

GPU-Based Segmented-Beat Modulation Method for Denoising Athlete Electrocardiograms During Training

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Abstract

Sport-related sudden cardiac death (SRSCD), defined as “death occurring during sport or within one hour of cessation of training”, is the leading cause of death in athletes. SRSCD occurs in the presence of underlying cardiovascular diseases, some of which may be identified by processing electrocardiographic recordings acquired during training (TECGs). A fast and accurate processing of TECGs during or immediately after training is challenging since TECGs are typically highly corrupted by noise and interferences, which may jeopardize their interpretation and identification of abnormal morphologies. The present study evaluated the ability of GPU-based Segmented-Beat Modulation Method (GPU-SBMM) to provide a noise-free estimation of TECGs, and to improve the algorithm by GPU acceleration to make it compatible with modern hardware. In this research, 19 6-to-10 min TECGs (sampling frequency: 256 Hz), acquired from 8 subjects while performing 4 different exercise tasks (walk, run, low-resistance bike and high-resistance bike), were analyzed. Results indicate that GPU-SBMM application yielded a significant increase of SNR(dB) (from 1 ± 5 dB to 19 ± 5 dB; $p < 10^{-12}$), also when stratifying by exercise tasks. Additionally, a considerable average speedup of 7.67x is achieved using NVIDIA GeForce 740M GPU processor.

1. Introduction

Sport-related sudden cardiac death (SRSCD), defined as “death occurring during sport or within one hour of cessation of training”, is the leading cause of death in athletes. A recent estimate suggests that 1 in 40,000 to 1 in 80,000 athletes per year [1] suffer from a sudden cardiac event resulting in either death or a non-fatal arrhythmia. This occurrence is still 3-4 times more often for athletes as compared to non-athletes [2]. This increase in the events of SRSCD in athletes in recent past poses a serious concern for the physicians and trainers responsible for the health and well-being of players [3]. Davide Astori (1987-2018)

aged 31, Neil Fingleton (1980-2017) aged 36, Fabricio Paulino de Melo (1990-2017) aged 26 and Bernardo Ribeiro (1989-2016) aged 26 are a few examples of professional athletes who lost their lives due to sudden cardiovascular arrest lately and the incidents left families and fans completely heartbroken and full of questions.

SRSCD occurs in the presence of underlying cardiovascular diseases, some of which may be identified by processing electrocardiographic recordings (ECG) acquired during training (TECG), eventually using wearable devices [4]. According to data, the probability of the ECG to detect underlying cardiovascular abnormalities that could place the athlete at risk of SRSCD is superior to that of physical examination and history [5,6]. However, TECGs in the acquired raw form are affected by several additional noise factors such as electrode motion artefacts, muscular artefacts emanating from intense and regular physical activities like running, walking, gym training etc. that can make the signal of interest clinically useless [7]. Additionally, the transmission of large amount of TECG data consumes a great deal of energy and reduces the battery life of both the wearable device and the processing platform [8]. To extend battery life, high-end processing platforms are required to have in-time identification and alert generation for prevention of SRSCD. The Segmented-Beat Modulation Method (SBMM) [9,10] provides a template-based ECG filter with physiological heart-rate and morphological variability. It has previously been tested in applications relative to abdominal fetal ECG [11] and electromyography filtering from ECG corruption [12], but never to filter TECG. The highly parallelizable and independent nature of data processing with SBMM makes it suitable to be implemented on high performance computing programming structures and platforms. A CPU-based approach uses single instruction single data (SISD) programming structure executing one program statement operating on one data stream at a time. Whereas, GPU architecture is characterized by single instruction multiple data (SIMD) feature [13], which allows operations on multiple data points simultaneously. GPU provides a high-performance hardware platform for faster simulations. Thus, in this work, GPU-based SBMM (GPU-SBMM) is

proposed as performance improved version of the previously proposed CPU-based SBMM (SBMM) for the denoising of ECG data.

2. Materials and Methods

2.1. Data

Single-channel ECG recordings (sampling frequency: 256 Hz) from 8 subjects (3 male, 5 female), aged 22-32 years (mean 26.5 ± 5.5 years) were used. Measurements were taken using an Actiwave (CamNtech, Cambridge, UK) ECG recorder placed on the chest while participants were asked to perform one or more exercise tasks (walk, run, low-resistance bike and high-resistance bike) as summarized in Table 1. Data were taken from the “Wrists PPG During Exercise” database by Physionet [14,15]

All ECG recordings were band-pass filtered through a bidirectional 3rd-order Butterworth filter with cut-off frequencies of 0.5Hz and 40Hz. After that, the baseline was removed. Baseline was computed as a cubic spline interpolation of fiducial points, placed 90ms before R-peaks. Annotations of the reference ECG R-peak positions were provided in the Physionet database. The mean HR (heart rate) and HRV (HR variability measured as RR-interval standard deviation) was 104 ± 25 bpm and 54 ± 26 ms, respectively.

