

Empirical Mode Decomposition Based Real-Time Blood Pressure Delineation and Quality Assessment

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Abstract

Noise and artifacts compromise the fidelity of arterial blood pressure (ABP) waveform, resulting in unreliable parameter estimation and high false alarm rate. This study proposes empirical mode decomposition (EMD) based algorithm that integrates real-time ABP delineation and quality assessment. The data-driven decomposition ensures insensitivity to inter-subject variability. Adaptive EMD detrending procedure, combined with short-term memory parameter tracking, solves the problem of waveform morphology changes.

Delineation algorithm was tested on a publicly available expert annotated database consisting of 13079 beats. Algorithm showed sensitivity of 99.85% and positive predictivity of 99.76% for systolic blood pressure, and sensitivity of 99.89% and positive predictivity of 99.82% for onset detection. Six artifact types were simulated on available dataset and successfully detected using the algorithm. The frequency band separation of intrinsic mode functions (IMFs) proved as relevant feature for selective artifacts detection on the most affected IMFs.

1. Introduction

Arterial blood pressure (ABP) waveform contains rich physiological information about patient cardiovascular health state. Different artifacts, caused by damping, flushing of the arterial line, body movements or clinical activity [1] compromise the fidelity of the ABP waveform, resulting in reduced reliability of estimated parameters. Artifact presence can also result in high false alarm rates for automated monitoring systems in the ICU, causing medical staff to be less responsive and reducing the quality of the health care [2]. Automatic extraction and tracking of the basic parameters: heart rate, systolic, diastolic, and mean blood pressure, combined with the issues related to the artifact presence, impose the need for a reliable algorithm that unifies ABP delineation and artifact detection.

Accurate delineation and artifact detection are two

related tasks. The signal parts affected by noise and artifacts have to be detected either through abnormal values of the estimated parameters [3], or through analysis of the signal waveform [2]. In this paper, we propose a novel algorithm for automatic delineation (systolic blood pressure (SBP) and onset estimation) and ABP signal quality assessment that combines monitoring of the estimated parameters and tracking of the signal waveform changes. Algorithm uses empirical mode decomposition (EMD) based detrending procedure and adaptive threshold approach for coarse SBP and onset detection. Fine adjustment is done in the original signal domain in short time intervals surrounding the coarse estimation. Signal quality assessment is based on EMD spectral selectivity, and short-term memory parameter tracking. Data-driven decomposition inherent to EMD ensures algorithm's patient-specific adjustment.

2. Method

2.1. EEMD

Empirical mode decomposition (EMD) is an algorithm for signal decomposition into intrinsic mode functions (IMFs) using the sifting process [4]. EMD is adaptive signal decomposition method suitable for nonlinear and non-stationary signals. Due to the mode mixing problems associated with EMD decomposition, Ensemble Empirical Mode Decomposition (EEMD) is used [5]. EEMD is noise assisted EMD decomposition based on IMF averaging over the ensemble of the original signal with added Gaussian white noise realizations. Altogether 10 realizations of white noise were added to original signal and obtained IMFs were averaged to result in the final IMFs. After the IMF averaging procedure, most of the noise will cancel out, and the effect of mode mixing will be reduced. To reduce the computational cost and memory use and conform to real-time application, EEMD was done in a sliding window manner. Every window consisted of 4 seconds of the signal including 1.6 seconds overlap. The overlap served as guard band providing for EEMD edge effects, therefore, first and last 0.8 seconds of the IMF data in the window are ignored in processing.

Signals were decomposed into a fixed number of 7 IMFs, using 10 iterations in sifting process.

Figure 1 presents an original signal before (upper waveform) and after (lower waveform) EEMD adaptive detrending procedure. The detrended signal comprises the first five IMFs thus allowing for implementation of the threshold procedure.

2.2. Delineation algorithm

Coarse SBP estimation is done on the sum of the first five IMFs. The EEMD procedure does not cancel out all the added noise in the first IMFs, for these reasons the sum of the first five IMFs should be obtained by subtraction of all the rest IMF including residual from original signal. The resulting signal will be denoted $ABP_{IMF_{1-5}}$. SBP detection algorithm in short consists of coarse and fine detection procedure.

