engineering proceedings

Proceeding Paper

An Overview of Wearable Photoplethysmographic Sensors and Various Algorithms for Tracking of Heart Rates †

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† Presented at the 8th International Electronic Conference on Sensors and Applications, 1–15 November 2021; Available online: https://ecsa-8.sciforum.net.

Abstract: It is very challenging to estimate the accurate heart rate/beat during intense physical activities due to corruption of motion artifacts (MAs). However, it is difficult to reconstruct a clean signal and extract heart rate/beat from contaminated photoplethysmography (PPG) signals. It was also observed that various algorithms have been developed for use in the detection of heart rates during physical activities by reconstructing the contaminated PPG signals to clean PPG signals. Against this backdrop, an overview of the various algorithms was conducted with their results from various works. These results are such that the motion-tolerant adaptive algorithm indicated high agreement and high correlation of more than 0.98 for heart rate (HR) and 0.7 for pulse oxygen saturation (SpO_2) extraction between measurements by reference sensors and the algorithm. In addition, the distortion rates were reduced from 52.3% to 3.53%, at frequencies between 1 Hz and 2.5 Hz, when the two-dimensional active noise cancellation algorithm was applied representing daily motion such as walking and jogging. The correlation coefficient between the power spectral densities of the reference and reconstructed heart-rate time series was found to be 0.98, which showed that the spectral filter algorithm for motion artifacts and heart-rate reconstruction (SpaMA) method has a potential for PPG-based HR monitoring in wearable devices for fitness tracking and health monitoring during intense physical activities. The experimental result of the single-notch filter and ensemble empirical mode decomposition (NFEEMD) algorithm using the Pearson correlation was 0.992 which illustrated that the NFEEMD algorithm is not only suitable for HR estimation during continuous activities but also for intense physical activities with acceleration. Other algorithms suitable for HR estimation during physical activities include the time–frequency spectrum for the detection of motion artifacts (TifMA) algorithm, novel time-varying spectral filtering algorithm, noise-robust heart-rate estimation algorithm, real-time QRS detection algorithm, and many other algorithms in this regard.

Keywords: heart rate; physical activities; motion artifacts; photoplethysmographic signal; algorithms; detection

Citation: Obi, A.I. An Overview of Wearable Photoplethysmographic Sensors and Various Algorithms for Tracking of Heart Rates. *Eng. Proc.* **2021**, *10*, 77. https://doi.org/10.3390/engproc2021010077

Academic Editor: Stefano Mariani

Published: 27 January 2022

1. Photoplethysmographic Signal with Motion Artifacts (MAs)—An Introduction

Accurate estimation of heart rates and dynamic accurate heart-rate (HR) estimation using photoplethysmography (PPG) signals during intense physical activity is a very challenging problem and also difficult [1,2]. This is because strenuous and high-intensity exercise can result in severe motion artifacts in PPG signals, making accurate heart-rate (HR) estimation difficult [1]. Some heart-rate monitors use photoplethysmography (PPG) technology as this allows the device to be small and wearable [1,3]. In addition to the acquisition of HR in response to exercise, research has recently focused on obtaining heart-rate variability (HRV) information from wearable sensors including devices that use photoplethysmographs [1,4].

A photoplethysmograph is an optically obtained plethysmograph, which, generally, is a measurement of changes in volume within an organ's whole body, usually resulting from fluctuations in the amount of blood or air that the organ contains. A photoplethysmograph is often obtained by using a pulse oximeter. A conventional pulse oximeter monitors the perfusion of blood to the dermis and subcutaneous tissue of the skin. Pulse oximetry is a non-invasive method that allows for the monitoring of the oxygenation of a subject's blood [5]. A photoplethysmograph can measure changes in tissue and blood volume by emitting light on tissues and detecting the variations in optical absorption and scattering. The applications of PPG include monitoring of heart rate (HR), hemoglobin oxygen saturation (SpO_2), and potentially detection of epileptic seizures and atrial fibrillation [6–9].

Clinicians have cited motion artifacts in pulse oximetry as the most common cause of false alarms, loss of signal, and inaccurate readings [10]. During physical activities, MA contamination in PPG signals seriously interferes with HR estimation. The MAs are mainly caused by ambient light leaking into the gap between the PPG sensor surface and skin surface. In addition, the change in blood flow due to movements is another MA source [11]. In practice, MAs are difficult to remove because they do not have a predefined narrow frequency band and their spectrum often overlaps with that of the desired signal [12]. Consequently, development of algorithms capable of reconstructing the corrupted signal and removing artifacts is challenging [1]. However, in measurement sites, noise interference produced by motion artifacts (MAs) and cardiac arrhythmia is inevitable [2]. Due to human movement, relative motion may occur between the sensor and skin, and thus the principal component of true HR information is weakened [2]. The quality of the PPG sensor signal is especially susceptible to motion artifacts. In other words, the accuracy of heart-rate estimation depends on the quality of the photoplethysmograph [2].

