Fars Samann* and Thomas Schanze

Use of a trained denoising autoencoder to estimate the noise level in the ECG

Abstract: Noise level estimation plays an important role in many applications of signal and image processing, like denoising, compression and detection. Recently, deep neural networks have also been increasingly used for this purpose. In this paper, we develop an effective algorithm of noise level estimation of ECG segments based on trained denoising autoencoder (DAE) with a statistical thresholding method. An important observation is that a well-trained DAE model provides a clean representation of the corrupted training dataset. Two identical cascaded trained DAE models are considered to estimate the statistical properties, e.g., mean and standard deviation, from the trained DAE outputs after applying noise free aligned and jittered training dataset respectively. Two statistical thresholds are calculated from these statistical properties to classify whether the ECG segment is noise-free or jittered or noisy segment. The accuracy of the proposed method is quite promising in classifying and estimating unknown noise level.

Keywords: Noise level estimation, Trained denoising autoencoder, Statistical thresholding method

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1 Introduction

During the acquisition of biomedical signals, like electrocardiogram (ECG), it is usually corrupted with additive Gaussian white noise. The impact of the noise on the morphology of the ECG signal may be significant. In many

neural network applications, such as denoising, compression and detection, the noise level of the input signal of the training dataset must be estimated.

An important current state of art in noise level estimation, especially in image processing, are noise level estimation based on first detail coefficients of wavelet decomposition [1] and local principal component analysis [2], another approach is the use of neuronal networks [3, 4]. We aim here to develop a simple algorithm to classify whether the input segment is noise-free or noisy or jittered and to estimate the noise level of the noisy input. The proposed algorithm is based on a well-trained denoising autoencoder model [5] to estimate a clean representation of the noisy corrupted training dataset. Two identical trained DAE models are then used to calculate the statistical parameters (e.g., mean, and standard deviation) of noise-free dataset and jittered dataset. These parameters are used to estimate two statistical thresholds for the classification and subsequent noise level estimation.

2 Materials and methods

The proposed noise level estimation is based on two identical cascaded trained DAE models (Figure 1). They are used to define two thresholds from the statistical properties (e.g., mean μ and standard deviation σ) of their outputs.

Figure 1: Two identical cascaded trained DAE models are used, where the first DAE is used to detect the noise-free ECG segment through the estimated statistical properties of noise-free segment (μ_1 & σ_1), while the second DAE is used to differentiate between noisy and jittered ECG segment using the estimated statistical properties of jittered segment (μ_2 & σ_2).

*Corresponding author: **Fars Samann:** Technische Hochschule Mittelhessen (THM), FB Life Science Engineering (LSE), Institut für Biomedizinische Technik (IBMT), Wiesenstr. 14, 35390 Gießen, Germany, e-mail: fars.esmat.fathel.samann@lse.thm.de, Department of Biomedical Engineering, University of Duhok, 42001 Duhok, Kurdistan Region-Iraq

Thomas Schanze, Technische Hochschule Mittelhessen (THM), FB Life Science Engineering (LSE), Institut für Biomedizinische Technik (IBMT), Wiesenstr. 14, 35390 Gießen, Germany, e-mail: thomas.schanze@lse.thm.de

2.1 ECG segment preparation

The database of CPSC 2018 [6] is considered to establish training, testing and validation datasets of 300, 100, 100 QRS complex aligned ECG segments from 30, 10, 10 healthy patients respectively (segment length $m = 80$ samples and $f_{\text{sampling}} = 100$ Hz). All the ECG segments are filtered by a third-order low-pass Butterworth filter with $f_{\text{cutoff}} = 35$ Hz and then resampled from 500 Hz to 100 Hz using FIR antialiasing filter. Jittered training and testing datasets are created by introducing a random misalignment of maximum 5 samples. These uniformly jittered datasets are introduced for a more realistic threshold estimation and performance evaluation.

