percentage Error (%)	MCG_{B-B} (ms)	Beat Detection Accuracy (%)	HRV Percentage Error (%)
$E[x\_x]$	1	854.01	960.64	44.6	12.49	859.43	84.6	0.63
	2	940.47	768.19	65	18.32	936.82	96.2	0.39
	3	929.45	567.42	28.4	38.95	929.71	99.0	0.03
	4	745.00	775.15	94.8	4.04	746.99	99.9	0.26
	5	809.53	539.11	62.5	33.4	810.45	99.0	0.11
	6	1024.85	856.1	64.6	16.46	1025.5	99.9	0.06
σ	1	56.87	586.8	——-	931.82	340.19	——-	498.18
	2	84.06	516.46	——-	514.39	115.84	——-	37.81
	3	85.63	393.44	——-	359.46	93.46	——-	9.14
	4	55.1	214.71	——-	289.67	46.21	——-	16.13
	5	59.57	397.87	——-	567.9	59.04	——-	0.84
	6	64.2	465.04	——-	624.36	65.67	——-	2.29

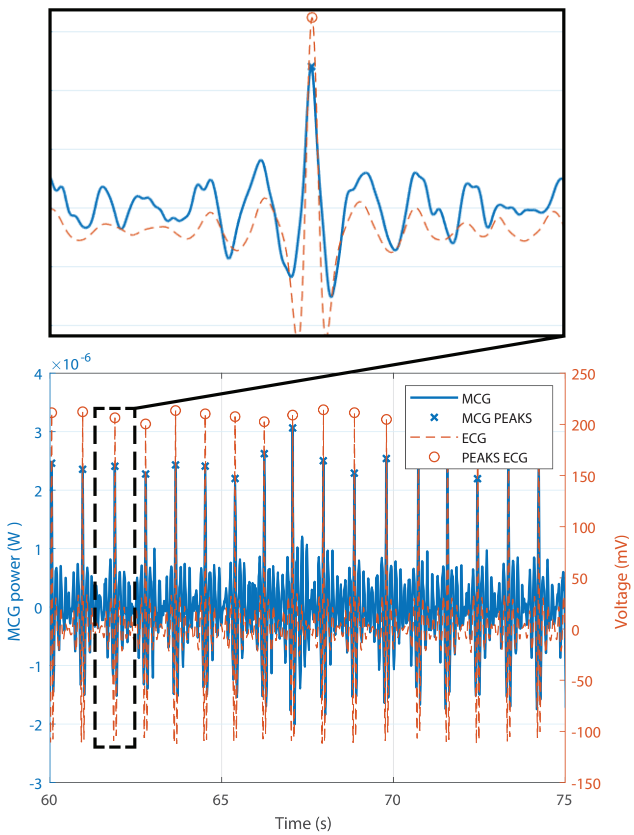

Fig. 7: Performance of the proposed BEAT ESTIMATION method in calculating HRV metrics from MCG signals: comparison of MCG vs. gold-standard ECG for subject 3.

environment (i.e., outside the clinic). However, the presence of high levels of noise associated with wearable MCG sensing can yield false results [41], [42]. In turn, methods that have high noise tolerance should be adopted to compensate for the low SNR.

To decide on the number of human subjects used for validation, we relied upon previous proof-of-concept studies on QRS detection. Referring to Table I, past studies (excluding neural network approaches) either did not use any human subject data or were limited to one to two human subjects. Here, 6 patients were used to conduct the experiment. Considering the first two subjects in Table III, the average beat detection accuracy is 90.4 %. By continuously adding subjects 3, 4, 5, and 6, the accuracy increases to reach 98.46 %, which is very close to the beat detection accuracy of the individual subjects. Thus, adding more subjects at this level of accuracy will not significantly affect the average beat detection accuracy. Furthermore, validation done on ECG signals from the MIT-BIH datasets showed that the accuracy saturates at around 99 % when adding more recordings. Finally, it is worth noting that the full 5 minutes of the recordings were used, unlike [2] where only ∼3 minutes of each recording were used due to noise. A more extensive study with more patients (including BMI and sex considerations) will be performed in the future. Also, respiratory movement will cause the sensor's coil to move, in turn generating voltage across its terminals according to Faraday's law. However, the respiratory frequencies are very low compared to the frequencies of the MCG signal, implying that they are filtered out.

