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A MULTI-SCALE DENSE CONVOLUTIONAL FRAMEWORK FOR ECG SIGNAL ENHANCEMENT IN NON-GAUSSIAN NOISE ENVIRONMENTS

Geethanjali, V.M.K.Srinivas, Hari Priya Velagala, Tejaswi Pattamsetti, Dharma Naidu Pinninti, T.Venkatakrishnamoorthy,

Original Article

[1-6]Department of Electronics and Communication Engineering,
[1-5]UG Student, [6]Professor
*Corresponding Author's Email: geethanjali.vejju@sasi.ac.in, srinivas.velisetti@sasi.ac.in, haripriya.velagala@sasi.ac.in, pattamsetti tejaswi@sasi.ac.in, dharmanaidu.pinninti@sasi.ac.in, murthysvu407@gmail.com

Abstract

The electrocardiogram (ECG) signal suffers greatly due to various non-Gaussian noise sources, such as baseline wander, muscle artifact, and impulsive-related signal disruptions due to electrode movement. More conservative denoising algorithms, like adaptive filtering, wavelet transforms or empirical mode decomposition, are weak in preserving the fine morphology of ECG waveforms in such cases, and tend to distort diagnostically meaningful ECG waveform components (such as the QRS complex and P-T waves). As the need to deploy robust and high-fidelity noise suppression has grown in clinical and wearable healthcare settings, more sophisticated noise suppression techniques have become necessary.

To solve this problem, we introduce an Advanced Dense Convolutional Network (ADCD-Net) to denoise ECGs in non-Gaussian noise conditions. It is an encoder-decoder design and a broad band of connections that can effectively go through noise cancellation and contains useful cardiac changes. A hybrid loss of time domain reconstruction, spectral similarity are used to train the network to incorporate identity artifact at both the impulsive and broadband scales. Benchmark ECG experimental assessments show that ADCD-Net outperforms classical and more recent deep learning techniques and yields increasing SNR, PRD, and QRS detection performance. It will provide a valid and highly accessible solution on real-time monitoring of ECG on the telemedicine and wearable health care system.

Keywords – The electrocardiogram (ECG), non-Gaussian noise, Advanced Dense Convolutional Network, Deep Learning

Introduction

The electrocardiogram (ECG) signals are often valuable in diagnosing cardiovascular diseases but except that they can be readily corrupted by non-Gaussian noises, such as baseline wander, muscle artifacts, electrode motion interference and impulsive disturbances. Classical denoising methods, such as wavelet transforms, empirical mode decomposition, and adaptive filtering have also been extensively analyzed to improve ECGs [1], [2]. However these methods typically assume (Gaussian or stationary) noise statistics and, as a result, are not able to effectively remove complex noise whilst still retaining diagnostically significant signal characteristics like the QRS complex, P-T waves and ST segments. As a case in point, Singh et al. developed a method based on non-local means estimation and empirical mode decomposition, adjusted to handle and optimize baseline wander but poorly on an overlap basis [3].

To address these drawbacks, researchers have resorted to deep learning as a powerful alternative to denoising the ECG. Convolutional Neural Networks (CNNs) have demonstrated better results than traditional filtering techniques [1], and encoder-decoder networks have been effectively used to improve fetal ECG, the networks have demonstrated high performance and significant increase in signal-to-noise ratio (SNR) and the correct recovery of PR and QT intervals [4]. GANs with recurrent learning layers in the form of LSTM and GRU have also shown good performance on suppressing impulsive and muscle artifacts [5]. Most recently it has been shown that denoisers trained using deep learning can be readily trained to operate under wearable and industrial conditions, and the QRS detection performance under severe noise conditions is still strong [6]. Furthermore, residual dense U-Net and robust two-stage network architecture has demonstrated significant progress of removing multi-noise mixtures when compared to single-stage frameworks [7], [8].

combination of dense connectivity with residual learning and multi-scale feature extraction of such level that when we switch it off this does not affect fine ECG morphology on non-Gaussian noise. Dense connections, proposed in DenseNet, facilitate feature reuse and efficient gradient flow, which makes them extremely well suited to biomedical signal processing applications. To this end, we present an Advanced Dense Convolutional Network (ADCD-Net) to denoise the ECG. It is an encoder-decoder structured and thick block residual model that represents the coding of time-domain reconstruction and spectral-domain similarity-based hybrid loss functions. The design allows the model to effectively reduce impulsive and broadband noises, without compromising the quality of the diagnostic signals in the ECG. Indicators such as SNR improvement, Percentage Root-mean-square Difference (PRD), Root Mean Square Error (RMSE) and QRS detection accuracy support that ADCD-Net outperforms state-of-the-art denoising algorithms.