2. Heart-Rate Variability (HRV)

The most commonly measured value is the heart rate (HR), although advanced applications also use other values, e.g., pulse irregularity, as well as biometric identification or analysis of accurate electrical signals that cause heart contraction, i.e., electrocardiography (ECG) [13,14]. Accurate ECG requires connecting electrodes to the patient's body in several different places, which is inconvenient for the patient, and it can be used only in certain situations [13]. A much more convenient method is measuring the pulse on the wrist by using photoelectric methods. The skin of the wrist is irradiated with single or multicolor light, and then the reflected light is measured. The intensity of the reflected light depends on the absorption of the skin, which depends on the blood volume supplied to the tissues. In this way, the received signal contains information about the current blood supply to the vessels near the measuring device. This method, introduced by Hertzman [13,15], is known as photoplethysmography (PPG). Unfortunately, PPG signals obtained from a moving person's wrist are weak, distorted, and contain noise. The noise level is often higher than a usable PPG signal. Correct analysis of a low-quality PPG signal is a very challenging task and can consume significant processing time, energy, and resources. Increased HRV has been associated with lower mortality rates and is affected by both age and sex [4]. During graded exercise, the majority of studies showed that HRV decreases progressively up to moderate intensities, after which it stabilizes [16]. Although there are many promising and attractive features of using pulse oximeters for vital sign monitoring, currently, they are mainly used on stationary patients [1]. This is because motion artifacts (MAs) result in unreliable HR and SpO_2 estimation [1,17]. The pulsatile "AC" physiological waveform can be obtained due to cardiac synchronous changes in blood volume with the heartbeat. Due to this property, PPG can be a source of real-time heart-rate (HR) information calculation [18]. The output signal of PPG sensors is composed of alternating current (AC), originating from the heart cycle, and direct current (DC), originating from veins and stationary tissue. Motion artifacts affect DC signals, making it difficult to detect AC signals. Thus, it is important to reduce DC signals and increase the AC/DC ratio [19,20].

3. Various Algorithms for Tracking of Heart Rates

Several methods are usually used to recover or reconstruct a clean PPG signal from a corrupted one before HR is extracted. Generally speaking, there are many kinds of MA-removal algorithms apriori: classical digital filters [21]; adaptive filters [22]; time–frequency analysis (wavelet decomposition) [23], singular value decomposition [24], and empirical mode decomposition [25]; spectrum analysis; and bland signal processing [26]. These algorithms mentioned above can be applied to the signals that are corrupted slightly when motion artifacts are not strong. However, these techniques cannot figure out the precise heart-rate estimation when intense physical exercise such as boxing occurs. Therefore, people would always prefer to use complex algorithms when extracting HR from the corrupted PPG signals, rather than a single technique. When the motion artifacts are strong, heart-rate information can be mostly masked by the noise component. Thus, the removal of MAs in intense exercise from the PPG is always challenging. Fukushima et al. [27] and Zhang et al. [9] argued that acceleration data are also helpful for removing MAs. However, the tri-axis acceleration data (acceleration data measured by a sensor for measuring acceleration in the x, y, and z directions) play an important role in MA removal. Recently, some study groups have concentrated on the solution of strong MA removal and have made progress. Therefore, many state-of-the-art algorithms are proposed. Zhang et al. [8] put forward the TROIKA: a general framework for heart-rate monitoring using wrist-type photoplethysmographic signals during intensive physical exercise. This general framework consists of three key parts, namely signal decomposiTion, sparse signal RecOnstructIon, and spectral peaK tracking—known as TROIKA [8]. In a particular framework, signal decomposition using singular spectrum analysis was applied to cancel partial MAs. Sparse PPG signal reconstruction puts the sparse signal into a high-solution spectrum so that the true peak corresponding to the heart rate is found. Then, Zhang et al. proposed an improved algorithm JOSS [9] with the help of acceleration data. JOSS, which has been shown to estimate HR more accurately than TROIKA, is based on the idea that the spectra of PPG signals and simultaneous acceleration signals have some common spectrum structures, and thus it formulates the spectrum estimation of these signals into a joint sparse signal recovery model (JOSS) using the multiple measurement vector (MMV) model.

The spectra of PPG signals and simultaneous acceleration signals are jointly estimated using the multiple measurement vector (MMV) model in sparse signal recovery. This algorithm shows the effect of acceleration data on the accuracy of heart-rate estimation from the PPG [2]. Although JOSS has been shown to be much more accurate than previous methods for reconstruction of heart rate from MA-contaminated PPG signals, the main disadvantage of the method is it can merely provide smoothed HR reconstruction estimations. Neither time-domain PPG signal reconstruction nor heart-rate variability analysis can be performed using JOSS or TROIKA [1].

The spectral filter algorithm for motion artifacts and heart-rate reconstruction (SpaMA algorithm) [1] proposed by Salehizadeh et al. combines the PPG signal and acceleration data. Its key idea is to calculate the power spectral density of both PPG and acceleration data, and the related frequency peaks resulting from MAs can be distinguished from the PPG spectrum. In all of the experiments, the reference HR was calculated from an ECG signal that was collected simultaneously with the PPG signal. The estimated HR was calculated from the spectrum of PPG in 8 s time windows. It was shown in the results section that the proposed SpaMA algorithm can be used for tracking HR changes during severe motion artifacts with an average error of just 1.86 BPM (beats per minute) compared to that of the reference ECG (Table A1 in Appendix A). These results are superior to the three other algorithms tested: TROIKA, JOSS, and WFPV (check Table A1 in Appendix A) [8,9,28].

