Available online at www.sciencedirect.com

ScienceDirect

Journal of Electrocardiology 51 (2018) 265 – 275

JOURNAL OF
Electrocardiology

www.jecgonline.com

A new multi-stage combined kernel filtering approach for ECG noise removal

Mazhar B. Tayel, PhD, Ahmed S. Eltrass, PhD,* Abeer I. Ammar, MSc

Department of Electrical Engineering, Faculty of Engineering, Alexandria University, Alexandria, Egypt

Abstract Electrocardiogram (ECG) signals are contaminated with different artifacts and noise sources which increase the difficulty in analyzing the ECG signals and obtaining accurate diagnosis of heart diseases. In this paper, a new multi-stage combined adaptive filtering design based on Kernel Recursive Least Squares Tracker (KRLST) and Kernel Recursive Least Squares with Approximate Linear Dependency (ALDKRLS) algorithms is proposed for removing artifacts and noise sources, while preserving the low frequency components and the tiny features of the ECG signal. The capability of the proposed approach is demonstrated by investigating several ECG signals from the MIT-BIH database and comparing the results with other adaptive filtering techniques. The results show that the combined ALDKRLS-KRLST approach is much superior in terms of attenuating artifacts components, sensitivity of ECG peak detection, and heart diseases diagnosis. This reveals the effectiveness of the proposed technique as an effective framework for achieving high-resolution ECG from noisy ECG recordings.

Keywords: ECG; Adaptive filters; Least Mean Square; Recursive Least Square; Kernel; Baseline wander

Introduction

The electrocardiogram (ECG) is a representation of the electrical activity of heart muscles, which is widely used in several clinical studies for interpretation and identification of heart disorders. According to the most recent statistics, provided by the World Health Organization (WHO), heart diseases remain the main specific reason of mortality in any region of the world. The ECG signal is a low amplitude voltage signal that can be distorted easily by different sources of noise, which cause poor signal quality and inaccurate clinical diagnosis. The most common noise sources are the Power Line Interference (PLI) which consists of a 60 Hz (or 50 Hz in some countries) sinusoid and its harmonics, the Baseline Wonder (BW) resulting from respiratory or patient movement with frequency ranges from 0.15 Hz to 3 Hz, and the ElectroMyoGraphy (EMG) which is an electrical potential with a broad spectrum generated by muscle cells [1]. These noise sources should be suppressed or cancelled to obtain reliable and high-quality ECG recording and consequently to provide accurate heart disease diagnosis. ECG noise removal is very important for accurate analysis in many ECG applications, e.g., beat classification [2], QRS detection [3], analysis of asymptomatic arrhythmia [4], fetal ECG signal extraction from the maternal abdominal ECG [5], ECG signal data compression [6], and the detection of heart diseases or disorders [1].

ECG noise removal is a very challenging and crucial task because of the time-varying and non-stationary nature of the ECG noise, especially its spectral overlap with the ECG signal. Several approaches have been proposed for removing different noise sources from the ECG signal. Blind Source Separation (BSS) techniques such as the Principal Component Analysis (PCA) and Independent Component Analysis (ICA) require linearly independent multichannel ECG recordings to be utilized in ECG noise removal [7]. These

Abbreviations: ALD, Approximate Linear Dependency; ALDKRLS, Kernel Recursive Least Squares with Approximate Linear Dependency; AF, Atrial Fibrillation; AFDB, Atrial Fibrillation Data Base; B2P, Back-to-the-Prior; BSS, Blind Source Separation; BW, Baseline Wonder; ECG, electrocardiogram; EMD, Empirical Mode Decomposition; EMG, ElectroMyoGraphy; FNs, False Negatives; GPs, Gaussian processes; ICA, Independent Component Analysis; KAF, Kernel Adaptive Filter; KLMS, Kernel Least Mean Square; KRLST, Kernel Recursive Least Squares Tracker; LMS, Least Mean Square; MIT-BIH, Massachusetts Institute of Technology–Beth Israel Deaconess Medical Center; MSE, Mean Square Error; NKLMS, Normalized Kernel Least Mean Square; PCA, Principal Component Analysis; PLI, Power Line Interference; PSD, Power Spectral Density; RLS, Recursive Least Square; TPs, True Positives; WHO, World Health Organization; WT, Wavelet Transform.

* Corresponding author at: Department of Electrical Engineering, Faculty of Engineering, Alexandria University, Alexandria, Egypt.
E-mail address: ahmed.eltrass@alexu.edu.eg

https://doi.org/10.1016/j.jelectrocard.2017.10.009
0022-0736/

techniques provide good performance but with a high computational cost and a large amount of operating memory. Over the past several years, methods based on the Wavelet Transform (WT) were proposed to filter signals that have multi-resolution characteristics such as the ECG signal [8,9]. Recently, artificial neural networks have also been employed to remove the Gaussian and Baseline Wonder (BW) noise in ECG signals [10]. One of the common and effective methods used in ECG noise removal is the adaptive filter architecture, which is based on minimizing the error between the input ECG signal contaminated with different noise sources and a reference signal having a good correlation with the ECG noise source in order to estimate the noise characteristics [4]. The adaptive filtering techniques have a superior performance in tracking the non-stationary changes in both the ECG signal and the noise source.