2.2 Trained denoising autoencoder

We consider our previous work on estimating the optimal hidden units for denoising autoencoder. The proposed DAE model consists of single hidden layer with hyperbolic tangent as activation function [5], where the DAE model is trained with corrupted training and validating dataset of different noise levels (SNR= 5dB, 15dB and 25dB). While a corrupted testing dataset with SNR= 10dB is considered for estimating optimal number of hidden neurons, it is found to be 12. The weights and biases are optimized during the training process to reduce the error of reconstruction. Mean square error (MSE) and adaptive moment estimation (Adam) are used as loss function and optimizer respectively for the compilation of DAEs model. The proposed DAE is developed using ‘tensorflow’ library for machine learning in Python 3.7.

2.3 Statistical threshold estimation

We assume the additive noise has Gaussian distribution. The statistical threshold value th depends on the mean μ and the standard deviation σ [7],

$$th = \mu + \sigma c, \quad (1)$$

where the $c = q(p)$ is the critical value which is calculated using the quantile function q for specific probability p as shown in Figure 2. The quantile function, known as an inverse cumulative distribution function, specifies the value of a random variable where its probability being less than or equal to the given probability [7]. Two statistical thresholds th_1 and th_2 are considered for classifying ECG segments. We estimated the first threshold th_1 after applying clean aligned training dataset by considering the mean μ_1 and the standard deviation σ_1 of the highest peak (see Figure 3). Then, the mean μ_2 and the standard deviation σ_2 are estimated after applying

jittered training dataset to calculate th_2 (see Figure 4). For th_1 and th_2 , we considered probability equals to $p_1 = 90\%$ and $p_2 = 95\%$ to estimate the c_1 and c_2 , respectively (see Figure 2).

Figure 2: The quantile function of the normal distribution.

Figure 3: The density distribution of means and standard deviations of QRS aligned training dataset obtained from the first DAE model.

Figure 4: The density distribution of means and standard deviations of jittered training dataset obtained from the second DAE model.

2.4 Classification algorithm

Since we trained the DAE model with QRS aligned-noisy training dataset, so the relation between the input and the output of the trained DAE model is directly related to the representation of QRS aligned ECG segments. Therefore, the aim of classification is to make sure that a jittered ECG segment will not be considered as a noisy segment.

Figure 5: Flow chart of the proposed classification algorithm.

We consider the Euclidean distance (Ed1 and Ed2) between the input and the output of first and second trained DAE model (DAE1 and DAE2) respectively, with aids of two statistical thresholds to classify whether the unknown ECG segment is either noise-free, noisy or jittered (see Figure 5). Since both DAE1 and DAE2 provide a clean representation of noisy segment, therefore, the DAE1 is used to detect the noise-free segments because the noisy and jittered segment have high Ed1 at the output of DAE1. However, the noisy segment has very small Ed2 at the output of DAE2 due to the noise reduction by DAE1, while the Ed2 of jittered segment is little bit high due to jittering effect.

2.5 Noise level estimation methods

2.5.1 Proposed method

When an ECG segment is classified as a noisy segment, then the noise level is estimated by considering the residual signal

$r[i] = x[i] - \tilde{x}[i]$, where $x[i]$ is the input ECG segment of the DAE1 model, while $\tilde{x}[i]$ is the output ECG segment of the DAE2 model. We assume that the standard deviation of the noise level approximately equals to the standard deviation of $r[i]$,

$$\sigma_{est} \approx \sigma(r[i]). \quad (2)$$

2.5.2 Noise level estimator based on first level detail coefficients D1

The noise level estimation is based on the median absolute deviation (MAD) from the first level detail coefficients d1 to compute the standard deviation as follows [1],

$$\sigma_{est} = MAD / 0.6745, \quad (3)$$

where $MAD = median(|D1|)$ is the median absolute deviation of the wavelet first level coefficients. We consider a mother wavelet 'sym4' with three levels decomposition.