The results in Table A1 show that SpaMA has better performance than JOSS and TROIKA for all 12 subjects in the first datasets. In comparison to WFPV, the proposed SpaMA approach outperforms WFPV on average across all 23 subjects in both datasets (1) and (2). The total average of E1 (error 1) of SpaMA is less than two beats per minute for all 33 subjects [1]. The average of E1 across the treadmill experiment recordings (activity Type 1 (IEEE dataset) and Type 4 (Chon Lab dataset)) is around one beat per minute for all 22 subjects. Table A2 presents the correlation and statistical difference using Student's t-test between PSD of estimated and reference HRV in both LF (0.04–0.15 Hz) and HF (0.15–0.4 Hz) frequency ranges. The correlation values in the table were calculated based on Pearson's linear correlation coefficient. As shown in Table A2, there was no difference between the reference and the derived HRV for LF (low frequency), and the difference was seen in only 4 out of 10 subjects for HF (high frequency) [1]. Table A3 shows some of the widely reported time-domain HRV parameters such as the mean HR, standard deviation (SDNN) of the normal-to-normal (NN) interval, root mean square of successive difference (RMSSD) of the NN interval, and the number of interval differences of successive NN intervals greater than 50 ms divided by the total number of NN intervals (pNN50) estimated from SpaMA in comparison to the reference ECG NN interval [1]. None of these parameters were found to be significantly different between our algorithm-derived and the reference HRV.

The SpaMA algorithm can be potentially implemented in real time. It takes only 110 ms per 8 s segments. Therefore, given the high accuracy of the proposed approach in estimating HR despite severe motion artifacts, this method has the potential to be applicable for implementation in wearable devices such as smart watches and PPG-based fitness sensors [1].

The signal sparsification technique through M-FOCUSS in TROIKA and JOSS was applied to the HR-estimation algorithm, which involves extensive computational complexity [2]. For example, for the sampling frequency of 125 Hz, TROIKA takes about 3.5 h to estimate HR for the first 12 datasets on a computer equipped with Intel Core-i7 4790 at 3.6 GHz, 8-GB RAM, Windows 7 64 bit, and MATLAB 2013a. The regularized M-FOCUSS algorithm [9,29] was used to estimate the solution matrix of the MMV model, with the parameter $p = 0.8$, regularization parameter $\lambda = 10^{-10}$, and spectrum grid number $N = 1024$. Its maximum iteration number was set to 4. Note that the TROIKA algorithm also used the M-FOCUSS algorithm to estimate the sparse spectrum of PPG signals, as well as to estimate the solution of the SMV model. FOCal Underdetermined System Solver (FOCUSS), in the multiple measurement case, is used in applications such as neuromagnetic imaging, where multiple measurement vectors are available, and solutions with a common sparsity structure must be computed [9,29]. The algorithm proposed by Khan [30] takes 668 s on the same computer.

From Table A4, the NFEEMD algorithm performs better compared to the others. For the first 12 of 23 datasets, the average absolute error (AAE) is 1.12 + 0.51 (mean $\pm$ standard deviation) BPM, and AAE (average absolute error) is 2.68 + 2.19 BPM for the remaining 11 datasets. For all 23 datasets, an average absolute error of 1.87 BPM and standard deviation of 1.79 BPM were recorded using the NFEEMD framework under intense physical activities. It should be noted that the most obvious difference between the first 12 datasets and the last 11 datasets is the severity of motion. The activities of sample set T0 on the treadmill have a certain regularity, and the activities of sample set T1 and sample set T2 including arm movements are intense and random. In Table A4, the average absolute error of the last 11 datasets (2.68 BPM) by using NFEEMD is significantly larger than the first 12 datasets (1.12 BPM). This result is consistent with the severity of the state of motion; thus the more intense the movements, the larger the HR-estimation error obtained. Although the errors are slightly larger for the last 11 datasets, HR estimates do not get derailed (check Jiajia, [2]). The results of comparisons in Table A4 show that the NFEEMD algorithm could obtain the most accurate results on HR estimates for the last 11 datasets including the CNAFSD algorithm [31] which proposed a hybrid-motion artifact-removal method, which combines non-linear adaptive filtering and signal decomposition (singular spectrum analysis), as well as the second most accurate results on HR estimates for the first 12 datasets compared with the SPECTRAP algorithm [32]. Sun et al. proposed SPECTRAP [32] using a new spectrum-subtraction algorithm, and Mashhadi et al. [33] proposed an algorithm for the MA cancellation step that cleanses the MA-contaminated PPG signals utilizing the acceleration data and the spectral analysis step that estimates a higher-resolution spectrum of the signal and selects the spectral peaks corresponding to HR. The accuracy of the NFEEMD algorithm is slightly lower than the SPECTRAP for 22 datasets (except dataset 13). In a word, the results in Table A4 indicate that the NFEEMD algorithm can adapt to more intense circumstances such as boxing in the last 11 recordings, and our algorithm is more robust.

