A Signal Abnormality Index for Arterial Blood Pressure Waveforms

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Abstract

Fidelity of the arterial blood pressure (ABP) waveform is often critical to computations that involve processing of the waveform. The ABP waveform may be used for cardiac output (CO) estimation, suppression of ECG-based false alarms, and tracking long term trends such as mean pressure. An abnormal ABP waveform may cause these applications to give undesirable results. In this paper, we present a signal abnormality index (SAI) algorithm that detects abnormal beats in ABP waveforms. The algorithm flags ABP beats by intelligently setting constraints on physiologic, noise/artifact, and beat-to-beat variation values. Compared to an expert annotator, the algorithm's sensitivity=1, specificity=0.91, positive predictive value=0.73, and negative predictive value=1. We also perform a sensitivity analysis to show SAI's robustness. Finally, we use SAI to identify clean ABP segments from our study population and show that CO estimation error is 30% less in the clean subset than in the entire population.

1. Introduction

The arterial blood pressure (ABP) waveform is a key source of information for determining hemodynamic state of a patient. By processing ABP waveforms, one can track trends such as mean pressure and heart rate. As input to a hemodynamic model, ABP is useful in estimating cardiac output [1], arterial compliance, and peripheral resistance. Combined with an ECG signal, ABP is useful in reducing false alarms generated by bedside monitors [2].

However, these applications rely on a clean ABP waveform, in which beat-to-beat features such as mean pressure, duration of systole, and beat period may be reliably obtained. We define a beat as *anomalous* when any feature in the beat becomes obscured. Median filtering helps to reduce some sporadic anomalies, but fails as anomalies become more frequent. In the real-world environment such as an intensive care unit (ICU), beat-to-beat features often become obscured due to noise/artifacts and physiologic disturbances. Therefore, it is important to design an algorithm that can flag anomalous beats in the ABP waveform (Figure 1).

In this paper, we present the signal abnormality index (SAI). The algorithm outputs at a beat-level time resolution and intelligently detects abnormal beats by imposing a series of constraints on physiologic, noise/artifact, and beat-to-beat variability. SAI does not distinguish between anomalies arising from physiologic disturbances such as an arrhythmia and non-physiologic phenomena such as noise.

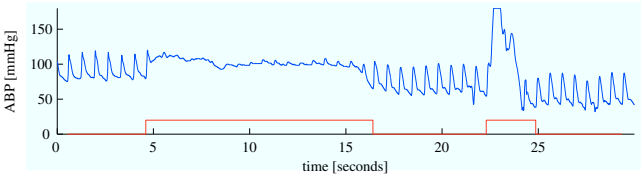

Figure 1. A clinical ABP waveform with regions of abnormality. Signal abnormality index (SAI) is shown on bottom, raising a flag in regions of abnormality.

The SAI algorithm was evaluated on clinical ABP waveforms from the Multi-Parameter Intelligent Monitoring for Intensive Care II (MIMIC II) database [3]. The database has physiologic waveform data from over 3500 ICU patients hospitalized at Beth Israel Deaconess Medical Center, Boston, USA. MIMIC II has 120 patient records that contain simultaneous ABP waveforms and thermodilution cardiac output (gold-standard) measurements. Using the 120 records, we quantified the performance of the SAI algorithm in 3 ways: comparing the algorithm's performance to a human expert, analyzing the sensitivity of the algorithm's output, and determining whether cleaner waveform segments yield better cardiac output estimates.

2. Methods

Figure 2 shows an overview of the SAI algorithm. First, a beat detection algorithm [4] marks the onset of each beat. The onset markers allow for feature extraction at beat-level resolution. For each beat, features such as heart rate, systolic blood pressure, diastolic blood pressure are obtained. Features are then evaluated by a series of abnormality criteria, which check for noise level, physiologic ranges, and beat-to-beat variations. The output of each abnormality criterion is binary, '0' for no flag (clean beat) and '1' for

flag. Finally, the outputs of all abnormality criteria are combined via the logical OR operation.