2.2. GPU-based Segmented-Beat Modulation Method (GPU-SBMM)

GPU-SBMM was implemented in MATLAB using Parallel Computing Toolbox built-in functions. GPU-

SBMM takes as input the noisy ECG signal, the R-peak positions vector and some initial settings (ECG sampling frequency and gain). To enter GPU-SBMM processing, data have been copied from the CPU to the GPU device through the ‘gpuArray()’ function. Each cardiac cycle, which in GPU-SBMM can be processed independently from the others, was segmented into QRS and TUP segments.

After the segmentation of cardiac cycles into QRS and TUP segments, a resampling of TUP segments is performed to match the TUP length of median cardiac cycle (mCC) of all beats in a single recording. A peak correction is applied to identify and correct falsely detected peaks.

Finally, GPU-SBMM performs a filtering procedure that reconstructs a clean ECG signal from the one corrupted by noise recording. All the for-loops for segmentation, modulation, correlation optimization and reconstruction steps are implemented as vectorized cell array statements using ‘cellarray()’ function. The computed clean ECG from the GPU processor is then sent back to CPU using ‘gather()’ function. The distribution of workload for GPU-SBMM is shown in Figure 1.

2.3. Computing Platform

All GPU experiments were performed on NVIDIA GeForce GT 740M processing machine with compute capability 3.5 based on the Kepler architecture and 64GB GPU memory with bandwidth of 173 GB/s.

All CPU experiments were performed on Intel® Core i5 with 2 cores and an operating frequency of 1.8 GHz.

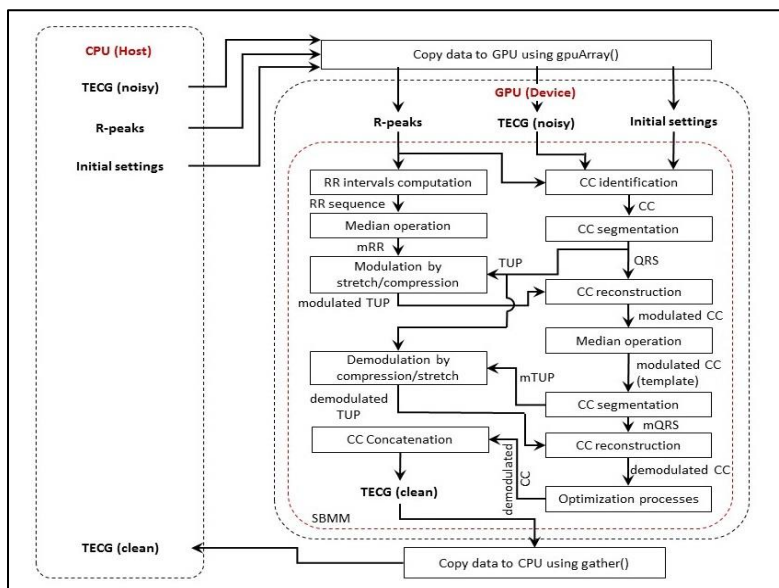


Figure 1. Distribution of workload for GPU-based Segmented-Beat Modulation Method.

2.4. Assessment of signal quality improvement

To quantify the reliability of the GPU-SBMM in reducing the level of noise affecting the ECG signals, the signal-to-noise ratio (SNR) expressed in decibel (dB) was computed before (noisy) and after (clean) GPU-SBMM processing according to equation (1):

$$SNR (dB) = 10 \log_{10} \left[\left(\frac{A_{Signal}}{A_{Noise}} \right)^2 \right], \quad (1)$$

where A_{Signal} (mV) is the signal amplitude and A_{Noise} (mV) is the noise amplitude. Amplitudes of ECGs being close to deterministic (pseudo-periodic) signals, were computed as mean of the maximum-minus-minimum values over the beats. Whereas, amplitudes of noise signals being close to Gaussian stochastic signals were computed as 4 times standard deviation [12]. All amplitude values were computed over the entire length of the study records.

2.5. Assessment of speed of execution improvement

For each ECG signal, GPU-SBMM runtime ($t_{GPU-SBMM}$, s) was computed. Moreover, each ECG signal was processed with the sequential SBMM implementation [10] and the SBMM runtime (t_{SBMM} , s) was computed. To show the effect on performance after GPU resource enhancement, speedup factor ($Speedup(x)$), defined by Amdahl's law [16] as an improvement in the speed of execution of a task on two computing architectures with different resources, was computed for each ECG signal using equation (2):

$$Speedup(x) = \frac{t_{SBMM}}{t_{GPU-SBMM}}. \quad (2)$$

2.6. Statistical analysis

Differences between SNR before and after GPU-SBMM processing have been evaluated by using a paired Student's t-test. Values are reported as mean \pm standard deviation (SD), unless otherwise specified. The two-sided significance level was set at 5% ($p < 0.05$).