2.5.3 Noise level estimator based on PCA with local thresholding method

The principal component analysis (PCA) is a transformation of the data to a new subspace, where the few first components often represent most parts of the dataset. The PCA method compute the eigenvectors (PCA coefficients) $\mathbf{W} \in \mathbb{R}^{m \times m}$ and eigenvalues $\mathbf{D} \in \mathbb{R}^{n \times m}$ of the dataset matrix $\mathbf{X} \in \mathbb{R}^{n \times m}$, where n corresponds to observations, and m corresponds to variables. We compute the variance of each principal component in $\mathbf{D}$. Since we are targeting noise, we neglect the principal components of high variance, which represent the signal, based on a specific threshold. The local threshold is calculated by computing the average variance of the local noise level σ_{local}^2 from the onset duration of the ECG segments [2],

$$Th_{local} = f \sigma_{local}^2, \quad (4)$$

where f is an adaptive factor with range between 1 to 3. The modified matrix $\hat{\mathbf{D}}$ is considered to compute the estimated noise level (σ_{est}) by the inverse PCA transformation,

$$\sigma_{est} = \sigma(\mathbf{W}^{-1}\hat{\mathbf{D}}). \quad (5)$$

3 Results

To check the performance of the noise level estimators, the 100 QRS-aligned ECG segments of the testing data set are corrupted with Gaussian white noise of different $SNR_t = 3\text{dB}$, 5dB , 10dB and 15dB , which are equivalent to average noise level $\sigma_{ref} = 0.117, 0.093, 0.052$ and 0.029 respectively. The

standard deviation of the error is considered as a metric of evaluation,

$$\sigma_{error} = \sigma(\sigma_{ref} - \sigma_{est}). \quad (6)$$

The accuracy of classifying noise-free, noisy and jittered of testing dataset is shown in table 1. Our proposed method is compared with D1-wavelet and PCA based method in estimating noise level. The average estimated standard deviation of the noise σ_{est} and the standard deviation of the error σ_{error} are located in table 2.

Table 1: The accuracy of classification algorithm.

Testing dataset	Accuracy %
Noise-free	95
Jittered	77
Noisy ($\sigma_{ref} = 0.117$)	86
Noisy ($\sigma_{ref} = 0.093$)	97
Noisy ($\sigma_{ref} = 0.052$)	100
Noisy ($\sigma_{ref} = 0.029$)	93

Table 2: The average reference standard deviation σ_{ref} of the noise vs the average estimated standard deviation σ_{est} of the noise.

Noise level σ_{ref}	D1-wavelet method		Local PCA		Proposed method	
	σ_{est}	σ_{error}	σ_{est}	σ_{error}	σ_{est}	σ_{error}
0.117	0.140	± 0.0097	0.207	± 0.0291	0.115	± 0.0021
0.093	0.111	± 0.0085	0.191	± 0.0232	0.092	± 0.0023
0.052	0.064	± 0.0055	0.170	± 0.0128	0.054	± 0.0028
0.029	0.037	± 0.0036	0.161	± 0.0072	0.034	± 0.0034

Figure 6: The estimated noise level σ_{est} of each ECG segment in case of noisy testing dataset with $\sigma_{ref} = 0.117$.

Figure 6 clearly shows that the proposed method is very effective in estimating the σ_{est} comparing with the other methods. Moreover, the proposed method estimated the σ_{est}

with very small standard deviation of the error σ_{error} for all noise levels. Contrarily, the local PCA method overestimated the noise level σ_{est} with very high σ_{error} because this method is very sensitive to the adaptive thresholding factor. The D1-wavelet method is also overestimated the noise level σ_{est} , this is because the detail coefficients D1 may contain some part of the ECG signal.

4 Discussion and Conclusions

We introduced an approach to estimate the noise level of ECG data. It uses QRS aligned ECG segments and two identical cascaded autoencoders in combination with novel methods for the separation of noisy and jittered data and noise level estimation. The approach has been successfully tested, using wavelet and PCA-based methods for noise estimation. The obtained results indicate that machine learning based methods (e.g. [3, 4]) can be used to separate jittered from noisy data and for denoising.

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