Given an input ABP segment of n beats, the overall output (define as y) is a binary sequence of length n. For the segment, a cumulative SAI (cSAI) is defined as

$$Y \equiv \text{fraction of flagged beats} = \frac{1}{n}\sum_{k=1}^{n} y[k]$$

where $y[k]$ is the SAI of the k-th beat. cSAI, with a continuous domain of $0 \leq Y \leq 1$, is a useful measure of the abnormality of an entire waveform segment. (e.g. a segment of 50 beats with 4 flagged would yield a cSAI of 0.08.)

The rest of this section explains several components of the SAI in detail and proposes methods for algorithm evaluation.

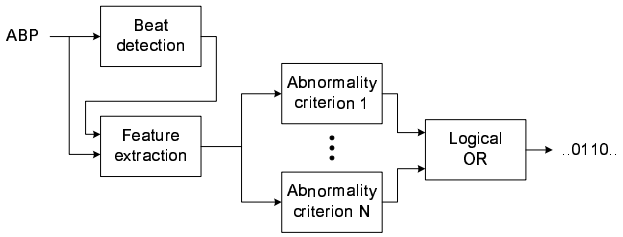

Figure 2. SAI block diagram. Input is an ABP waveform. Output is a binary string, assigning a value (no flag=0, flag=1) to each beat in the ABP waveform.

2.1. Feature extraction

The feature extraction algorithm obtains a set of features shown in Table 1. For each beat, P_s and P_d are the local minimum and maximum around the pressure onset point. P_m is the average pressure between adjacent onsets. T is the time difference between adjacent onsets. Noise level is defined as the average of all negative slopes in each beat.

Table 1. ABP features

Feature	Description
P_s	Systolic blood pressure
P_d	Diastolic blood pressure
P_p	Pulse pressure $(P_s - P_d)$
P_m	Mean arterial pressure
T	Duration of each beat
f	Heart rate $(60/T)$
w	noise: mean of negative slopes

2.2. Abnormality indexing

With blood pressure features available, the SAI algorithm is ready to interpret them. Table 2 lists the criteria for flagging a beat.

Table 2. SAI logic

Feature	Abnormality criteria
P_s	$P_s > 300$ mmHg
P_d	$P_d < 20$ mmHg
P_m	$P_m < 30$ or $P_m > 200$ mmHg
f	$f < 20$ or $f > 200$ bpm
P_p	$P_p < 20$ mmHg
w	$w < -40$ mmHg/100ms
$P_s[k] - P_s[k-1]$	$\lvert\Delta P_s\rvert > 20$ mmHg
$P_d[k] - P_d[k-1]$	$\lvert\Delta P_d\rvert > 20$ mmHg
$T[k] - T[k-1]$	$\lvert\Delta T\rvert > 2/3$ sec

The first 4 criteria in Table 2 impose bounds on the physiologic ranges of each feature. For example, any beat with a diastolic pressure of less than 20mmHg is flagged.

The 5th criterion is the noise detector. With high frequency noise, there will be large negative slopes in the waveform. Based upon this observation and by inspecting ABP data, we decided that any beat with a mean negative slope less than -40mmHg$/100$ms is flagged. Note that this noise detector is not useful for identifying low frequency noise such as baseline wander.

The final 3 criteria compare ABP features between adjacent beats. Large sudden changes in beat-to-beat features are likely indications of abnormality. For example, if the $(k-1)$-th systolic pressure and the k-th systolic pressure differs more than 20mmHg, then the k-th beat is flagged.

2.3. Algorithm evaluation

Using 120 patient records from the MIMIC II database, the SAI algorithm was evaluated in 3 ways:

1. Compare the algorithm's performance to a human expert in detecting anomalies in ABP waveform segments. Ideally, the algorithm should be in perfect concordance with the human.
2. Analyze the sensitivity of algorithm's output to perturbations of each threshold parameter in Table 2. A robust algorithm would be relatively insensitive to such perturbations.
3. Determine whether cleaner waveform segments, as indicated by low cSAI values, yield better cardiac output estimates.