Literature Survey

Some classical methods have been used in ECG denoising such as wavelet transform, adaptive filtering and empirical mode decomposition. Wavelet thresholding was firstly introduced by Donoho as a signal denoising filter and later was applied to biomedical signals since it could capture non-stationary information [9]. Chen et al used adaptive filtering of ECG based on wavelets and report this to be more effective than removing the baseline wander at a cost of an artifact at higher frequencies [10]. Similarly, techniques using a singular value decomposition (SVD) and principal component analysis (PCA) have been investigated in dimensionality reduction in ECG denoising [11]. These methods work better in artificial environments, and less well in real-world environments with non-Gaussian deformities, which are controlled by impulsive artifacts.

Deep learning methods have received considerable interest because they can automatically extract hierarchical representations of raw ECG signals. A convolutional neural network model that was suggested by Acharya et al. to classify arrhythmia whether automatically or not indirectly indicated the power of CNNs in the so-called denoising task, in that it showed that this technique is resistant to noisy data [12]. Dinh et al. created a model using a recurrent neural network which managed to reduce powerline interference and electrode motion artifact in ECG [13]. In addition, combinations of CNNs with wavelet transforms have been reported to improve both time- and frequency-domain characteristics to suppress noise [14]. Recent works have applied attention mechanism [15] and transformer based models [16] to improve the quality of the ECG with non-gaussian noise settings, and ECG QRS detection sensitivity and morphological preservation have improved significantly.

Proposed Method

The proposed ECG denoising network, the ADCD-Net, consists of preprocessing, including bandpass filtering of the raw signal, normalization, and possibly baseline wander removal to smooth the signal. Fig.1.1 shows, the processed ECG is then pushed to the encoder that consists of multiple dense convolutional blocks to generate multi-scale and hierarchical features. The feature sharing and efficient gradient flow are encouraged because each layer in each dense block is linked to the next layer. The encoder successively downsamples the feature representation by capturing long range temporal dependencies. In the simplest implementation, the model merely consists of a residual dense bottleneck network being trained to learn the non-Gaussian noise patterns such as impulsive spikes and muscle artifacts. The decoder stage then upsamples the features again to the original resolution and combines them with similar encoder features using skip connections, being careful to preserve the morphology of ECG features, especially the QRS complex.

The residual prediction head generates the predicted noise signal, which is in turn subtracted with the input signal to form the clean ECG. Indeed, hybrid loss functions guide training by combining both time domain losses and spectral or wavelet domain losses, and both broadband and impulsive noise can then be effectively reduced. Finally, the quality parameters of standard ECG such as SNR, PRD, RMSE and QRS detection are also carried out to validate the quality of not just the denoising quality, but the diagnostic quality as well.