Coarse procedure done on adaptively detrended original signal, $ABP_{IMF_{1-5}}$, detects all the local maxima in $ABP_{IMF_{1-5}}$ and using adaptive threshold TH_1 straightforwardly discards the low amplitude candidates. Coarse procedure is depicted on bottom waveform in Figure 1, the candidates discarded at coarse level are marked by black squares.

Fine adjustment is done on the original signal. Maximum found in the short time interval N_1 around coarse SBP estimation is considered a candidate for a true SBP estimate. In the following step the time interval between finely adjusted peaks is checked and used to discard candidates closer than adaptive time threshold T_1 . The fine procedure is presented on upper waveform of Figure 1. The peak candidates discarded at this level are encircled.

For onset detection, sum of the first 4 IMFs is used, denoted as $ABP_{IMF_{1-4}}$. This sum is obtained by subtraction of IMF_5 to IMF_7 and residual from the original signal. Onset points are detected on $ABP_{IMF_{1-4}}$ based on the estimated time instant of the SBP peaks using the following detection procedure:

1. Find the minima in the interval of length T_2 prior to each SBP time estimate in $ABP_{IMF_{1-4}}$.
2. Choose minimum that is lower than TH_2 and closest to SBP point.

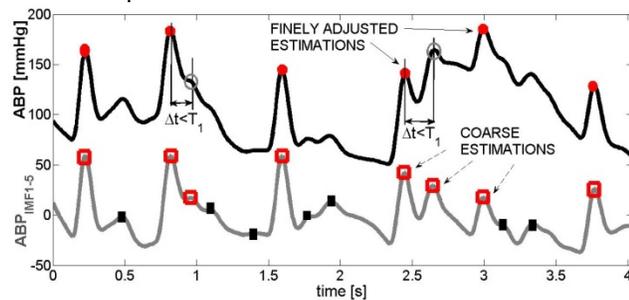


Figure 1. Coarse (bottom waveform) and fine (upper waveform) SBP estimation procedure.

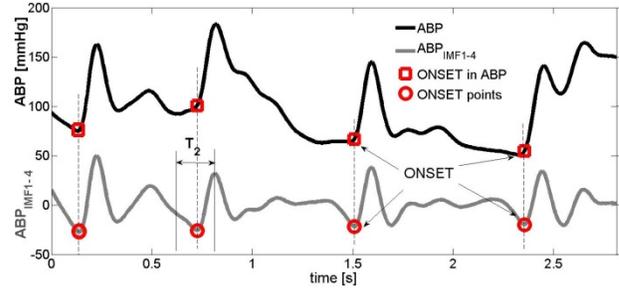


Figure 2. Onset detection.

Threshold values, presented in Table 1, were derived through analysis of physiological limitations [1,3] and algorithm implementation on different ABP waveforms. Thresholds are adaptively updated using the procedure explained in 2.4.

Table 1. Threshold parameters for estimation of SBP and onset time localization

Name	Description
TH_1	35% of average SBP amplitude in $ABP_{IMF_{1-5}}$
T_1	60% of average peak-to-peak (PP) interval
N_1	15% of average peak-to-peak (PP) interval
TH_2	20% of average SBP amplitude in IMF domain
T_2	30% of average peak-to-peak (PP) interval

2.3. Quality assessment

There are six main types of artifacts that appear in practice [1]: saturation to ABP maximum, saturation to ABP minimum, reduced pulse pressure artifact, square wave artifact, high frequency noise and impulse artifact.

Saturation to ABP maximum, saturation to ABP minimum and square wave artifacts produce similar IMFs upon EMD decomposition. Namely, in the presence of these artifacts the signal is either constant or with monotonic amplitude changes which remain in the residual after decomposition, thus the amplitudes of all IMFs are negligibly small disabling detection of SBP peaks. On the borders of the square wave and on the decreasing side of the saturation to ABP maximum, false detection can occur, but these peaks will be discarded as high frequency noise.