The aim of this work is to propose a new multi-stage Kernel Adaptive Filtering approach for ECG noise removal with high accuracy and low computational cost. The proposed approach is based on Kernel Recursive Least Squares with Approximate Linear Dependency (ALDKRLS) [11] and Kernel Recursive Least Squares Tracker (KRLST) [12] algorithms. The remaining parts of this paper are structured as follows. The Theory section presents the structure of Kernel Adaptive Filtering (KAF), followed by an explanation of the proposed multi-stage ALDKRLS-KRLST filtering design for ECG noise removal. The Results section discusses the results of the proposed filtering approach, followed by a critical comparison with other existing adaptive filtering techniques. The sensitivity performance and the assessment of classification accuracy are also presented in the Results section. Finally, the discussion and conclusions are provided.

Theory

Conventional filters are not efficient in ECG noise removal because of the ECG data nonlinearity and the overlapped spectra between ECG signal and noise, while adaptive filters are capable of resolving these difficulties. An Adaptive filter is a digital filter which self-adjusts its transfer function according to an optimizing linear or nonlinear algorithm with an unknown environment input signal [13]. Linear adaptive filtering algorithms have a good performance with only linear data. For nonlinear data like the ECG signal, the mapping between the desired signal and the input signal is nonlinear so that nonlinear adaptive filters achieve better performance than linear filters. Kernel Adaptive Filter (KAF) is a type of nonlinear adaptive filters. Different KAFs were already utilized in ECG noise removal such as the Kernel Least Mean Squares (KLMS) and the Normalized KLMS (NKLMS) [14].

Kernel Adaptive Filtering (KAF)

Kernel methods offer an efficient online solution to deal with many problems in nonlinear signal processing. The main idea of kernel filtering is to transform the input data into a high-dimensional feature space in order to use the linear structure of this space to implement well-established linear adaptive algorithms such as the LMS [15] and RLS [11]. Kernel methods have the advantages of having convex loss functions, and of being moderately complex to implement [13,16].

Consider N pairs of training data $\{x(i), y(i)\}_{i=1}^{N}$, where $x(i)$ is the input vector at time i, and $y(i)$ is the output signal with $f_i(.)$ be the learned function at time i. When a new sample is available at time i, the function $f_i(.)$ makes a prediction $\hat{y}(i) = f_i(x(i))$. The aim of online learning is to update the prediction function sequentially by minimizing the cost or loss function J. With kernel methods, the prediction function $f(.)$ usually takes the form:

$$f(x) = \langle W, \varphi(x) \rangle_H = W^T \varphi(x) \tag{1}$$

where $\varphi(x)$ is the transformed data or the nonlinear mapping of the input data included by a Mercer kernel $k(x,x')$ which maps the input x to a high dimentional feature space H, W is a weight vector in H that should be estimated, and $\langle ., . \rangle_H$ denotes the inner product in H space. Updating the prediction function amounts for updating the weight vector W by minimizing the loss function J. The loss function J in Kernel Adaptive Filtering is chosen to be the Mean Square Error (MSE) due to its appropriate properties such as smoothness, low computational complexity, and convexity which is a very important feature that prevents the algorithms from being stuck in a local minima when solving the optimization problem of minimizing the loss function J. The loss function J can be expressed as:

$$J = E\left[|y(i) - f(x)|^2 \right] \tag{2}$$

Linear algorithms such as LMS and RLS are then applied to calculate W and obtain the optimum solution. Note that the online system requires updating its solution when new data becomes available, and the functional representation of classical kernel-based algorithms increases linearly with the number of processed data. This leads to a growing complexity for each consecutive update.

KRLST and ALDKRLS algorithms

KRLST algorithm

In order to obtain feasible online kernel algorithms, complexity growth can be reduced by representing the solution using only a subset of relevant bases according to certain criterion. Most KAFs are designed specifically for stationary data which is not the case for ECG recordings. Therefore, the non-stationarity behaviour of ECG data should be tracked with new KAF algorithms that include a mechanism for computing the solution which provides more weight to more recent data. Based on these considerations, the KRLS Tracker (KRLST) algorithm [12] is employed, for the first time, to track the non-stationary ECG data that exhibit nonlinear relationships by forgetting past information and by tracking changes in the target latent function. In this algorithm, a sensible mechanism for tracking is followed by handling the uncertainty about the input–output relationship, which can be considered as the latent function, and studying