A Windowed Impulse Rejection Filter for HRV Artifact Detection

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Abstract— **Heart Rate Variability (HRV) has been garnering a lot of attention from medical researchers and biomedical engineers due to its ability to expose crucial information about the status of the nervous system and the health of the human heart. Although time domain analysis of a HRV signals can yield a wealth of information, frequency domain analysis has been gaining in popularity. This is mainly due to the identification of distinct frequency bands that reflect specific components of the nervous system. Nonetheless, signal artifact can severely distort the extracted time and frequency domain parameters alike and thus rendering the information obtained from the signal unusable. In this paper, we propose the use of a Windowed Impulse Rejection (WIR) based artifact detection algorithm. Our performance evaluation demonstrated that our method performs with a higher level of accuracy than its competitors. Also, in terms of complexity, it outperformed the Moving Average algorithm.**

Index Terms—**Heart Rate Variability, Electrocardiography, biological signal processing, signal filtering.**

I. Introduction

Nowadays, with the rapid growth of the elderly population, health monitoring is playing a more important role in the early detection and prevention of various diseases related to the cardiovascular system and mental health. Heart rate variability (HRV), in addition to reflecting the general health of the heart, has gained a reputation for being a powerful tool in the assessment of the autonomic functions [1]. That made the topic even more appealing to biomedical engineers and medical researchers alike. Its analysis has power of early prognoses of cardiovascular diseases [2-3], measurement of mental workload [4], among others. The source information for HRV is a continuous beat-to-beat measurement of inter-beat intervals and is defined as the variations over time of the period between consecutive heartbeats.

According to the Task Force of the European Society of Cardiology and The North American Society of Pacing and Electrophysiology report [5], several types of parameters, based on time or frequency domain analysis, may be computed. Time domain analysis includes calculation of the mean value (mSD), the standard deviation (SDNN), the standard deviation of averaged values in segments (SDANN), the average of standard deviations in segments (SDANN index). The frequency domain analysis includes calculation of the Power Spectral Density (PSD) of ECG signal that is divided into several bands: ULF (0.04-0.0033 Hz), VLF (0.0033-0.04Hz), LF (0.04-0.15Hz), HF (0.15-0.4Hz), as well as the ratio of power in LF band to power in HF band (usually called the LF/HF balance). A complete HRV sequence analysis requires 2-5 minutes of captured ECG signal.

Nonetheless, the HRV sequences contain artifacts such as ectopic beats, arrhythmic events, and information damage that severely deteriorate the PSD estimation and thus the quality of HRV analysis [6]. Various methods have been proposed to correct artifacts such as the ones described in [7-11]. However, these algorithms still have their limitations under specific circumstances as it will be shown in this paper.

The remainder of the paper is organized as follows: section 2 reviews related algorithms and sources of HRV artifacts. In section 3, we describe two existing artifact detection algorithms and introduce our own. Section 4 comprises the evaluation of the proposed algorithms, in comparison with existing ones, using scenarios for various artifacts. Finally, section 5 summarizes the paper's findings and provides perspectives for future works.

II. Background and Related Work

A. Sources of Artifacts in HRV Signals

Numerous types of arrhythmias can severely alter an HRV signal. This study focuses only on HRV signals collected from subjects that do not have a history of heart disease. Usually the purpose of HRV data collected from such subjects is mostly to assess fatigue, mental stress level and wellbeing of the autonomous nervous system (ANS) in general. If we discount pathological arrhythmias, then an artifact in an HRV signal can mostly originate from two possible sources:

- Ectopic heartbeats: These are small variations in an otherwise normal cardiac rhythm. They are mostly referred to as Premature Ventricular Contractions (PVCs) and generally are harmless.
- Measurement noise: HRV signals are extracted from ECG measures. Any electrical noise or measurement interruption suffered during the collection of the ECG signal can be reflected as an artifact in the HRV signal.

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To better understand the causes of artifacts, whether they have a physiological or a measurement source, Table 1 divides these artifacts into categories along with a description of how they would be manifested in an HRV signal. Note that these are the very most common artifacts usually encountered. Other categories or sub-categories of artifacts could be defined. While the artifacts presented in table 1 represent most of the prevalent noise patterns, infinite possible arrangements of such artifacts can combine together to create more complex noise conditions.

