# A New Filtering Method for Smoothing Intracardiac Records Preserving the Steepness of A, V, H Waves

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## Abstract

*A new data-driven filtering method based on masked empirical mode decomposition and non-linear normalization of noise in separate spectral bands is introduced here.*

*Its preserves the steepness of rapidly changing sections of intracardial electrograms (such as A, V, and H waves) and surface electrocardiogram (such as QRS complex) and at the same time smooths the rest of the recording.*

*Data-driven filtering method efficiency and ability not to change morphology of surface electrocardiogram and intracardial electrograms was proved on clinical records dataset.*

## 1. Introduction

A comprehensive examination of cardiac electrical phenomena uses simultaneous recording of surface (ECG) and intracardiac (IEGM) leads. However, ECG/IEGM recordings are often corrupted by noise during. The presence of noise in heart activity recordings reduces its readability and complicates automatic location of the key points of the ECG/IEGM waveforms.

There are a number of signal processing techniques for filtering noise in ECG/IEGM recordings, varying in noise elimination efficiency, computational complexity, and ability not to distort ECG/IEGM morphology. Most of them have adjustable parameters that the user optimizes according to the noise characteristics encountered in the recording. However, this approach proves insufficient in a situation where the characteristics of the record change rapidly and frequently, e.g. during stimulation of the heart with a series of stimulation pulses or during induced fibrillation. These scenarios occur frequently in clinical practice and cannot be avoided because they are the key to performing interventional cardiology. In addition, this approach may fail in a situation where the noise in each of the leads has a different characteristic or when noise level changes during the recording.

Both problems are simultaneously solved by a data-driven filtering approach. In this approach, each lead is filtered based on its morphology, and the degree of filtering is determined by the steepness of the signal. This allows the ECG recordings to be filtered so that the slow-changing segments are smoothed while the fast-changing segments retain their spikiness. The signal filtered in this way retains the qualities that are essential for the visual evaluation of the signal and also for its automatic measurement.

## 2. Method

A data-driven filtering method is introduced here. Its performance was compared with conventional filtering method applied to the same dataset of clinical recordings.

### 2.1. Dataset

The dataset is set of ECG/IEGM recordings acquired during real-world cardiology interventions on adult patients.

Recordings were made using surface electrodes and intracardiac electrophysiological catheters placed in the high right atrium (HRA), bundle of His (HIS 1,2 and HIS 3,4), the activity in the coronary sinus (CS 1–10) was sensed with a decapolar catheter, whose CS 9,10 paired electrode was placed proximal to the catheter and CS 1,2 pair of electrodes was placed distal to the handle of the catheter.

The EP WorkMate 4.2 device with sampling rate of 2000 Hz and voltage resolution of 78 nV/LSB was used for acquisition of simultaneously acquired signals.

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## 2.2. The data-driven filtering method

The proposed data-driven filtering method combines empirical mode decomposition, signal decomposition into spectral bands, and nonlinear signal normalization. The idea behind the data-driven filtering method is to automatically decompose the raw signal into its sub-signals where the noise components can be easily identified.

The principle of the data-driven method, depicted in Fig. 1, is to decompose ECG/IEGM records into a set of their intrinsic mode functions using masked empirical mode decomposition. Masked empirical modal decomposition [1] is an improved version of empirical modal decomposition [2], which adds artificially created sine waves (so-called masking frequencies) with a defined frequency to the decomposed signal so it can influence the frequency content of the resulting intrinsic mode functions.

A set of masking frequencies is preselected to split the raw signal into an intrinsic mode functions containing the individual power-line noise harmonics. In this paper, the set of masking frequencies is chosen as integer multiples of the 50 Hz frequency, since the raw recordings are disturbed by noise coming from the European distribution network operating at this fundamental frequency. However, a set composed of multiples of 60 Hz for non-European distribution networks or even a set derived from the recording's power spectrum density will serve just as well. The decomposition process is complete when all harmonic components are decomposed into intrinsic mode functions.