In comparing to a human expert annotator, 246 ABP segments were randomly selected, each 10 seconds long. For each segment, the SAI algorithm outputs '1' if any beat is flagged as abnormal, '0' otherwise. Similarly, the human identifies any abnormality and classifies each segment using the following convention:

$--$ No irregularity—regular, homogeneous beats with negligible artifacts and noise.

$-+$ Minor irregularity—clean waveform with minor timing irregularity of beats and/or minor artifacts. Key morphologic features are still clearly identifiable.

$+-$ Irregularity present—all beats similar, but one beat stands out from others with timing or shape, and/or artifact present obscuring a portion of a beat.

$++$ Major irregularity present—more than one beat patently dissimilar from other beats, and/or artifact present completely obscuring key features of beats.

Notice that human annotations have 2 gray zones ($-+$ and $+-$), which are used when the waveform's abnormality is not completely obvious.

For sensitivity analysis, the abnormality criteria are tested independently each other. A parameter value in Table 2 is perturbed while all other abnormality criteria are not applied. We observe the impact on cSAI across the entire study population, which includes over 30 million beats. Sensitivity is defined as follows:

$$\text{Sensitivity} \equiv \left.\frac{dY}{d\hat{\theta}}\right|_{\hat{\theta}=1}$$

where Y is the cSAI and $\hat{\theta}$ is the normalized parameter value. Normalization allows for sensitivity comparison between different abnormality criteria.

In a recent study [1], we evaluated 11 different cardiac output (CO) estimation methods from ABP waveforms. The gold standard for comparison was thermodilution CO (TCO). We study the performance of 3 CO estimation algorithms (Table 3) in this paper.

Table 3. Cardiac output estimation algorithms

CO estimation method	**CO** $= k \cdot$ **below**
Mean Pressure	P_m
Windkessel [5]	$P_p \cdot f$
Liljestrand & Zander [6]	$\frac{P_p}{P_s+P_d} \cdot f$

For our study population, a 1-minute ABP segment is extracted at the time of each TCO measurement. Estimated CO and cSAI are obtained for each 1-min ABP segment. For the entire population, the error metric is $\sigma(CO - TCO)$, the standard deviation of the difference between estimated CO and TCO. The error is evaluated as a function of cSAI. We begin the experiment by examining σ of the entire population with no discrimination due to cSAI. Then, 1-min segments with high cSAI values (poor waveform quality) are progressively eliminated. The goal is to examine whether CO estimation error decreases for cleaner waveforms.

3. Results

3.1. SAI versus human

Table 4 shows the distribution of the 246 comparisons of SAI versus a clinician (ATR). Note that SAI performance is worse in the two grays zones ($-+$ and $+-$). However, only 22% of data fall into these categories. Table 5 lists important statistics derived from the distribution, both exclusive (3rd column) and inclusive (4th column) of the gray zones.

Table 4. SAI versus human: distribution

SAI					
1	14	13	9	37	
0	142	26	5	0	
	$--$	$-+$	$+-$	$++$	human

Distribution of the 246 ABP waveform segments. SAI key: 0 no flag, 1 flag. Human key: $--$ no flag, $-+$ probably no flag, $+-$ probably flag, $++$ flag

Table 5. SAI versus human: statistical summary

PPV	$P(+\|1)$	0.73	0.63
NPV	$P(-\|0)$	1	0.97
Sensitivity	$P(1\|+)$	1	0.90
Specificity	$P(0\|-)$	0.91	0.86

3rd column excludes gray zones, 4th column includes gray zones. PPV=positive predictive value, NPV=negative predictive value, $P(*|*)$ are conditional probability notations for PPV, NPV, etc.

3.2. Sensitivity analysis

Figure 3 plots cSAI as a function of 3 abnormality criteria. Notice that each criterion flags only a small fraction of beats, and the slope of the curves are not steep but also nonzero at $\hat{\theta} = 1$. Table 6 lists the sensitivity of every parameter. The results indicate that our study population had no waveform with $P_s > 300$mmHg or $P_m > 200$mmHg.

