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Effects of denoising strategies on R-wave detection in ECG analysis*

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Abstract— **The use of ECG in cardiovascular health monitoring is well established. The signal is collected using specialised equipment, capturing the electrical discharge properties of the human heart. This produces a well-structured signal trace, which can be characterised through its peaks and troughs. The signal can then be used by clinicians to diagnose cardiac disorders. However, as with any measuring equipment, the ECG output signal can experience deterioration resulting from noise. This can happen due to environmental interference, human issues or measuring equipment failure, necessitating the development of various denoising strategies to reduce, or remove, the noise. In this paper, we study typically occurring types of noise and implement popular strategies used to rectify them. We also show, that the given strategy's denoising potential is directly related to R-wave detection, and provide best strategies to apply when faced with specific noise type.**

I. INTRODUCTION

Electrocardiography (ECG) is the study of the electrical activity of the heart. It is used clinically in the diagnosis of cardiac disorders such as atrial fibrillation [1]. ECG measures the relative change of electric potential in the body, exploiting the conductive properties of human skin. As such, the depolarisation and subsequent repolarisation of the cardiac muscle provides a well-structured signal trace, which can be characterised through specific intervals and segments, so called QRS complex [2]. One drawback of ECG is the possibility of the signal being corrupted with various types of noise, be it due to the nature of measuring equipment, human physiology or a random circumstance. This can cause misdiagnosis and can potentially hinder the efforts of clinicians [3]. A substantial body of literature concerned with denoising strategies, aimed specifically at ECG signals [4], [5], [6] can be attributed to the importance of ECG, especially in clinical settings.

A variety of methods have been designed and/or appropriated from different fields [7] to remove noise from ECG data, among them Discrete Wavelet Transform (DWT), Empirical Mode Decomposition (EMD), Variational Mode Decomposition (VMD), Non-local Means (NLM) and others. In the recent years, a number of implementations based on Deep Neural Networks (DNN) [8] and Variational Autoencoders (VAE) [9] have gained traction but are yet to enjoy the same popularity as above mentioned analytical methods. Ultimately, the choice of the denoising strategy is dictated by the application area, condition of the ECG signal and its response to each denoising method [5].

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DWT methods have become the de-facto preference of the community in the recent years [2], [6], [4]. By combining both, time- and frequency-domain analyses, DWT is well suited to inherently non-stationary signals such as ECG [5], [2]. These methods use wavelet functions to decompose the signal, along with its afflicting noise, into approximating components. These components are later used to find and remove the potential sources of noise, and for its subsequent reconstruction [4].

The use of the above methods in conjuction with one another also presents a viable denoising strategy, especially when accounting for each method's individual shortcomings. Indeed, the use of combined approaches has been studied before [5], [10]. Significant attention has also been given to methods based on EMD and VMD respectively [11], [12]. A study done by Lahmiri [5] compared the use hybridised methods based on EMD and VMD pre-processing and subsequent DWT thresholding using a variety of wavelets. This in particular includes the use of EMD and VMD, which are used as an initial pre-processing step for further decomposition and thresholding using DWT. The authors in [10] have used NLM as an initial step before decomposing the signal with EMD.

In this exploratory study, we focus on the effects of the most popular denoising strategies on various, commonly occurring types of noise, showing how capable the method is when faced with particular noise modality. We then use expert annotation as groundtruth, for the subsequent detection of the R-wave under said noise conditions and provide the strategy best suited to their denoising. We implement and test various denoising strategies capable of dealing with common types of noise. We then perform a validation of the methods using popular R-wave detection algorithm. Finally, we show the effects of various denoising strategies on R-wave detection.

The paper is structured as follows: First, in Section II we introduce the dataset, including the types of noise. We then address the methods contained therein in Section III. We explain the experimental setup in Section IV and show the results in Section V. We conclude in Section VI.

II. DATA

A. Types of noise

This paper will consider common types of noise, emblematic of physiological data [13]. These include Additive White Gaussian Noise (AWGN), Baseline Wander (BW), Powerline Interference (PL) and Motion Artefacts (MA). This list should not be treated as exhaustive - these types of noise have been chosen to best exemplify the signal collected 'in-the-wild'.

1) Additive White Gaussian Noise: AWGN is a common model of signal noise, stipulating equal energy across all spectral bands. This type of noise is naturally occurring and is often described as being accountable for a variety of deficiencies stemming from imperfect information channels, such as ECG leads [13].