Subsequently, the intrinsic mode functions are nonlinearly modified. Specifically, each internal mode function is divided by its own envelope. This non-linear procedure suppresses the useful signal (the higher the amplitude, the more it will be suppressed), so that the remaining noise becomes dominant in the intrinsic mode function. In order to preserve the energy of already changed internal mode functions, each one is multiplied by the median of its own envelope.

After performing this non-linear modification for each of intrinsic mode functions, all the modified intrinsic mode functions are summed, representing the cumulative noise in recording. Finally, this cumulative noise is subtracted from the raw signal, leaving a legible ECG/IEGM.

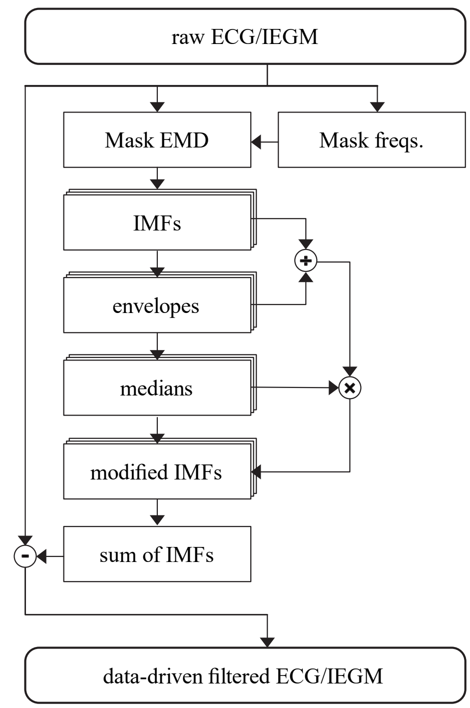


Figure 1. Principle of data-driven filtering method.

## 2.3. Cascade filtering

In order to obtain a signal that would serve as a gold standard for filtering quality evaluation purposes a different filtering approach was applied on dataset. All raw recordings were digitally filtered using a cascade filter. The cascade filter consists of a series of IIR (infinite impulse filter) notch (band-stop with narrow bandwidth) filters with a frequency given by integer multiples of 50 Hz and a quality factor of Q = 3.

## 3. Results

The data-driven filtering method was able to completely eliminate noise in both intracardiac and surface recordings. The morphology of the ECG/IEGM waveforms was not adversely affected.

## 3.1. Efficiency of the data-driven filtering

The data-driven filtering method is effective enough to completely eliminate noise in both ECG and IEGM recordings. A visual demonstration of the effectiveness of the data-driven filtering method is shown in Fig. 2, where the black curve represents the data-driven filtered signal and the gray curve shows the raw recording.