TABLE 1: RELAXATION TECHNIQUES PREFERENCE INDEX NOTATION

Category Number	***Cause(s) of Artifact***	***Possible Result(s)***
1	-Undetected heartbeat. -An interruption in the ECG recording	-An upward peaking impulse composed of one data point.
2	-Erroneously detected heartbeat between two correctly detected heartbeats. -Ectopic heartbeat between two normal heartbeats. In this case, the ectopic beat does not affect the previous or following normal beats.	-A downward peaking impulse composed of one or two data points.
3	-Ectopic heartbeat that replaces the upcoming normal heartbeat. This means, instead of a normal heartbeat, an ectopic beat is displayed.	- A downward peaking impulse composed of one data point followed by an upward peaking impulse composed of one data point.
4	-A string of erroneously detected heartbeats due to noise in the ECG signal. Such artifacts can be drastically reduced by properly filtering noisy ECG signals or cropping severely corrupted parts of these signals.	-Most likely is manifested in a string of upward and downward peaking impulses.

B. Existing Artifact Detection Algorithms

Few artifact detection algorithms have been proposed. For instance, [10] suggests the use of a simple thresholding filter where each HRV sample is compared to a predefined and static lower and upper bound. Any sample falling outside of the bound is considered erroneous. Nonetheless, such approach has limited efficiency on dynamic signals where the heart rate frequently changes. Also, it is difficult to find the optimal thresholds as each signal inherently has different characteristics.

Another approach is proposed by [8] and [9] and makes use of a sliding average window filter. In [9], for each sample, the window consisting of the previous 30 seconds worth of data is averaged to produce a value upon which a lower and an upper thresholds are based. The sample is considered to be an artifact if it falls outside the boundary of these thresholds. In [8], the algorithm involves the selection of a window size of (2N+1) data points, averaging the N data points on either side of the central point, excluding the central point if it lies a specific fraction outside of window average, then advancing to the next data point. Algorithms [8] and [9] are fairly similar, therefore, we have chosen to further investigate algorithm [9] in the next sections of the paper.

Since all non-pathological HRV artifacts are manifested as impulses, reference [7] proposes an impulse rejection filter. The algorithm has a lower execution complexity and produces better results. This algorithm will be thoroughly investigated in the next sections of the paper.

Reference [11] provides a good discussion of simple filters used to detect pathological arrhythmias in HRV signals. Nonetheless, such work falls outside the scope of this paper since it focuses on signals captured from healthy subjects.

III. ARTIFACT DETECTION ALGORITHMS

In this section we will present two algorithms for filtering out artifacts from HRV signals. The first two algorithms were introduced in [9] and [7]. We also introduce our method that uses a Windowed Impulse Rejection Filter. Before we delve into the algorithms, the following variables must be defined:

- X(i) is the original unfiltered HRV signal (input to the HRV removal algorithm)
- S(i) is the filtered HRV signal (output of the HRV removal algorithm)

A. Moving Average (MA) Filter Based Algorithm

This algorithm is based on the work presented in [9]. For each sample, a window containing the previous 30 seconds of HRV data points is averaged to produce the Expected Inter Beat Interval (EIBI) value. Then, an erroneous sample is detected and corrected using the following test:

$$S(i) = \begin{cases} X(i), & \theta \times EIBI \leq X(i) \leq \propto \times\, EIBI \\ Interpolate(X(i)), & Otherwise \end{cases} \quad (1)$$

where α ∈]1,∞[and θ ∈]0,1[. Reference [9] sets α to 2 and θ to 0.6. The idea behind this algorithm is simple; each new sample must be somewhat similar to a window of samples that preceded it. If a sample is therefore found to be significantly different than its predecessors, it is judged to be erroneous and therefore corrected.

On the other hand, a special arrangement has to be made for the first 30 seconds of the record, as there are not enough samples that precede them to fill a window. For these particular samples, the EIBI produced from the first window in the record can be used in the calculation of their thresholds.

B. Impulse Rejection (IR) Filter Based Algorithm

This algorithm is presented in [7]. It makes use of an impulse rejection filter that uses the median function to detect and correct possible HRV artifacts. The following test statistic is employed,

$$D(i) = \frac{|X(i) - X_m|}{1.483 \times med\{|X(i) - X_m|\}} \quad (2)$$

where med {.} is the median operator applied over the entire record of |X(n)-Xm| and Xm is the median of X(n). The filtered signal is then calculated as:

$$S(i) = \begin{cases} X(i), & D(n) < \\ Interpolate(X(i)), & D(n) \geq \end{cases} \quad (3)$$

where □ is a pre-defined threshold. For this paper, we set the value of □ to 4.