EEMD frequency selectivity was used for high frequency noise and impulse artifact detection. First three IMFs contain most of the noise, and their sum, the HF signal ($ABP_{IMF_{1-3}}$), is used for noise detection. High noise activity increases the number of oscillations and the

amplitude of the $ABP_{IMF_{1-3}}$ resulting in longer line length in a short window. For these reasons, the line length (LL) was used as a measure of high frequency activity:

$$LL(t) = \int_{t-T_3/2}^{t+T_3/2} \sqrt{1 + \frac{\partial ABP_{IMF_{1-3}}(\tau)}{\partial \tau}} d\tau$$

Average $ABP_{IMF_{1-3}}$ line length was calculated around SBP and onset points. If the HF activity of the $ABP_{IMF_{1-3}}$ signal was higher than adaptive threshold TH_3 in the interval of the length T_3 around a SBP point, SBP and onset pair was considered corrupted. The detection of increased HF activity measured by LL is illustrated in Figure 3.

Impulse artifact can be modeled through addition of *sinc* function to the original signal [1], which causes a sudden rise of the signal trend. Using the spectral selectivity of the EEMD, the trend can be isolated, as the sum of the IMF_6 , IMF_7 and residual, $T_{ABP} = ABP - ABP_{IMF_{1-5}}$. Impulse artifact is detected if the difference between the T_{ABP} in SBP time instants and the average T_{ABP} measured in SBP time instants was higher than adaptive threshold TH_4 . Impulse artifact is as well detected in onset points if the ABP amplitude in onset points is higher than the average T_{ABP} in onsets.

The average amplitude distance between SBP peaks and onset points in ABP signal, denoted as OSPP, serves as an estimate of pulse pressure. Reduced pulse pressure artifact is detected if the OSPP for a given SBP and onset pair was less than 0.5 of average OSPP, or if it was lower than 20 mmHg. Detection of reduced pulse pressure artifact is presented in Figure 4.

Empirically derived values of the parameters used for artifact detection are given in Table 2.

Table 2. Artefact detection parameters.

Name	Description
T_3	60% of average peak-to-peak (PP) interval
TH_3	150% of average HF activity
TH_4	45% of the average OSPP

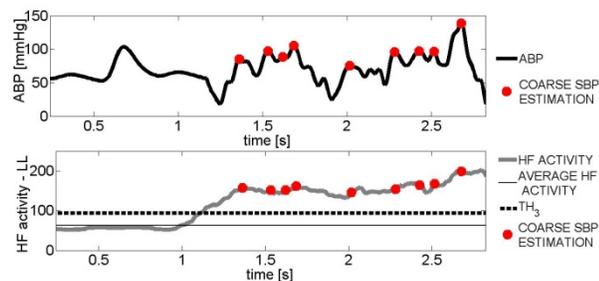


Figure 3. High frequency activity detection

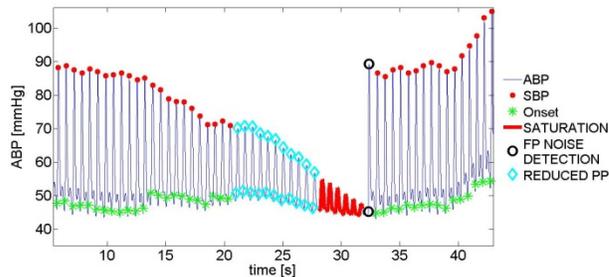


Figure 4. Example of reduced PP detection. Note the period when PP artifact also fulfills the preconditions for saturation to minimum value. False positive (FP) noise detection occurs at the end of this artifact.

2.4. Parameter adjustment

To enable time varying threshold strategy, we used advanced parameter adjustment. Every parameter p used in the algorithm is recalculated after processing of each data window. The value p presents adaptively obtained average parameter value used for threshold calculation. Parameter adjustment is defined as follows:

$$\begin{aligned} avrPks &= avrPks * 0.8 + pks * 0.2 \\ inf &= \min(1, pks / avrPks) \\ p &= p * (1 - inf * \alpha) + p_w * inf * \alpha \end{aligned}$$

$avrPks$ represents the average number of SBP peaks detected in one window, while pks represents the number of peaks detected in the current window. Inf represent the influence of the parameter calculated from the current window, denoted as p_w , on parameter value, p . If the number of peaks detected in the window is small, the inf will reduce the impact on the parameter value. α is a regulation parameter and ranges from 0.3 to 0.5 for different parameters.

2.5. Evaluation procedure

SBP detection was evaluated on the only annotated publicly available CSL benchmark database (<http://bsp.pdx.edu>). CSL consists of two 60 minutes long expert annotated ABP recording from different patients. Additionally, this database contains reference annotations of the delineation algorithm proposed in [6]. Signals in the database were sampled at 125 Hz, and contain 13079 beats. Positive predictivity (Pp) and sensitivity (Se) were used to evaluate the algorithm's performance. Pp is defined as the ratio of number of true positive peaks and the sum of all the detected peaks. Se is defined as the ratio of number of true positive peaks and the number of all the expert annotated peaks.