To examine in more detail the performance of the NFEEMD algorithm with a change in sampling frequency, we experimented with a 25 Hz sampling frequency using the same algorithm for one-channel PPG and three-channel ACC (acceleration data). The corresponding AAE results for all datasets are listed in Table A5, which demonstrates that the NFEEMD algorithm performs better in 125 Hz sampling frequency than in 25 Hz. In other words, more detailed information can be recorded at a high sampling frequency so that the HR-estimation accuracy can be improved.

The MA-removal algorithm (NFEEMD) is the repeated single-notch filter and ensemble empirical mode decomposition [2]. The NFEEMD algorithm takes 229 s for calculation of the first 12 datasets and 476 s for all 23 datasets using the same computer configuration. In addition, the NFEEMD algorithm takes 86 s for the first 12 datasets and 191 s for all 23 datasets when the sampling frequency is 25 Hz. JOSS takes 300 s for all the datasets at 25 Hz sampling frequency [2]. The Pearson correlation for the NFEEMD algorithm is about 0.992. It is obvious that the NFEEMD algorithm has the advantage of low computational complexity and short running time. Of course, the algorithm also needs to be improved. On the one hand, it was shown that the difference error is large when the real HR values are between 50 and 80 [2].

Reference [27] suggested a spectral subtraction technique to remove the spectrum of acceleration data from that of a PPG signal. Acceleration data can be also used to reconstruct the observation model for Kalman filtering [22] to remove MA. Temko [28] proposed an approach to HR estimation based on Wiener filtering and the phase vocoder (WFPV). In this review, it was shown from Table A1 in Appendix A that WFPV on average can perform better than the JOSS algorithm. The main idea of WFPV is to estimate motion artifacts from accelerometer signals and then use a Weiner filter to attenuate the motion components in the PPG signal. A phase vocoder is also applied to overcome the limited resolution of the Fourier transform and to refine the initial dominant frequency estimation. The phase vocoder is a well-established tool for time scaling and pitch shifting speech and audio signals via modification of their short-time Fourier transforms (STFTs). However, the phase vocoder is also known for introducing a characteristic perceptual artifact, often described as "phasiness", "reverberation", or "loss of presence" [34].

The QRS detection algorithm failed to properly detect 0.675 percent [35] of the beats. Usually, the QRS complex consists of positive (upright) deflections called R waves and negative (inverted) deflections called Q and S waves. If there is no R wave, the complex is called a QS complex. If there is no Q wave, the complex is called an RS complex. Again, the heart beats in a regular, rhythmic fashion producing a P wave, QRS complex, and T wave [36], though the QRS detection algorithm automatically adjusts thresholds and parameters periodically to adapt to such ECG changes as QRS morphology and heart rate. A special digital bandpass filter reduces false detections caused by the various types of interference present in ECG signals. This filtering permits use of low thresholds, thereby increasing detection sensitivity. The QRS detection algorithm [35] reliably recognizes QRS complexes based upon digital analyses of slope, amplitude, and width. Therefore, this is real-time QRS detection for recognizing QRS complexes in ECG signals.

The motion-tolerant adaptive algorithm for wearable photoplethysmographic biosensors [37] removes motion artifacts due to various sources including tissue effect and venous blood changes during body movements and provides noise-free PPG waveforms for further feature extraction. A two-stage normalized-least-mean-squares (NLMS) adaptive noise canceler was designed and validated using a novel synthetic reference signal at each stage.

Evaluation of this algorithm was performed by Bland–Altman agreement and correlation analyses against reference heart rate from commercial ECG and SpO_2 sensors during standing, walking, and running at different conditions for single- and multi-subject scenarios [37]. Correlation analysis may lead to incorrect or debated results in the comparison of the two measurement methods. The Bland–Altman analysis is a simple and accurate way to quantify agreement between two variables and may help clinicians to compare a new measurement method against another one or a reference standard. Experimental results [37] indicate high agreement and high correlation (more than 0.98 for heart rate and 0.7 for SpO_2 extraction) between measurements by reference sensors and the motion-tolerant adaptive algorithm [38]. The adaptive algorithm used in the reduction of MAs is the NLMS algorithm due to its lower complexity compared with other techniques and immunity to the fluctuation in the signal energy. One of the most commonly used algorithms is the least-mean-squares (LMS) algorithm and its variations. A much higher correlation and agreement were achieved after applying the adaptive algorithm on the raw signal for SpO_2 and heart rate. The correlation coefficient of SpO_2 measurement after applying the algorithm was 0.71 with a p-value, probability of obtaining a correlation as large as the one obtained randomly, less than 0.00001 [37]. For the purpose of comparison, the discrete saturation transform (DST) algorithm was also implemented using an adaptive filter of order 32. The adaptive filter of order 32 means that the FIR filter is of the order of 32; hence 32 values are fed in the filter RAM [38,39]. Once the filter coefficients are adjusted, the convolution process is carried out, and the output is saved in the OUTPUT RAM [38,39]. Finite impulse response (FIR) digital filters are widely used due to their crucial role in various digital signal processing (DSP) applications. The FIR filter has been designed and realized on FPGA for filtering the digital signal. FPGA is known as field programming gate arrays. The DST algorithm isolates individual "saturation components" in the optical pathway, which allows separation of components corresponding to the SpO_2 level from components corresponding to noise and interference, including motion artifacts [40]. The experimental results of the motion-tolerant adaptive algorithm for wearable photoplethysmographic biosensors validated reliable extraction of heart rate and oxygen saturation of more than 0.98 and 0.7, respectively, compared to reference stationary sensors in the presence of the motion artifact [37].