C. Windowed Impulse Rejection (WIR) Filter Based Algorithm

One of the problems in the previous algorithm (IR) is that it is not sensitive to major changes in the heart rate. It looks at the record as a whole. Many ECG sensors are wearable and therefore monitor the heart activity while the user performs various actions. An example of such application is an ECG monitor that an athlete might wear during exercising to collect her or his heart rate and HRV parameters. During such activities, the heart rate tends to change considerably. Nonetheless, such changes in the heart rate are not accounted for in the previous algorithm.

The aforementioned weakness can be overcome using a windowed approach, by segmenting the record into small portions for evaluation. In fact, reference [7] proposes windowing for long records (with each window containing at least 5 minutes worth of samples). Nonetheless, we propose the use of small overlapping windows to account for the potential dynamic nature of the HRV signal. The motivation for overlapping the windows is to take into regard the signals continuous nature. It would be disadvantageous to treat adjacent windows completely independently while in reality one is a continuation of the other. Using equations (4) and (5), the number of windows needed to filter the signal is calculated:

$$d = \lceil \omega \times (1 - \propto) \rceil \quad (4)$$

$$l = \left\lceil \frac{(n-\omega)}{d} \right\rceil + 1 \quad (5)$$

Where α is the overlap factor that has the range $0.5 \leq \alpha < 1$ (for an overlap of at least 50%), ω is the window length, n is the total number of samples in the signal and l is the number of windows. This guarantees that every sample is tested at least twice with regards to its surroundings in order to judge whether it is an artifact, (except for the first d samples that are tested only once). We define $W_i(j)$ as the content of the i^{th} window with the first element corresponding to $X(i \times d)$ and the last element corresponding to $X((i \times d) + \omega)$.

For each window, the following array is calculated:

$$P(j) = \frac{|W_i(j) - W_m|}{med\{|W_i(j) - W_m|\}} \quad (6)$$

Where med {.} is the median operator applied over the entire record of $|W_i(j)\text{-}Wm|$ and Wm is the median of $W_i(j)$. The filtered signal is therefore calculated using the following equation:

$$S((i \times d) + j) = \begin{cases} W_i(j), & P(j) < \\ Interpolate(W_i(j)), & P(j) \geq \end{cases} \quad (7)$$

Where i ranges from 0 to $(l-1)$ and j ranges from 1 to ω. For this paper, we have set α to 0.5, ω to 30 and □ to 7.

IV. Assessment of the Algorithms

In order to assess the strengths and weaknesses of the previously presented algorithms, three recordings containing artifacts representative of the ones highlighted in table 1 are discussed. The records were chosen to underline the differences between the algorithms presented in section III. They were picked from numerous measurements performed on 20 subjects, 13 males and 7 females with an average age of 26.7 years. These measurements were originally made for a stress monitoring study and reused in this paper. The recording sessions varied in time from 3 minutes to 4 hours. The measurements were made using Zephyr Bioharness, an ECG sensor with a sampling frequency of 250Hz. The sensor is shaped like a belt that is worn on the torso. All data collected by the sensor is sent via a Bluetooth link to a nearby computer.

Note that in order to investigate a probable situation that we have not encountered in our measurements, the rise in the heart rate in the recording of Scenario 3 is simulated. However, the artifact at the end of the record is not simulated. All references to categories of artifacts are based on the Table 1 classification.

A. First Scenario: Category One and Four Artifacts

In this scenario, two categories of artifacts can be recognized. A series of erroneously detected heartbeats can be observed towards the beginning of the record. Such artifacts belong to category 4. The last artifact is caused by either an undetected heartbeat or an interruption in ECG measurement and therefore belongs to category 1.

Figure 1 shows the same record being filtered using all three artifact detection algorithms. As it can be seen, the MA algorithm performs the worst as it misses several artifacts of both categories. Nonetheless, the performance of the MA algorithm might be improved by tweaking the values of α and θ in equation (1). Nonetheless, from our numerous simulations, we were not able to find values of α and θ that universally perform better than the IR and WIR algorithms. Some α and θ values work well for some scenarios but perform poorly for others. This shortcoming is caused by the fact that the MA algorithm does not explicitly look for impulses, but instead compares samples to the average of previous ones. This approach disregards variance of the signal which strongly affects how the signal behaves and how the thresholds should be chosen.