2) Baseline Wander: BW is noise typical to idle physiological function [14]. Its source can be attributed to patient respiration or motion artefacts [15]. It is manifested as a low-frequency oscillation of the ECG.

3) Power-line Interference: This type of noise frequently happens due to the exposure to the power line of the device, either through its cables or the patients themselves [16]. It can be shown to be a steady 50/60Hz oscillation on top of the desired signal.

4) Motion Artefact: As a result of the movement brought on by the patient's, the electrodes can shift, resulting in a gradual wander of the signal as well as transient, high frequency oscillation [13].

B. Databases

In this work, we employ the MIT-BIH Arrhythmia Database [17], [18], commonly used for validating state-of-the-art algorithms [19]. It includes a total of 46 MLII-lead signals which we use for the analysis of the signal in the presence of noise. Here, we utilise the signals, sampled at 360Hz, of one minute in length. In order to synthesise the noise on the ECG signal we further utilise the MIT-BIH Noise Stress Database [20]. The database includes the noise extracted from ECG signals, which we make use of in our work, particularly BW and MA.

III. METHODS

A. Denoising fundamentals

1) Discrete Wavelet Transform: DWT considers the use of low- and high-pass filter banks as a decomposition mechanism [21]. This ensures that, in the process, the signal along with the overlaying noise is decomposed as part of their low-frequency approximation coefficients and high-frequency details. The process of decomposition to a signal level is formalised, for low and high pass filter banks, as follows [21]:

$$A[k] = \sum_{N} x[n] \times h[2k-n] \tag{1}$$

$$D[k] = \sum_{N} x[n] \times g[2k-n] \tag{2}$$

2) Stationary Wavelet Transform: SWT is intimately related to DWT, with the exception of oversampling of the coefficients. The main difference between DWT and SWT is the lack of decimation step during the convolution of the signal [22], instead padding with zeros. This results in the decomposed levels maintaining the length of the original signal.

3) Empirical and Variational Mode Decomposition: EMD is based on the assumption of non-stationary and non-linear nature of the signals, often exhibited in ones collected 'in-the-wild' [23]. The basic formulation of the EMD makes use of Intrinsic Mode Functions (IMFs), which can be defined as the decomposition of signal into n empirical modes and residue given by [5]:

$$x(t) = \sum_{i=1}^{n} c(i) + r_n \tag{3}$$

where $x(t)$ is our signal, $c(i)$ is the IMF and r_n denotes the residue at level n.

VMD decomposes the signal into Variational Mode Functions (VMFs), by extracting the signal's center frequency ω_n along with modes u_n at level n. It follows that the sum of all modes, across all levels, would be the original signal [23].

4) Non-local Means: NLM approach has been explored in ECG before [10]. The basic assumption is that the samples exhibit a non-local similarity due to their structured form. The idea behind NLM, is that denoising follows an estimate of the surrounding samples, windowed in patches. As such:

$$\hat{u}(m) = \frac{1}{Y(m)} \sum_{n \in N(m)} w(m,n)x(n) \tag{4}$$

For further notes about NLM applied to ECG denoising, we refer to [10].

5) IIR Filtering: We additionally employ a simple IIR comb filter, centered on 60Hz, as a basic measure of denoising. A 60Hz element, along with its harmonics, can be easily removed with a comb filter. This method will be used as a control of other denoising approaches, in order to establish whether basic filter is capable of outperforming an engineered denoising solution.

IV. EXPERIMENTAL SETUP

In this section we will outline the experimental setup, which served as a platform for the evaluation of the methodologies under various noise stress conditions. The synthesis depends on the source of the signal: for simple AWGN and PL noise the use MATLAB functions (MATLAB 2020b) is sufficient to create a viable testbed. Noise such as MA and BW was taken from the Noise Stress database, and as such, is not subject to randomness. Here we assume that we have access to the entirety of the recording for each noise type ($>$ 30 mins for MA and BW). This is also the main assumption behind the use of only 1 minute data segments from MIT-BIH Arrythmia database - the type of noise and its length greatly affects the denoising result.

A. Denoising Evaluation

In order to evaluate the performance of the denoising strategies, we use 2 distinct signal evaluation metrics - SNR improvement and Mean Square Error (MSE). These metrics are considered state-of-the-art in literature [24] and have been previously used to evaluate methods which make use of MIT-BIH Noise Stress test database [24]. To formalise the

TABLE I

TABLE OF DENOISING PARAMETERS FOR DIFFERENT METHODOLOGIES.