As there is no database that contains expert annotations for onset points, algorithm was compared to another state of the art onset detection algorithm (WABP) [7]. The

evaluation is done on the same CSL database using the same evaluation measures.

Performance of the proposed quality assessment method was evaluated through simulation. Six artifact free ABP segments each one minute long were used as a base for the simulation. We used an artifact generation tool provided in [1] to simulate different artifacts.

3. Results

SBP detections are marked as true positives if in their critical neighborhood (defined as 4 samples from each side i.e. 0.032 seconds) exist an expert annotated SBP; else they are marked as false positive. Expert annotations that do not have SBP detections in the critical neighborhood were counted as false negatives. The algorithm initializes in average in the first 4 seconds after which the parameter adjustment procedure allows for correct delineation. Algorithm performance in SBP detection is shown in Table 3.

Onset detection was compared with WABP [7]. As there are no reference expert annotation, validation was done manually. The performance of the proposed algorithm is compared with WABP performance as shown in Table 4.

Simulated artifacts were generated using random valued input parameters, with restriction that the first 10 second of the signal were not corrupted. For every one minute segment, 3 simulations for every artifact were done, 108 simulations in total. Simulation was considered successful if the corrupted part of the signal was detected. Algorithm detected all of the corrupted signal parts.

Table 3. SBP detection.

	TP	FP	FN	Pp	Se
Signal 1	5667	17	8	99.7%	99.86%
Signal 2	7383	15	12	99.8%	99.84%
Gross	13050	32	20	99.76%	99.85%

Table 4. Onset detection.

	TP	FP	FN	Pp	Se
Proposed algorithm	13032	24	14	99.82%	99.89%
WABP	13000	50	20	99.62%	99.85%

4. Discussion

Arterial blood pressure contains rich information about patient cardiovascular health; however, different artifacts reduce the reliability of the estimated parameters.

We proposed a novel delineation and quality assessment algorithm based on EEMD decomposition.

EEMD frequency selectivity is used for both delineation and artifact detection. The algorithm adaptively modifies the parameters, which combined with EEMD algorithm provides for waveform inter-subject variability. The performance of the algorithm on this small database is comparable to other algorithms in literature [6,7]. However, the more extensive testing is needed on larger annotated ABP database. It should be noted that sudden changes in ABP spectral content, for example at the beginning of saturation or square wave artifacts, change the allocation of spectral components in the IMFs, and can cause false noise detections in the near vicinity of the starting and ending points of the artifacts.

Algorithm is suitable for real-time application as the processing of one 4 second long window takes in average 0,66 second in Matlab. For real-time scenario the minimum applicable window shift is 0.8s, which introduces delays of approximately one heart beat at the average heart rate.

Acknowledgements

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References

- [1] Li Q, Mark RG, Clifford GD. Artificial arterial blood pressure artifact models and an evaluation of a robust blood pressure and heart rate estimator. *BioMedical Engineering OnLine* 2009, 8:13.
- [2] Asgari S, Bergsneider M, Hu X. A Robust Approach Toward Recognizing Valid Arterial-Blood-Pressure Pulses. *IEEE transactions on information technology in biomedicine* 2010, 14:166-172.
- [3] Sun JX, Reisner AT, Mark RG. A signal abnormality index for arterial blood pressure waveforms. *Computers in Cardiology* 2006;33:13–16.
- [4] Huang NE et al. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. *Proc R Soc Lond* 1998; 454: 903-995.
- [5] Wu Z, Huang NE. Ensemble empirical mode decomposition: A noise-assisted data analysis method. *Advances in Adaptive Data Analysis* 2009; 1:1–41.
- [6] Aboy M et al. An Automatic Beat Detection Algorithm for Pressure Signals. *IEEE Transactions on Biomedical Engineering* 2005; 52: 1662-1670.
- [7] Zong W, Heldt T, Moody GB, Mark RG. An open-source algorithm to detect onset of arterial blood pressure pulses. *Computers in Cardiology* 2003; 30:259–262.

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