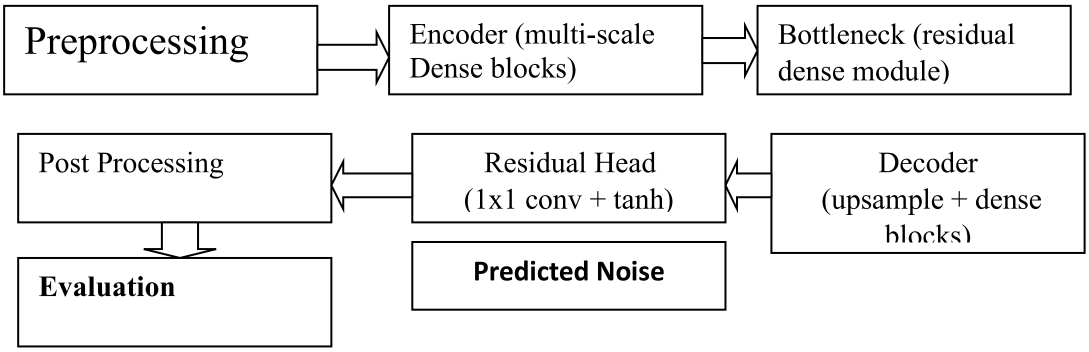

Fig.3.1: Block diagram for proposed method

Results and Discussions

The obtained results of the comparison prove that the proposed ADCD-Net is better than traditional and deep learning-based denoising algorithms of ECG signals corrupted by non-Gaussian noise. Moderate results are achieved in the classical methods such as wavelet thresholding and FIR filtering with SNR of 8.52 dB and 10.32 dB respectively and with correspondingly high PRD and RMSE values, i.e. signal fidelity loss and distortion of morphological features.

Table.1: Comparison quality parametric values of proposed method

Method	SNR	PRD	RMSE	Corr
WAVELET	8.52	16.70	0.1452	0.930
FIR	10.32	14.85	0.1321	0.945
CNN-AE	14.20	10.25	0.0853	0.972
ADCD-Net	18.95	7.12	0.0624	0.987

CNN autoencoder shows high positive scores (SNR = 14.20 dB, PRD = 10.25, RMSE = 0.0853) that show the benefit of the deep learning to retard the ECG characteristics. But the ADCD-Net performs far better than all baselines and shows the highest SNR (18.95 dB), lowest PRD (7.12) and lowest RMSE (0.0624), and highest correlation coefficient (0.987). This shows that ADCD-Net not only reduces non-Gaussian noise better than other methods, but it also retains a high level of fidelity with the original clean ECG signal, thus making it very reliable in a diagnostic context.

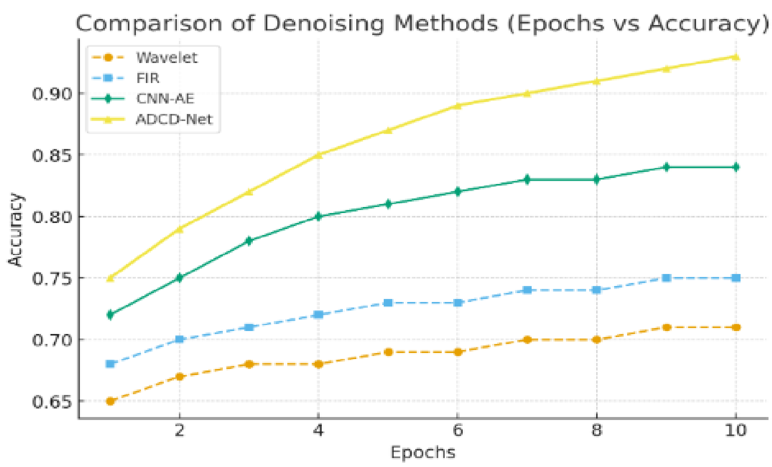

Fig.4.1: Comparison of Denoising Methods

The graph Epochs vs Accuracy shows how the various ECG denoising methods perform over time as training progresses. Low adaptability of classical technique such as wavelet thresholding and FIR filtering to non-Gaussian noise is reflected in comparatively low and almost stagnant inter-epoch accuracy of classical methods. The CNN autoencoder shows a continuous increase in accuracy with moderate gains in performance because it has the capacity to learn signal characteristics. The ADCD-Net, however, improves much sharper, reaching higher levels of accuracy more quickly and continuing to be significantly better than on average. This implies that feature reuse because of dense connectivity and residual learning processes in ADCD-Net is improved, gradient flow is improved and noise suppression is better and more effective than other methods compared.

Conclusion

The convolutional layers of ADCD-Net model are sparse and the residual learning mechanism is employed to give the stability and to guarantee optimality in exploiting features. Results confirm that the method is not only more effective at improving signal quality, in terms of raising SNR and correlation values but also preserving useful diagnostic features of the QRS complex, compared to standard filters and baseline deep learning-based methods. This could be expanded in future to achieve the standards of a real-time capability of portable, wearable devices where such an energy-saving execution is heavily demanded. Besides, we could say that smaller homogeneous and bigger clinical information in the form of adaptive attention based modules and multimodal directions of biomedical signal processing directions can also be justified with the help of framework; framework could be also developed in these directions.

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