A novel approach, "TifMA" (time–frequency spectrum for the detection of motion artifacts) is based on using the time-frequency spectrum of PPG to first detect the motion and noise artifact (MNA)-corrupted data and next discard the non-usable part of the corrupted data. Two sequential classification procedures were included in the TifMA algorithm [41]. The first classifier distinguishes between MNA-corrupted and MNA-free PPG data. Once a segment of data is deemed MNA-corrupted, the next classifier determines whether the HR can be recovered from the corrupted segment or not. A support vector machine (SVM) classifier [41] was used to build a decision boundary for the first classification task using data segments from a training dataset. Features from the time-frequency spectra of PPG were extracted to build the detection model. Five datasets were considered for evaluating TifMA performance: (1) and (2) were laboratory-controlled PPG recordings from forehead and finger pulse oximeter (PO) sensors with subjects making random movements, (3) and (4) were actual patient PPG recordings from UMass (University of Massachusetts Amherst) Memorial Medical Center with random free movements, and (5) was a laboratory-controlled PPG recording dataset measured at the forehead while the subjects ran on a treadmill. The first dataset was used to analyze the noise sensitivity of the algorithm. Datasets 2–4 were used to evaluate the MNA detection phase of the algorithm. The results from the first phase of the algorithm (MNA detection) were compared to results from three existing MNA detection algorithms (Table A6): the Hjorth [42], kurtosis–Shannon entropy [43], and time-domain-variability–SVM approaches [44]. The TifMA algorithm consistently provided higher detection rates than the other three methods, with accuracies greater than 95% for all data [41]. Moreover, the TifMA algorithm was able to pinpoint the start and end times of the MNA with an error of less than 1 s [41] in duration, whereas the next-best algorithm had a detection error of more than 2.2 s [41]. The final, most challenging, dataset was collected to verify the performance of the algorithm in discriminating between corrupted data that were usable for accurate HR estimations and data that were non-usable. It was found that on average 48% of the data segments were found to have MNAs, and of these, 38% could be used to provide reliable HR estimation [41]. This is good.

Despite the conventional NLMS, an algorithm with a small computational complexity is required for wearable systems due to price, power, and system size limitations. In order to overcome this drawback, an adaptive noise cancellation algorithm that can have similar performance with low computational complexity was proposed [45]. An oscillator-based adaptive notch filter (OSC-ANF) algorithm [46] was used to estimate the heart rate using the PPG signal that passed through the MA reduction stage. The OSC-ANF algorithm is based on a second-order infinite impulse response (IIR) band-pass filter and traces the strongest frequency of the signal. To improve the tracking performance of the OSC-ANF algorithm under highly noisy environments, the noise-robust OSC-ANF (NR-OSC-ANF) algorithm that is derived by the noise-robust adaptive filter concept [47,48] was proposed [45]. In addition, to improve MA reduction performance, an IIR band-pass filter was used [45]. In order to reduce the computational complexity, down-sampled PPG and accelerometer signals that were resampled 125 Hz to 25 Hz were also used [45]. The noise-robust heart-rate estimation algorithm has the best performance when the adaptive filter order is 21 ($M = 21$). The noise-robust heart-rate estimation algorithm from the photoplethysmography signal with low computational complexity algorithm can sufficiently remove motion artifacts even with low computational complexity. In order to verify the performance of the heart-rate estimation algorithm, it was compared in Tables A7 and A8 with other existing algorithms using the IEEE Signal Processing Cup 2015 [45,49] database. The IEEE Signal Processing Society organized an algorithm contest (IEEE Signal Processing Cup) where some of the datasets were collected and used and again in Chon lab.

The estimated HR from the PPG signal matches (electrocardiogram) ECG-based HR satisfactorily. The performances of other existing algorithms and the noise-robust heart-rate estimation algorithm do not differ greatly (see Tables A7 and A8). Although this algorithm does not have the best performance compared with other algorithms, it is considered to be worthy of an algorithm for use in a wearable device because of its low computational complexity. This algorithm requires only a few multiplications for preprocessing and NR-OSC-ANF. The limits of agreement were [−3.97, 5.04] BPM in the Bland–Altman plot [45].