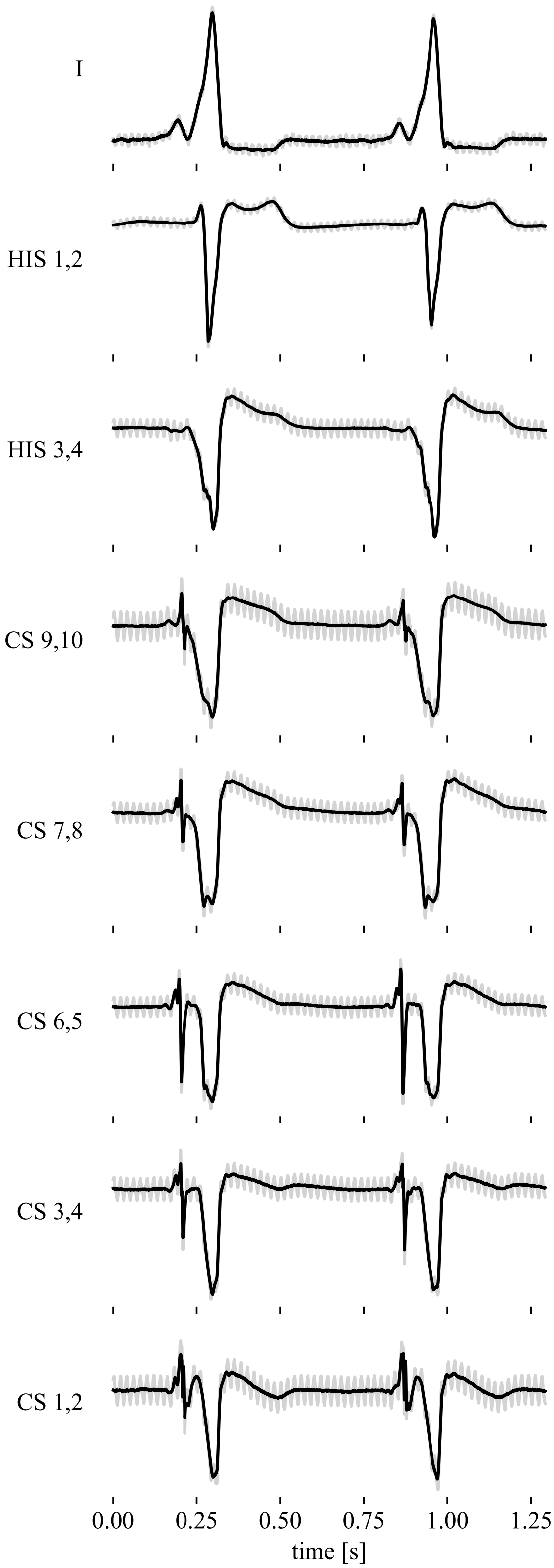


Figure 2. Comparison of filtered (black) and raw (gray) ECG and IEGM recordings.

Performance was also evaluated by comparing the estimated signal-to-noise ratio of raw ECG/IEGM recordings with its data-driven and cascade filtering versions. Results are shown at Table 1.

Table 1. Performance of filtering methods.

| Recording | Signal to noise ratio (estimated) |
|---|---|
| Raw | 12 dB |
| Data-driven filtered | 30 dB |
| Cascade filter filtered | 26 dB |

## 3.2. The ability of data-driven filtering not to distort the ECG/IEGM morphology

Data-driven filtering works better than cascaded filtering in situations where the raw recording voltage level changes rapidly. This occurs in the presence of pacing pulses or extrasystoles in the recording, or when the QRS complexes or waves A, V, H are steep.

The difference between data-driven filtering and cascade filtering is noticeable precisely at these moments. The ECG/IEGM recording filtered by the data-driven method does not contain any distortion, but the ECG/IEGM recording filtered by the cascade filter contains ripples in places of sharp signal breaks, as can be seen from comparison of Fig. 3 and 4.

## 4. Discussion

There are a number of filtering methods for ECG/IEGM filtering. None of these are universally applicable due to the complexity of ECG/IEGM morphology and the variety of sources of noise and interference. Therefore, the characteristics of the filtering method are selected based on the ECG/IEGM processing requirements. Desirable properties of filtering methods include high efficiency of noise suppression, minimal distortion of the morphology of the processed signal, usability without setting parameters by the user, the possibility of ECG/IEGM filtering in real time, low computational complexity and the possibility of adapting to time-varying noise.

The presented data-driven filtration method meets the requirement for high noise suppression efficiency and minimal ECG/IEGM distortion. It is resistant to human error due to the fact that there is no need to set its parameters and it works with the same settings on all intracardiac leads as well as all surface leads. It can cope with changes in the noise characteristics during the course. It automatically adapts to fluctuations in the frequency of the electrical distribution system.