In our work, we introduced BEAT ESTIMATION as a novel method that achieves high accuracy in computing HRV metrics from MCG recordings with low SNR. In brief, the method identifies heart beats within noisy heart beat recordings and these beats are subsequently used to estimate HRV metrics. When tested on ECG signals obtained from the MIT-BIH dataset, the percentage error between the average R-R intervals (traditional approach) and beat-to-beat (B-B) intervals (proposed approach) was very low. Validating on this dataset provided confidence that HRV metrics can indeed be estimated using B-B intervals instead of R-R intervals. This is an important finding for signals where R-peaks are non-obtainable due to high noise, such as in our MCG recordings. When tested on MCG signals obtained using wearable sensors on human subjects, high accuracies were achieved in both beat detection and HRV metric estimation. Quantitative results are summarized in Table. III. Compared to our previously reported method that estimated HRV metrics from R-peak detection within the MCG recording [2], the proposed BEAT ESTIMATION approach is considerably more reliable and accurate. Note that missing a couple of beats is sufficient to induce high standard deviation % errors, thus explaining the results indicated in Table III.

Today's clinically acceptable "gold standard" for HRV entails the measurements acquired through ECG. An example is the note on the blood oxygen application measurements of the Apple Watch Series 6 indicating that it is "not intended for medical use [43]. In turn, our goal is to get as close to the ECG accuracy as possible, hence the comparison vs. the ECG performance in Table III. Notably, the HRV percentage error we demonstrate for the mean beat-to-beat interval is as low as 0.63%. In the literature [44], standard deviation of consecutive heart beats, has been identified as the metric associated with the greatest amount of error. Of the five (5) PPG devices identified in [43], only 1, with a mean$\pm$SD device-observer difference of -1.2$\pm$15.87mmHg for systolic blood pressure, was recommended for self/home measurements in adults [45]. As for the others, they were not suitable for outpatient clinical trials as their reliability values compared to the reference (ECG) was about 77%. In our work, the highest HRV percentage error achieved for average beat-to-beat interval was 0.63%. Of course, even though previous wearable devices have reported errors in HRV when compared to ECG, these devices can still be considered for non-clinical-grade applications that leverage their utility and cost-benefit [46].

It is worth noting that BEAT ESTIMATION assumes that the average duration of heart beat (noted as 0.85s in Section II-A) of the patient will not deviate much from the average value obtained from the auto-correlation profile. If significantly shorter or longer heart beat durations occur (e.g., due to sudden movements of the patient during the recording or other conditions), the results for that interval might be inaccurate as the window size of the reference beat is fixed. In the future, this limitation can be overcome by developing a tracker that adjusts the window size of the reference beat based on the difference in timing between two current successive heart beats.

VI. CONCLUSION

BEAT ESTIMATION is an effective method of estimating HRV metrics from MCG signals acquired through wearable sensors that exhibit noise levels higher than that of the signal. The method detects beats, as opposed to R-peaks, and uses the intervals between beats to subsequently calculate HRV metrics. When tested on six (6) ECG recordings from the MIT-BIH dataset, an accuracy of 99.9% in beat detection and a negligible HRV percentage error was achieved, validating this method as an accurate means of comparison between HRV obtained through R-R and B-B. Upon applying it on MCG data acquired on six (6) human subjects, the resultant beat detection accuracy were 84.6%, 96.24%, 99%, 99.9%, 99%, and 99.9%, respectively. This is a remarkable improvement as compared to our previously reported method of R-peak detection on MCG signals that resulted in R-peak detection accuracies of 44.6%, 65.0%, 28.4%, 94.8%, 62.5%, and 64.6%, respectively.

HRV acquired from seamless and non-contact MCG sensors can have crucial clinical impacts in applications as diverse as Arrhythmia detection, cardiac function assessment, cognitive workload classification, and more. Future work will consider motion and subjects in non-sitting positions, necessitating the study of a variable window size for T_{AVG} (i.e., recalculation of T_{AVG} throughout the recording). Ultimately, BEAT ESTIMATION can be applied to other periodic, low-SNR signals, besides MCG.

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