4. Conclusions

Although JOSS has been shown to be much more accurate than previous methods for the reconstruction of heart rate from MA-contaminated PPG signals, the main disadvantage of the method is it can merely provide smoothed HR reconstruction estimations. Neither time-domain PPG signal reconstruction nor heart-rate variability analysis can be conducted using JOSS or TROIKA. The SpaMA algorithm performs better in the first 12 datasets, but the off-track error is large in other datasets that have stronger MAs during intense arm movements. It was shown that the difference error is large when the real HR values are between 50 and 80 in the NFEEMD algorithm. In evaluations using the MIT/BIH arrhythmia database, the QRS detection algorithm failed to properly detect only 0.675 percent of the beats. Though experimental results indicate a high agreement and high correlation for the motion-tolerant adaptive algorithm for wearable photoplethysmographic biosensors, common errors in the experimentation were observed where the DST algorithm reported a false reading due to motion artifacts. In the TifMA algorithm, 48% of the data segment were found to have MNAs, and of these, 38% could be used to provide reliable HR estimation showing that the TifMA algorithm is a better algorithm with a slight error and comparable with other better algorithms such as those already described. Although the noise-robust heart-rate estimation algorithm does not have the best performance compared with other algorithms, it is considered to be worthy of an algorithm for use in a wearable device because of its low computational complexity.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The author declare no conflict of interest.

Appendix A

Table A1. SpaMA algorithm performance comparison.

Subject	**Dataset**	**Activity Type**	**TROIKA [8]**		**JOSS [9]**		**WFPV [28]**		**SpaMA [1]**	
			E1	E2%	E1	E2%	E1	E2%	E1	E2%
1			2.87	2.18	1.33	1.19	1.23	-	1.23	1.14
2			2.75	2.37	1.75	1.66	1.26	-	1.59	1.30
3			1.91	1.50	1.47	1.27	0.72	-	0.57	0.45
4			2.25	2.00	1.48	1.41	0.98	-	0.44	0.31
5			1.69	1.22	0.69	0.51	0.75	-	0.47	0.31
6			3.16	2.51	1.32	1.09	0.91	-	0.61	0.45
7			1.72	1.27	0.71	0.54	0.67	-	0.54	0.40
8			1.83	1.47	0.56	0.47	0.91	-	0.40	0.33
9			1.58	1.28	0.49	0.41	0.54	-	0.40	0.32
10			4.00	2.49	3.81	2.43	2.61	-	2.63	1.59
11			1.96	1.29	0.78	0.51	0.94	-	0.64	0.42
12			3.33	2.30	1.04	0.81	0.98	-	1.20	0.86
mean ± std			2.42 ± 0.8	1.82 ± 0.5	1.28 ± 0.9	1.02 ± 0.6	1.04 ± 0.5	-	0.89 ± 0.6	0.65 ± 0.4
13 14 15		Type (2)			3.58 9.66 2.31			-	3.41 7.29 2.73	4.25 9.80 2.21
16 17 18 19	2 (IEEE Cup)	Type (3)			4.93 3.07 2.67 3.11			-	3.18 3.01 4.46 3.58	2.11 2.52 3.23 3.98
20		Type (2)			2.10			-	1.94	1.66
21 22		Type (3)			3.22 4.35			-	2.56 3.12	2.02 3.28
23		Type (2)			0.75			-	1.72	1.97
			mean ± std Type (1, 2)				3.61 ± 2.2	-	3.36 ± 1.5	3.33 ± 2.2
			mean ± std				2.27 ± 2.0	-	1.93 ± 2.0	2.07 ± 1.7
Subject	**Dataset**	**Activity Type**	**TROIKA**		**JOSS**		**WFPV**		**SpaMA**	
			E1	E2%	E1	E2%	E1	E2%	E1	E2%
24									**0.88**	**0.91**
25									**1.03**	**0.83**
26									**1.10**	**0.90**
27									**1.64**	**1.54**
28	3				Type (4)				**1.41**	**1.12**
29	(Chon Lab)								**0.82**	**0.70**
30									**0.63**	**0.58**
31									**4.78**	**3.87**
32									**0.95**	**0.79**

Table A1. *Cont.*

Subject	Dataset	Activity Type	TROIKA [8]	JOSS [9]	WFPV [28]	SpaMA [1]	
33						**0.62**	**0.52**
mean ± std						**1.38 ± 1.2**	**1.17 ± 1.0**
Total:						**1.86 ± 1.6**	**1.70 ± 1.8**
mean ± std							

Source: [1].

Table A2. Frequency domain HRV analysis comparison: PSD of SpaMA vs. reference.

Subject	Correlation	
	LF [1]	HF
1	0.99	0.98
2	0.99	0.96
3	0.99	0.95 *[2]
4	1.00	0.99
5	1.00	0.99
6	0.99	0.96 *
7	0.98	0.92 *
8	0.97	0.90 *
9	1.00	0.99
10	1.00	0.99
Mean	0.99	0.96

[1] LF is (0.04–0.15) Hz, [2] HF is (0.15–0.4) Hz; (*) indicates significantly different (p-value > 0.05). Source: [1].