On the other hand, the IR algorithm, not only compares the samples to the median of the signal, but also takes into account the median of the variance of the median (see equation 2). The WIR algorithm uses a similar approach, but applying it on overlapping windows of the record.

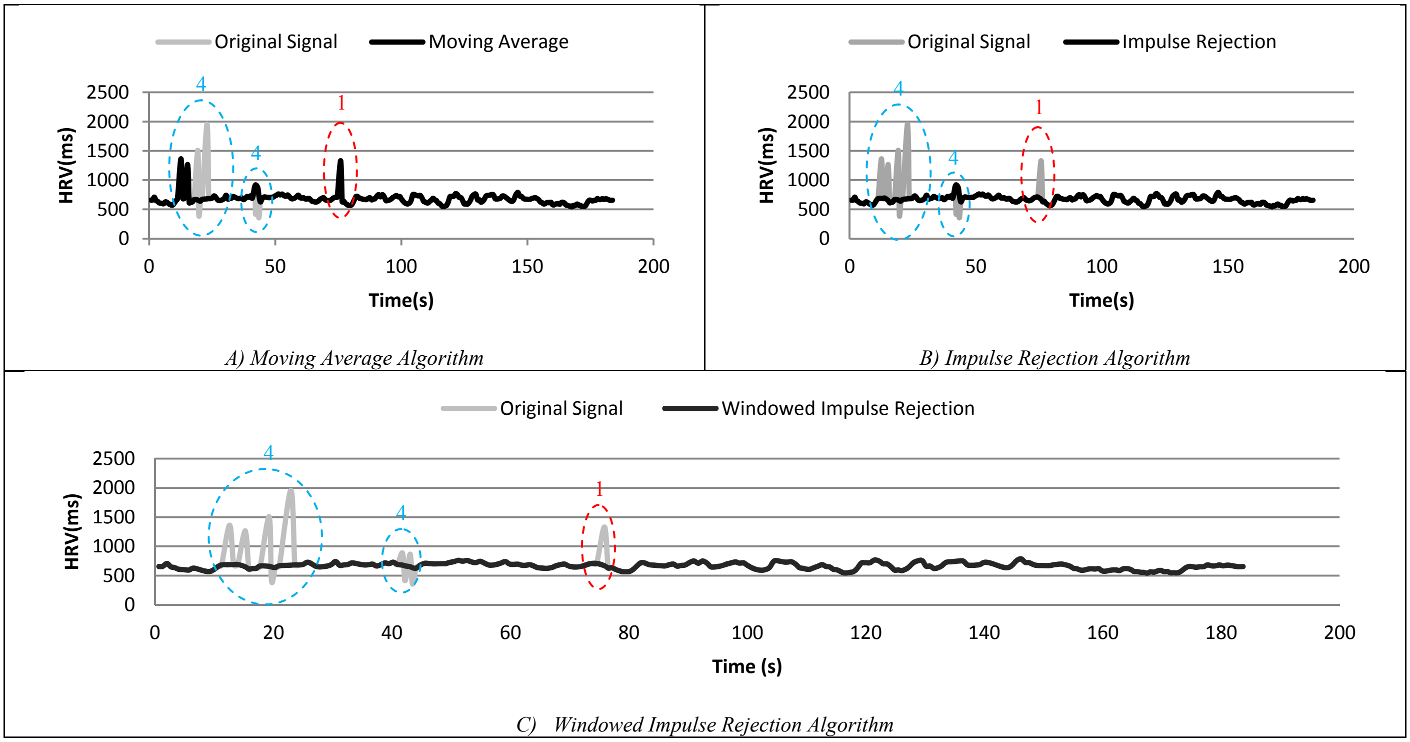


Figure 1: Using Various Artifact Removal Algorithms on Scenario 1 HRV Record

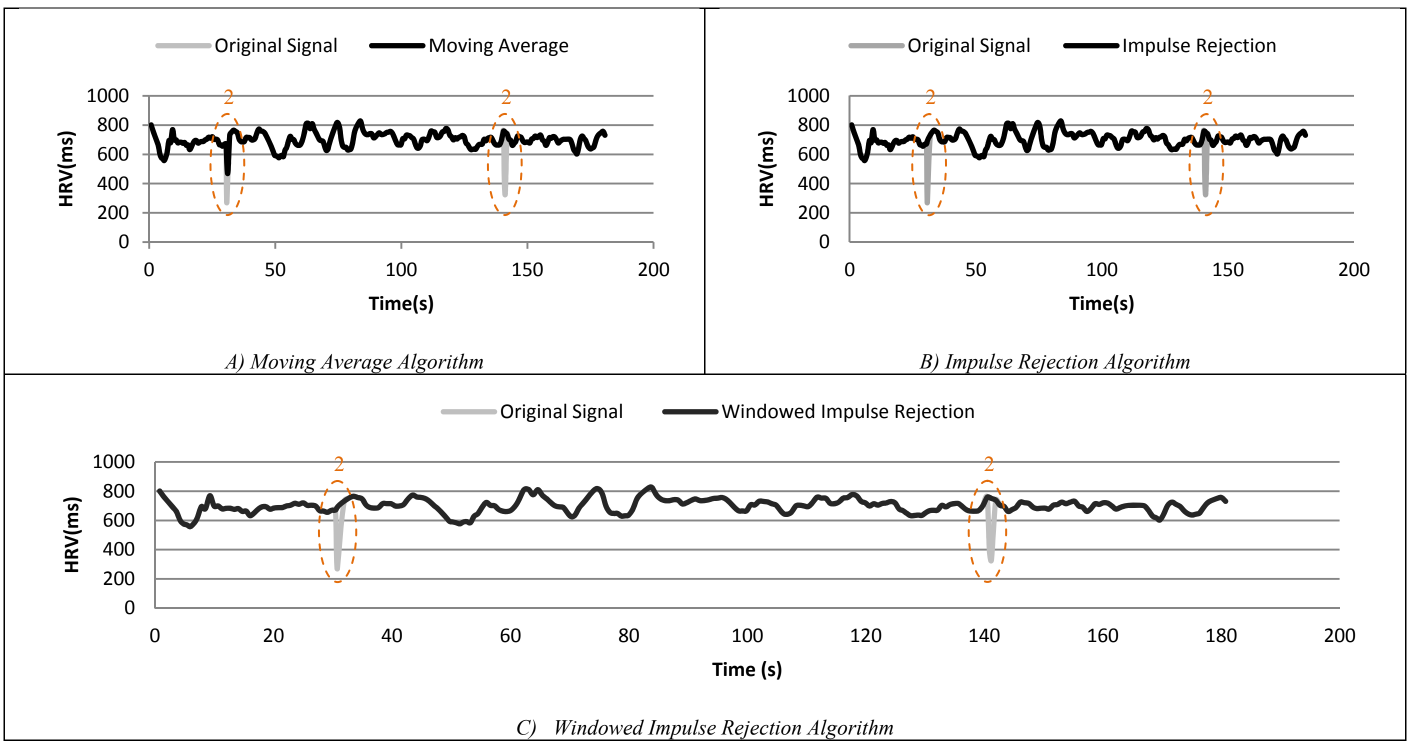
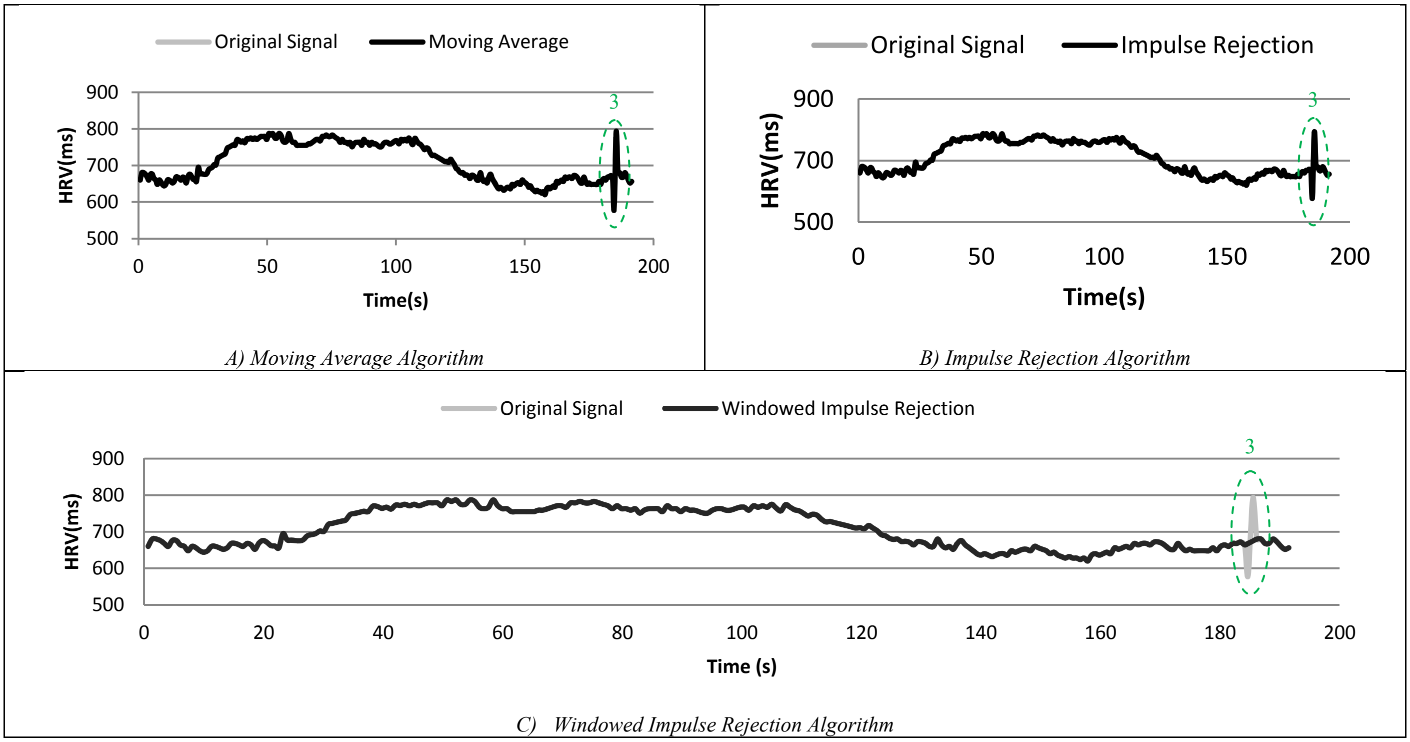