Method	Params
Wavelet-based	Wavelet → *sym4* Threshold → *soft SURE* Decomp level → 4
NLM	Patch width → 15 Search Neighbourhood → 50
IIR	Q factor → 10 Center frequency → 60Hz

methods, given a true signal $x(n)$, its noise-polluted version $y(n)$ and a denoising output estimate $\hat{x}(n)$, we can define the metrics for N signal instances as follows:

$$\text{SNR}_{imp} = 10 \times log \times \frac{\sum_{n=1}^{N}(y(n) - x(n))^2}{\sum_{n=1}^{N}(\hat{x}(n) - x(n))^2} \tag{5}$$

$$\text{MSE} = \frac{\sum_{n=1}^{N}(x(n) - \hat{x}(n))^2}{N} \tag{6}$$

B. R-wave Detection Evaluation

In order to perform R-wave detection, we use the available MIT-BIH Arrythmia annotations. We assume that the annotations of a Normal, Paced, Left and Right Bundle Branch constitute a viable heartbeat for our analysis. We further utilise the Pan-Tompkins QRS detector [25], [26] due to its versatility and popularity. To evaluate the peak detection we use sensitivity and accuracy analysis, given by [27].

V. RESULTS

A. AWGN-based denoising

The use of AWGN as a basis for denoising shows how the capabiity of each strategy when faced with random perturbations. As the SNR of the system decreases, so does the denoising potential of all employed strategies. Top half of Figure 1 shows the effects of all denoising methods with decreasing AWGN noise. Understandably, the worst performing of method is IIR_COMB, incapable of reducing the noise floor of the signal across all frequencies. When averaged across all inputs, DWT shows the largest relative improvement in SNR. This is likely due to the fact, that during the decomposition of the signal, the ECG trace is the most evident signal structure, and is clear enough for the algorithm to threshold properly.

B. PL/MA/BW-based denoising

The bottom half of Figure 1 shows the MSE result for the various denoising strategies, as applied to different type of noise. The denoising of PL understandably yields the best result on average, as this type of noise is highly predictable, structured and at high frequency. Conversely, due to the low-frequency nature of BW, the methods which are mostly capable at denoising higher-frequency components, struggle when presented with this type of noise. This is evident in Figure 2. The best performing strategy for MA was found to be NLM, performing well when faced with transient high frequency noise.

The addition of IIR_COMB in method comparison showed that the use of a simple filter can be viable in the face of

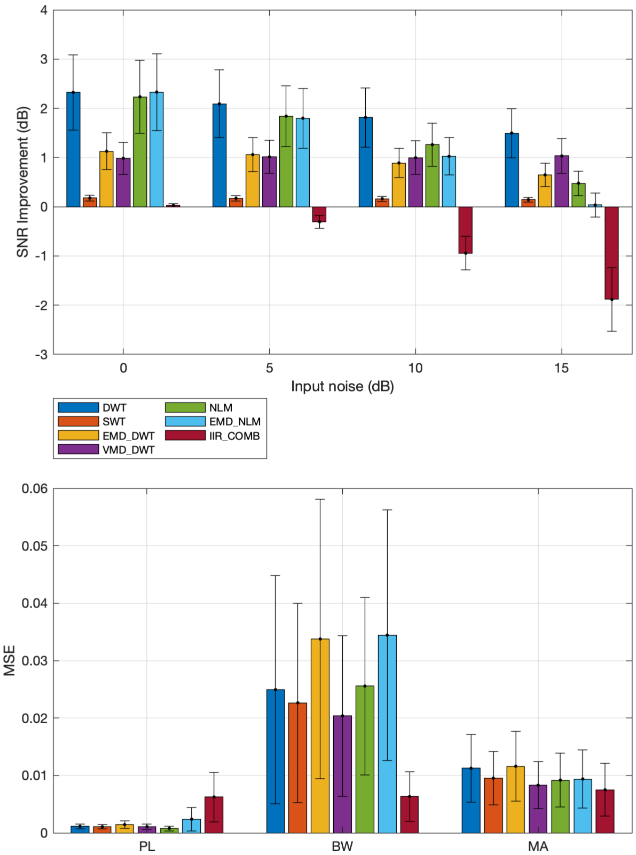

Fig. 1. SNR improvement (top) of various denoising and filtering methods per decreasing AWGN noise and MSE per noise type (bottom) for each denoising strategy.

typical noise. This can be attributed to its relative simplicity over other methods - note that the parameters governing the methods were not optimised over each noise type, opting instead for a general approach, which gave best results on average. This can also explain the poor performance of the EMD-based methods on BW - it is likely that the extraction of the final residual was poor, compared to the removal of transient high-frequency noise, such as MA, or more structured noise such as PL.