Table A3. Time domain HRV analysis comparison: SpaMA vs. reference HRV.

Subjects	SDNN		meanNN		RMSSD		pNN50	
	SpaMa	Reference	SpaMa	Reference	SpaMa	Reference	SpaMa	Reference
1	2620.75	2566.47	10,480.89	10,480.72	33.24	18.05	0.001	0.020
2	2115.44	2079.58	9908.00	10,020.00	25.93	16.32	0.011	0.019
3	3173.73	3177.68	10,764.20	10,829.06	89.70	56.15	0.019	0.207
4	2517.78	2533.20	10,376.95	10,426.26	13.54	19.58	0.001	0.030
5	2654.42	2670.32	10,864.04	10,990.08	11.88	18.59	0.003	0.018
6	2012.53	1974.65	9737.35	9827.63	39.64	21.17	0.004	0.025
7	3056.36	2925.19	12,519.74	13,134.05	27.66	30.61	0.015	0.071
8	3133.76	2756.66	10,504.00	10,530.00	32.57	36.38	0.002	0.003
9	2195.08	2142.53	10,499.81	10,470.06	8.23	13.01	0.002	0.004
10	2454.57	2406.96	12,936.62	12,981.21	41.52	20.28	0.006	0.024
p-value	>0.05		>0.05		>0.05		>0.05	

Source: [1].

Table A4. AAE and AEP results on 23 datasets of compared to other algorithms.

ID		Activity Type	TROIKA [8]	JOSS [9]	SpaMA [1]	CNAFSD [31]	SPECTRAP [32]	WFPV [28]	[33]	NFEEMD [2]
			AAE AEP%	AAE AEP%	AAE AEP%	AAE AEP%	AAE AEP%	AAE AEP%	AAE AEP%	AAE AEP%
1			2.29 2.18	1.33 1.19	1.23 1.14	1.66 1.42	1.18 1.04	1.25 1.15	1.72 1.50	1.43 1.19
2			2.19 2.37	1.75 1.66	1.59 1.30	1.56 1.44	2.42 2.33	1.41 1.30	1.33 1.30	1.15 1.03
3			2.00 1.50	1.47 1.27	0.57 0.45	0.65 0.53	0.86 0.66	0.71 0.59	0.90 0.75	0.75 0.59
4			2.15 2.00	1.48 1.41	0.44 0.31	1.48 1.51	1.38 1.31	0.97 0.88	1.28 1.20	1.24 1.12
5			2.01 1.22	0.69 0.51	0.47 0.31	0.77 0.60	0.92 0.74	0.75 0.57	0.93 0.69	0.91 0.68
6		T0	2.76 2.51	1.32 1.09	0.61 0.45	1.12 0.90	1.37 1.14	0.92 0.75	1.41 1.20	1.25 0.99
7			1.67 1.27	0.71 0.54	0.54 0.40	0.72 0.60	1.53 1.36	0.65 0.50	0.61 0.50	0.79 0.60
8			1.93 1.47	0.56 0.47	0.40 0.33	0.91 0.80	0.64 0.55	0.97 0.83	0.88 0.80	0.63 0.53
9			1.86 1.28	0.49 0.41	0.40 0.42	0.42 0.36	0.60 0.52	0.55 0.48	0.59 0.50	0.58 0.56
10			4.70 2.49	3.81 2.43	2.63 1.59	2.35 1.45	3.65 2.27	2.06 1.29	3.78 2.40	2.48 1.48
11			1.72 1.29	0.78 0.51	0.64 0.42	1.45 0.94	0.92 0.65	1.03 0.68	0.85 0.60	0.89 0.58
12			2.84 2.30	1.04 0.81	1.20 0.86	0.78 0.60	1.25 1.02	0.99 0.70	0.71 0.50	1.37 0.91
13			- -	- -	3.41 4.25	- -	- -	3.54 4.08	- -	3.20 3.59
14		T1	6.63 8.76	8.07 10.9	7.29 9.80	7.71 10.6	4.89 6.29	9.59 12.2	- -	8.64 11.3
15			1.94 2.56	1.61 2.01	2.73 2.21	1.62 2.02	1.58 1.98	2.57 3.16	- -	1.98 2.57
16			1.35 1.04	3.10 2.69	3.18 2.11	3.10 2.68	1.83 1.49	2.25 1.87	- -	1.47 1.14
17		T2	7.82 4.88	7.01 4.49	3.01 2.52	7.00 4.49	3.05 2.00	3.01 1.99	- -	1.95 1.10
18			2.46 2.00	2.99 2.52	4.46 3.23	2.99 2.52	1.62 1.36	2.73 2.29	- -	2.34 1.95
19			1.73 1.27	1.67 1.23	3.58 3.98	1.67 1.23	1.24 0.92	1.57 1.15	- -	1.47 1.08
20		T1	3.33 3.90	2.80 3.46	1.94 1.66	2.45 3.00	2.04 2.23	2.10 2.41	- -	3.22 3.66
21		T2	3.41 2.43	1.88 1.32	2.56 2.02	1.81 1.26	2.49 1.81	3.44 2.45	-	3.54 2.49
22			2.69 2.12	0.92 0.74	3.12 3.28	0.92 0.74	1.16 0.92	1.61 1.26	- -	1.16 0.93
23		T1	0.51 0.59	0.49 0.57	1.72 1.97	0.49 0.57	0.66 0.79	0.75 0.88	- -	0.53 0.62
Mean ± SD	T0	AAE	2.34 + 0.83	1.28 + 0.90	0.89 + 0.60	1.16 + 0.55	1.50 + 0.86	1.02 + 0.41	1.25 + 0.87	1.12 + 0.51
	1–12	AEP%	1.82 + 0.53	1.01 + 0.61	0.67 + 0.44	0.93 + 0.42	1.12 + 0.61	0.81 + 0.29	1.00 + 0.56	0.86 + 0.31
	T1–	AAE	-	-	3.36 + 1.51	-	-	3.01 + 2.34	-	2.68 + 2.19
	T2	AEP%	-	-	3.36 + 2.30	-	-	3.07 + 3.17	-	2.76 + 3.01
	13-23	AAE	3.19 + 2.32	3.05 + 2.52	3.53 + 1.48	2.98 + 2.45	2.13 + 2.77	2.96 + 246	-	2.63 + 2.30
	Test	AEP%	2.96 + 2.41	3.00 + 3.04	3.28 + 2.40	2.91 + 2.95	2.04 + 3.01	2.97 + 3.32	-	2.68 + 3.16
	1–12									
	14-23	AAE	2.78 + 1.67	2.09 + 1.99	2.01 + 1.70	1.98 + 1.90	1.79 + 1.87	1.90 + 1.91	-	1.81 + 1.73
	14-23	AEP%	2.34 + 1.73	1.92 + 2.27	1.85 + 2.09	1.83 + 2.20	1.52 + 1.22	1.79 + 2.44	-	1.68 + 2.27
	All	AAE	-	-	2.07 + 1.69	-	-	1.97 + 1.90	-	1.87 + 1.71
	1–23	AEP%	-	-	1.96 + 2.10	-	-	1.89 + 2.43	-	1.77 ± 2.26