Figure 2: Using Various Artifact Removal Algorithms on Scenario 2 HRV Record

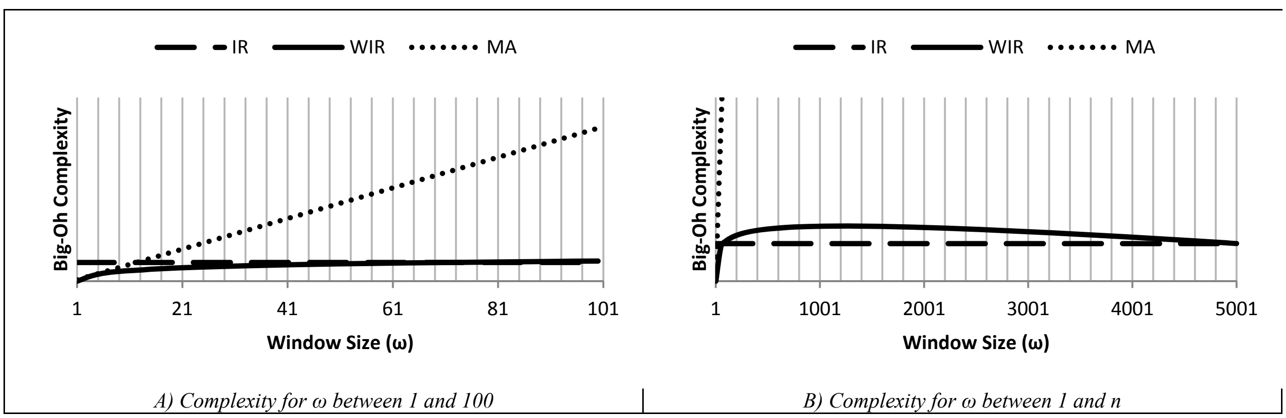


A) Moving Average Algorithm

B) Impulse Rejection Algorithm

C) Windowed Impulse Rejection Algorithm

Figure 3: Using Various Artifact Removal Algorithms on Scenario 3 HRV Record



A) Complexity for ω between 1 and 100

B) Complexity for ω between 1 and n

Figure 4: A Comparison between the Complexities of the Three Algorithms

While the IR algorithm catches most the erroneous samples, it still misses few ones of type 4. Nonetheless, the WIR detects them all since it looks at the samples in a more localized manner through the use of windowing.