3. Results

An example of the ECG signal recorded during exercise before and after GPU-SBMM processing is shown in Figure 2.

SNR values for each activity before and after GPU-SBMM processing are given in Table 2. Mean SNR values

Table 1. Duration of ECG signals recorded for different subjects and activities.

Subject ID	Walk	Run	LRB	HRB
1	9:48	-	9:39	9:18
2	6:39	-	5:41	6:54
3	4:47	5:07	4:54	4:41
4	-	4:52	-	-
5	-	5:08	4:40	-
6	5:36	5:02	4:40	-
7	6:42	4:47	-	-
8	3:40	-	-	-

LRB-Low-Resistance Bike

HRB-High-Resistance Bike

computed for all noisy ECG and clean ECG signals were 1 ± 5 dB and 19 ± 5 dB, respectively; a significant increase ($p < 10^{-12}$) in SNR was observed after GPU-SBMM processing. Stratifying for each exercise task, a significant increase in SNR was also found (Table 2).

The calculated SBMM and GPU-SBMM runtimes are shown in Figure 3. The GPU implementation reduces the runtime of the noise reduction algorithm from 4.82 s to 0.63 s. Hence, the speedup achieved is 7.67 times higher than that of the CPU-based SBMM implementation.

4. Discussion

The present study proposed GPU-SBMM as performance improved version of SBMM for the denoising of ECGs. In the beat-wise segmentation, modulation and signal reconstruction steps characterizing GPU-SBMM, each beat can be processed simultaneously, because the processing of any individual beat is independent of the other, which is ideal for GPU processing. Because of the advantage that MATLAB is an interpreted language, inefficient for-loops in SBMM implementation have been replaced by vectorized statements to further optimize runtimes.

Improvement in SNR showed that GPU-SBMM is an effective and fast method for removal of exercise-induced noise factors in the ECG data. Comparative testing showed that the average speedup achieved for the four training activities is 7.67x. Offloading the heavy part of computation to the GPU processor which can either be a mobile platform or a desktop, the performance of the algorithm is increased. This allows an effective processing and analysis of ECG signals measured from wearable sensors through innovative software applications for the prevention of SRSCD [4].

For future recommendation, full benefits of parallelism for GPU-SBMM might be seen when used with big data (larger datasets or online ECG data processing). Moreover, a high denoising efficiency with ECGs makes GPU-SBMM a useful method for a wearable ECG sensing apparatus/setting.

Table 2. Comparative evaluation of SNR by activity.

Exercise tasks	No. of TEGCs	Before SNR (dB)	After SNR (dB)
Walk	6	-2±3	18±5*
Run	5	1±7	20±7*
Low Resistance Bike	5	3±5	20±5*
High Resistance Bike	3	3±6	20±6*

* p<0.05

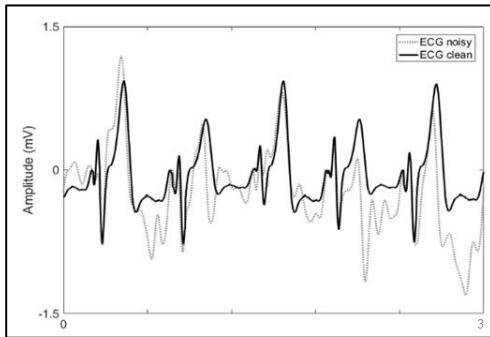


Figure 2. TEGC plotted for the exercise task High Resistance Bike for duration of 3 seconds.

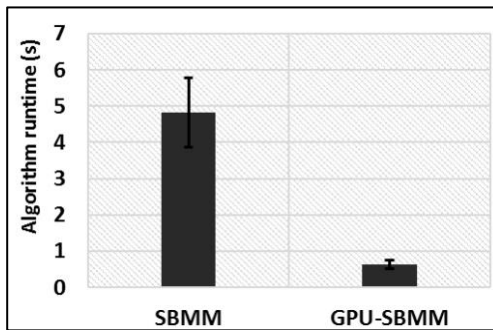


Figure 3. Runtime for CPU-based SBMM and GPU-based SBMM on NVIDIA GeForce GT 740 processor.

5. Conclusion

GPU-SBMM is an efficient and accurate algorithm for filtering TEGC, typically affected by high level of noise. Thus, it represents a potentially useful tool to fight SRSCD.

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