DEEP NEURAL NETWORKS FOR ARTIFACT REMOVAL FROM DATA GENERATED BY NONLINEAR SYSTEMS: HEART RATE MONITORING

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Abstract Overview

Artifacts are disturbances in the measured signal not originating from the process itself. This paper addresses the problem of heart rate monitoring from photoplethysmography (PPG) sensor where artifacts caused by body movements affect the quality of the measurement signal. The PPG signal is processed by using the singular values decomposition technique to reduce signal noise. To remove the artifacts caused by physical activity of the subject, 3-dimensional accelerometer signal is used as the auxiliary signal and a novel spectral subtraction approach is proposed for signal processing. The denoised signal is windowed into consecutive time segments, and for each time-window of the processed signal and acceleration data, feature extraction is performed. Ground truth heart rate values are obtained from an electrocardiograph sensor during different types of physical activities to capture a broad range of heart rate variations. A fully-connected deep neural network is used to build a model from extracted features and actual heart rate values.

Keywords

Deep Neural Networks, Artifact removal, Heart rate monitoring, Signal processing, Singular value decomposition,

Introduction

Chemical and industrial processes usually contain elements of stochastic noise and disturbances which degrade the performance of the processes. Extensive research efforts have been devoted to filtering noises and attenuating disturbances to improve the process system operation [1]. Artifacts, however, present challenges that necessitate further investigation. Artifacts are disturbances in the measured signal not originating from the process itself. Artifacts may arise due to the nature of the measurement devices the location of their installation, the sensing technology of the sensors, and the susceptibility of the measurements to ambient or surrounding conditions. In contrast to process noise, artifacts can have power spectral densities and characteristics similar to the signal being measured, thus confounding the artifacts and the signal. Biochemical and biomedical systems utilize various sensors and measurement technologies that are prone to artifacts. The effective detection and removal of artifacts from measured signals are important as they can lead to significant interpretive errors [2]. Although, several methods to purify the processed signal from stochastic

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noise exist and enhance the quality of the measurement, removing artifacts from a corrupted signal requires novel advanced techniques and historical information of the signal. The problem of artifact removal is a challenging task because artifacts in the signals can arise from several unknown sources. Furthermore, it is not obvious whether fluctuations in the signal are due to underlying variations or artifacts. Models relating artifacts to the observed effects in the output measurements are also unavailable as the origins and the effects of the artifacts vary substantially.

Approaches for artifact removal have focused on passive and active filtering techniques. Passive techniques isolate the measurement devices from external factors, yet it may not be always feasible or practical based on the process design and operation setup. Active filtering relies on the use of a reference signal to adaptively deconstruct the measured signal into components associated either with the artifacts or the underlying signal. Adaptive filtering techniques have been effective in adaptive noise cancellation applications where the on-line estimation of the time-varying correlations between the reference signal and the artifacts is possible. Nevertheless, numerous applications do not have a highly informative and conveniently obtainable reference signal. Recent advances in signal processing and deep learning can further advance the tools available for artifact removal, particularly in highly susceptible and sensitive applications.

One application where artifacts are prevalent and pronounced is the measurement of heart rate using photoplethysmography (PPG), a non-invasive and low-cost optical technique used to measure the heart rate variation. The PPG technique measures the rate of heartbeats by detecting changes in the backscattered light corresponding to volumetric changes in blood in peripheral circulation. The PPG measurements are highly susceptible to disruption from artifacts caused by motion of the device (usually worn as a wristband) and other noise sources such as ambient light interference and skin condition.

Motion is a major challenge in obtaining accurate measurements as constant movements result in poor contact between the measurement skin surface and the photosensor [3]. Motivated by the above considerations, a framework for artifact removal is developed with application to the heart rate estimation problem.

The PPG signal is first divided into consecutive overlapped time-windows to facilitate batch-wise processing and a bandpass filter used to reject undesired variations. Wavelet approximation and orthogonal signal reconstruction are then applied to reject the artifacts and noise in the signal. A feedforward neural network (FNN) has been utilized to estimate heart beats for a data set of 5 minutes experiment. The heart rate is estimated every two seconds. The comparison between estimated heart beats versus the actual values shows that regardless of the type of physical activity, especially during running which PPG signal is corrupted with intense motion artifact, the deep neural network model (DNN) is capable of the tracking the actual heart rate values.