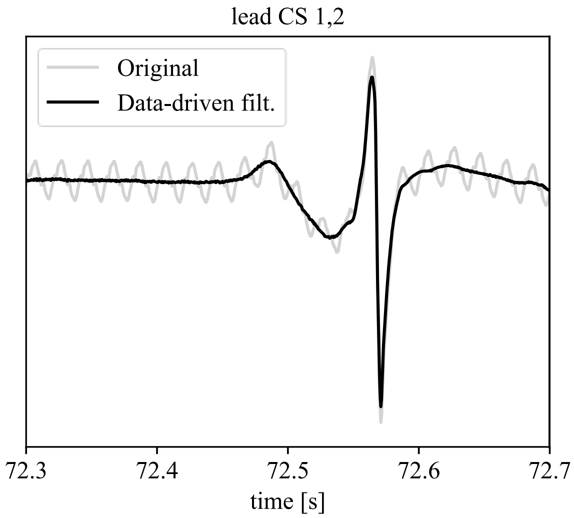


Figure 3. Detail of ECG/IEGM recording filtered by the data-driven method (black) and its raw version (gray).

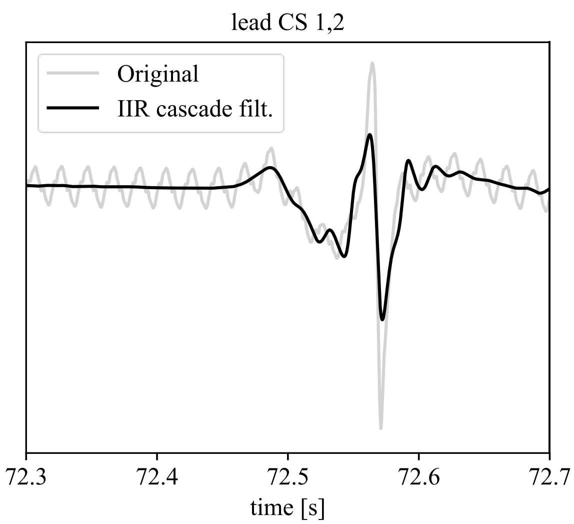


Figure 4. Detail of ECG/IEGM recording filtered by the cascade filter (black) and its raw version (gray).

From a practical point of view, it is important that data-driven filtering (in contrast to linear filtering using cascade filters) does not cause ripples in moments of rapid signal change, that is, in diagnostically significant moments whose serve to divide the ECG/IEGM into its particular waves and segments. (The presence of ripples is a problem because it makes both visual and automatic ECG/IEGM segmentation nearly impossible. In addition, the higher the quality of the notch filters, the more pronounced the ripple, which means that the more noise we want to filter, the greater the amplitude of these ripples.

The disadvantages of data-driven filtering include a higher (compared to common digital filtering using linear filters) computational complexity and, above all, the impossibility of real-time use, as its algorithm requires full length of the processed ECG/IEGM to be recorded. In addition, the method includes non-linear processing and automatically selects the degree of noise suppression in individual leads, so it can affect the total energy in the lead. This is not a problem when only ECG/IEGM morphology is of interest, but makes it impossible for voltage quantification purposes such as electrophysiological mapping.

The data-driven filtering is theoretically able to adapt to variable artefacts in ECG/IECG recordings, and in practice it does so on a pilot dataset, but for clinical use it would need to be tested on a much larger ECG/IECG datasets to verify the functionality of the data-driven filtering in all clinical scenarios.

## 5. Conclusion

The data-driven filtering method for smoothing ECG/IEGM records preserves the steepness of rapidly changing sections of IEGM (such as A, V, and H waves) and ECG (such as QRS complex) and at the same time smooths the rest of the recording. It has been proven on real-world clinical ECG/IEGM recordings that the data-driven filtering method removes noise even at high noise levels. Unlike other types of filtration techniques, the proposed method does not change the morphology of the signal, thus enabling both visual diagnosis and automatic ECG/IEGM classification that would not be feasible in the raw recordings.

## Acknowledgments

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## References

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