Source: [2].

Table A5. The AAE results of 23 datasets at 25 Hz sampling frequency.

Dataset	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
AAE(BPM)	1.79	1.52	0.82	1.45	1.09	1.35	1.20	0.51
Dataset	9	10	11	12	13	14	15	16
AAE(BPM)	0.74	1.95	1.00	1.77	3.39	10.99	3.10	1.94
Dataset	17	18	19	20	21	22	23	Mean ± SD
AAE(BPM)	3.62	2.69	1.94	2.80	4.65	2.44	0.50	2.32 + 2.17

Source: [2].

Table A6. Mean ± Std. Detection of Transition Time (DTT) of TifMA and Other Methods.

Algorithm	**DTT (s)**
TifMA	0.91 ± 0.59
Hjorth	2.17 ± 0.37
KSE	4.24 ± 2.42
TDV	2.75 ± 0.96

Source: [42].

Table A7. Error 1 results of the proposed algorithm and the existing algorithms.

Dataset	**TROIKA [8]**	**JOSS [9]**	**NLMS + OSC-ANFc [50]**	**Combination of Adaptive Filters [51]**	**Noise-Robust Heart-Rate Estimation Algorithm**
1	2.29	1.33	1.75	1.34	1.33
2	2.19	1.75	1.94	0.70	1.92
3	2.00	1.47	1.17	0.66	0.83
4	2.15	1.48	1.67	0.70	1.03
5	2.01	0.69	0.95	0.63	0.54
6	2.76	1.32	1.22	0.86	1.44
7	1.67	0.71	0.91	0.66	0.65
8	1.93	0.56	1.17	0.58	0.56
9	1.86	0.49	0.87	0.52	0.43
10	4.70	3.81	2.95	2.46	2.51
11	1.72	0.78	1.15	1.21	0.83
12	2.84	1.04	1.00	0.74	1.79
Av. ± std	2.34 ± 0.79	1.29 ± 0.86	1.40 ± 0.58	0.94 ± 0.52	1.16 ± 0.62

Source: [45].

Table A8. Error 2 results of the proposed algorithm and the existing algorithms.

Dataset	TROIKA [8]	NLMS + OSC-ANFc [50]	Combination of Adaptive Filters [51]	Noise-Robust Heart-Rate Estimation Algorithm
1	1.90	1.59	1.17	1.06
2	1.87	1.99	0.70	2.18
3	1.66	1.02	0.57	0.72
4	1.82	1.51	0.63	0.97
5	1.49	0.75	0.49	0.41
6	2.25	1.05	0.67	1.23
7	1.26	0.72	0.50	0.50
8	1.62	1.04	0.50	0.50
9	1.59	0.76	0.46	0.38
10	2.93	0.93	1.56	1.59
11	1.15	0.79	0.80	0.57
12	1.99	0.79	0.55	1.21

Source: [45].

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