C. R-wave detection

The analysis of the denoising data showed that, in the list of denoising strategies we consider in this work, there exist clear choices of strategy when faced with a particular type of noise. This is tabulated in Table II. The table considers the performance of the R-peak detection after the denoising for various methods. The best-performing strategies have been emboldened along with their performance in each category.

Among the understandable results, such as the prevalence of IIR_COMB for PL and BW, the table also shows that the NLM-based methods tend to dominate in FP discrimination, likely owing due to the removal of high frequency components of the signal.

VI. CONCLUSION

This study showed the importance of appropriate denoising strategy in ECG analysis. It has also addressed the performance of R-peak detection when applied to various denoised

TABLE II
R-PEAK DETECTION RESULTS. NOTE, THAT THESE RESULTS INDICATE PER-BEAT RESULTS USING ANNOTATIONS FROM MIT-BIH.

Type	Method	TP	FN	FP	Sen	Acc
5dB AWGN	DWT	3222	4	100	99.87%	96.87%
	SWT	3221	5	106	99.84%	96.66%
	EMD_DWT	**3224**	**2**	105	**99.93%**	96.78%
	VMD_DWT	3222	4	99	99.87%	**96.90%**
	NLM	3197	29	**88**	99.10%	96.46%
	EMD_NLM	3198	28	93	99.13%	96.35%
	IIR_COMB	3223	3	100	99.90%	**96.90%**
PL	**DWT**	**3224**	**2**	93	**99.93%**	**97.13%**
	SWT	**3224**	**2**	95	**99.93%**	97.07%
	EMD_DWT	**3224**	**2**	97	**99.93%**	97.02%
	VMD_DWT	**3224**	**2**	94	**99.93%**	97.10%
	NLM	3195	31	93	99.03%	96.26%
	EMD_NLM	3192	34	**92**	98.94%	96.20%
	IIR_COMB	**3224**	**2**	95	**99.93%**	97.07%
BW	**DWT**	**3224**	**2**	94	**99.93%**	**97.10%**
	SWT	**3224**	**2**	94	**99.93%**	**97.10%**
	EMD_DWT	**3224**	**2**	95	**99.93%**	97.07%
	VMD_DWT	**3224**	**2**	97	**99.93%**	97.02%
	NLM	3159	67	96	97.92%	95.09%
	EMD_NLM	3136	90	**93**	97.21%	94.48%
	IIR_COMB	**3224**	**2**	95	**99.93%**	97.07%
MA	DWT	3222	4	108	99.87%	96.64%
	SWT	3223	3	107	99.90%	96.69%
	EMD_DWT	**3224**	**2**	111	**99.93%**	96.61%
	VMD_DWT	**3224**	**2**	112	**99.93%**	96.58%
	NLM	3180	46	97	98.57%	95.69%
	EMD_NLM	3187	39	**95**	98.79%	95.96%
	IIR_COMB	**3224**	**2**	106	**99.93%**	**96.75%**

signals, and that the autonomous R-peak detection can be improved when using an engineered denoising strategy.

Further work would study the combinations of noise modalities and their effect on the R-peak detection.

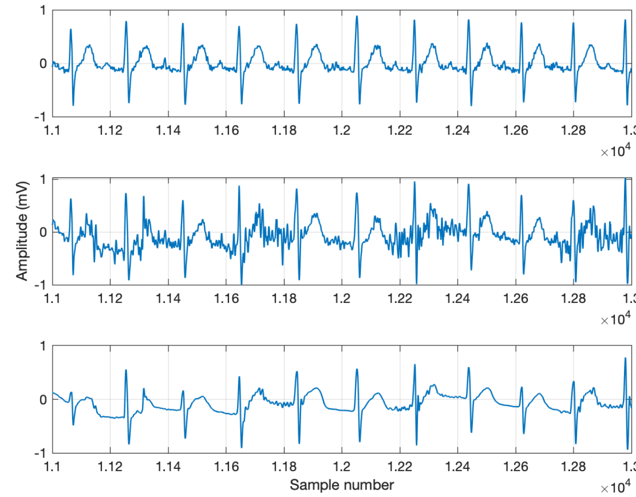

Fig. 2. Example showing the denoising of Record 215 between samples 11000-13000 (30s-36s). Top panel shows the clean data, middle panel is the MA-injected signal and bottom panel shows the signal denoised using NLM.

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