B. Second Scenario: Category Two Artifacts

In this scenario, two category 2 artifacts can be observed. Figure 2 shows that the algorithms perform similarly in detecting the artifacts, except for the MA algorithm that misses one of the erroneous impulses. Again, a modification in the values of α and θ in equation (1) renders better results for this scenario, but would not guarantee the same advantage for others.

C. Third Scenario: Category Three Artifacts

In this scenario, a simulated drop in the heart rate occurs at the beginning of the record. Such drop can naturally occur due to a cessation of activity. About a minute later, the heart rate rises again, perhaps due to the resumption of activity. Twin impulses are observed towards the end of the record. These are typical category 3 artifacts (ectopic beat producing opposing impulses). Figure 3 show that both the MA and IR miss the artifact. The IR algorithm considers the record as a whole and therefore when the median is calculated, it is skewed by the rapid change in the heart rate. On the other hand, the use of windows by WIR ensures a more localized assessment of the median. Although the MA algorithm uses a windowed approach, the downward and upward peaks are simply not far enough from the average of the window to be detected. Even when we changed the values of α as low as 1.4 and θ as high as 0.8 in equation (1), the peaks were still not detected.

V. Complexity Analysis

Many ECG sensors are now designed to be worn comfortably for long periods of time. The ECG sensor we used for this study, Zephy Bioarness , is one good example

[12]. Another promising sensor still under development is the Biopeak BioFusion PSM [13]. These sensors send their data using a Bluetooth connection to a nearby computing device. Of particular interest are mobile devices that can perform HRV analysis on the fly and send feedback to the user. Therefore, any HRV filtering algorithm must take execution time into account. The following is a complexity analysis, using big-Oh notation of the three algorithms.

Assuming that ω is the number of samples contained in every window for the MA algorithm, then it executes in $O(\omega \times n)$ time where n is the number of samples contained in the HRV signal. Therefore, the bigger the value of ω, the longer the execution time would be. For a value of ω in the vicinity of n, the complexity would cap off at $O(n^2)$. Nonetheless, it is unlikely that such large window size would ever be used.

The IR algorithm requires the calculation of a median, which in turn requires the values contained in the signal to be sorted. Assuming an efficient sorting algorithm is used that produces an average complexity of $O(n \times log(n))$ (such as quick sort or merge sort), then the overall complexity of the algorithm is $O(n \times log(n))$.

The WIR algorithm requires the calculation of the median over a window of size ω. This would produce l windows, where l is defined in equation (5). The value of l is directly dependent on the length of signal n, the window overlap factor α and the length of the window ω. The operation of median performed on each window costs $O(\omega \times log(\omega))$. Therefore, the total complexity of the algorithm is $O(l \times \omega \times log(\omega))$. Figure 3 shows a comparison between the complexities of the three algorithms (with respect to window size) for a data set of size $n=5000$. The performance of MA deteriorates drastically as ω grows since the average window has to be recalculated for every single sample. On the other hand, for very small values of ω, WIR performs better than IR. That quickly changes as ω grows. Eventually the performance of both algorithms converges as ω reaches n (which means only one window is used). Nonetheless, the performance of WIR and IR is comparable and far better than that of the MA.

VI. Conclusion

In this paper we have presented the Windowed Impulse Rejection Filter based Artifact Detection Algorithm. The algorithm is aimed at detecting artifacts in Heart Rate Variability signals. We have demonstrated that our method performs with a higher level of accuracy than existing ones. Also, in terms of complexity, it performs better than the Moving Average algorithm and somewhat similar to the Impulse Rejection Filter algorithm. Our immediate future work is to make use of the noise classification included in Table 1 to better handle artifacts according to their origin and impact on the signal (instead of simply interpolating a new sample to replace the erroneous one). Furthermore, we will employ the WIR algorithm to clean out artifact plagued HRV signals within a personalized stress management system.

VII. References

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