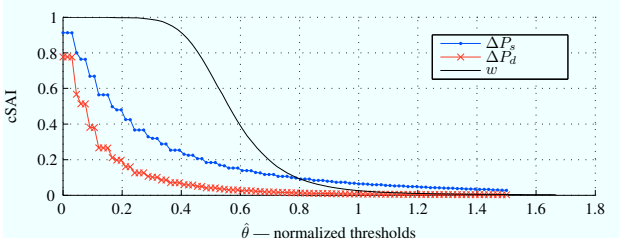

Figure 3. Perturbations to abnormality criteria. cSAI as a function of 3 parameters perturbations is shown. Sensitivity is defined to be the slope of each curve at $\hat{\theta} = 1$.

Table 6. SAI sensitivity

Feature	θ_0	$Y(\theta_0)$	|Sensitivity|
P_s	300	0	0
P_d	30	.010	.003
$P_{m,min}$	30	.007	.007
$P_{m,max}$	200	0	0
f_{min}	20	.001	.001
f_{max}	200	.047	.180
P_p	20	.028	.092
w	-4	.027	.160
$P_s[k] - P_s[k-1]$	20	.064	.080
$P_d[k] - P_d[k-1]$	20	.007	.013
$T[k] - T[k-1]$	0.7	.017	.033

3.3. Cardiac output estimation error

Figure 4 plots CO estimation error as a function of maximum accepted cSAI. Errors decrease for lower cSAI (cleaner waveform) values. For the Liljestrand algorithm, an error reduction of 30% is obtained. The mean pressure estimation algorithm is most robust to noise, as evidenced by its relatively flat line. This robustness is expected because of the simplicity and averaging nature of the mean pressure algorithm.

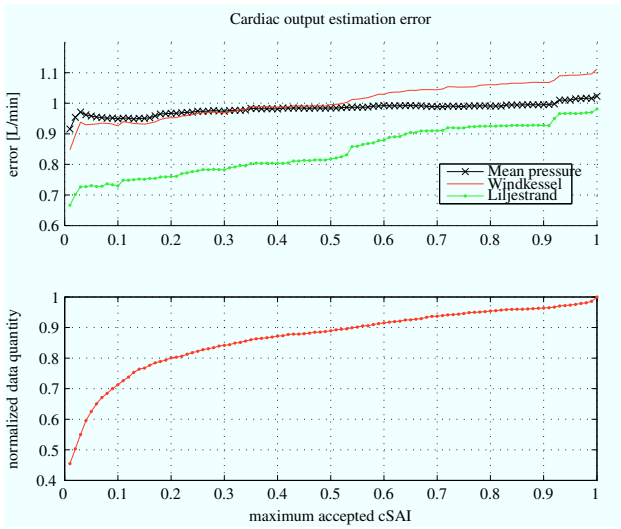

Figure 4. Cardiac output estimation error as a function of maximum accepted cSAI. Bottom plot shows that the amount of data also decreases as we restrict ourselves to cleaner waveforms.

4. Discussion and conclusions

Evaluating the performance of the SAI algorithm is non-trivial, primarily because of a lack in the quantitative definition of an 'abnormal' beat of an ABP waveform. Consequently, there is no established gold standard to compare against. Furthermore, the definition of abnormality can be application dependent. For example, beat quality needs to be higher for CO estimation than for mean pressure tracking because more features derived from each beat are used for the former.

From the sensitivity analysis, two abnormality criteria do nothing and have sensitivity of 0. Therefore, for our study population, they can be removed. Of the remaining criteria, pairwise correlation studies can be performed in the future to identify any redundant criteria.

In conclusion, we have presented an algorithm that detects anomalies in the ABP waveform. The SAI algorithm is in close agreement with a human expert (Table 5), is robust (Table 6), and has proven its effectiveness in its ability to select clean ABP waveforms to improve CO estimation.

Acknowledgments

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