Proposed Method

The first step toward estimating heart rate values is time-windowing which the online measurement signals are broken into consecutive overlapped time windows. Batchwise representation of PPG and 3-D acceleration data provides the benefit of using the information from the previous time-windows to obtain a more realistic estimation of the heart rate. Since outliers drastically decrease the performance of most of the learning techniques in terms of both training and estimation of the output, cleaning the input data is the cornerstone of heart rate estimation. From the physiological point of view, heart rate barely takes values outside of the range of [30, 200] beats per minutes (BPM). Considering this, the corresponding interval of [0.5, 3.3] Hz is considered as the meaningful range of heart rate variation, and a 6^{th} order Butterworth bandpass filter is utilized to attenuate all ripples with the frequency outside of the desired range.

The filtered signal is mapped into Henkel matrix to perform Singular Value Decomposition (SVD) signal processing technique. The processed Henkel representation of the signal is obtained by pruning small eigenvalues of the squared Henkel matrix as given below:

$$H_X \approx \sum_{i=1}^{d} U_i \sqrt{\lambda_i} V_i^T \quad (1)$$

where $H_X \in L \times J$ denote the Henkel matrix containing Blood Volume Pulse (BVP) measurements and $U_i \in L \times L$ and $V_i \in J \times L$ represent right and left eigen matrices corresponding to eigenvalue $\lambda_i, i = 1, \ldots, d$.

Although, bandpass filtering and SVD remove meaningless and high-frequency oscillations from the PPG signal, yet the existence of motion artifact remains the most critical obstacle toward heart rate estimation due to dominant frequencies of the motion artifact overlapped with that of the heart rate and consequently, the misleading behavior of the corrupted PPG signal. To further remove the noise and motion artifact from the PPG signal, we used the idea of using Cosine similarity between two signals as given below:

$$\cos(\theta) = \frac{N_{a_t} \cdot N_X}{\|a_t\| \|N_X\|}, t \in \{x, y, z\} \quad (2)$$

where $N_X \in R^n$ and $N_{a_t} \in R^n$ are the spectral power representation of a time-windowed PPG signal and 3-D acceleration data in direction $t, t \in \{x, y, z\}$, respectively. Its desired to use the variation of acceleration data as the source of the motion artifact to make the PPG signal uncorrelated (perpendicular) to all three acceleration signals. From (2), one has the following modified vector of the PPG signal as:

$$N_{X_t} = \left(I_n - \frac{N_{a_t}^T N_{a_t}}{N_{a_t} N_{a_t}^T}\right) N_X, t \in \{x, y, z\} \quad (3)$$

It can be shown that N_X and N_{a_t} are perpendicular [3]. Recall spectral subtraction approach for noise cancellation which is given by:

$$N_{X_t}^b = N_X^b - \alpha N_s^b \quad (4)$$

where α, b are positive scalers and $N_s \in R^n$ denotes the spectrum of the noise. By comparing (3) with the definition of spectral subtraction signal reconstruction given by (4), and setting $\alpha, b = 1$, we can establish an analogy between spectral subtraction and signal uncorrelation. The following figure demonstrates the location of the most dominant peaks corresponding to the heart rate before and after similarity based spectral subtraction.

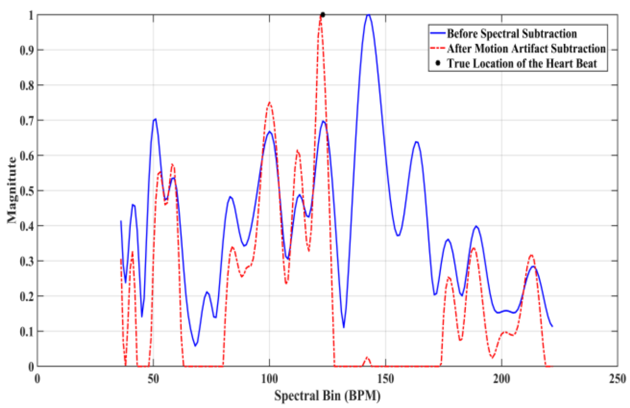

Figure 1. Specttrogram of the original PPG signal (solid line), spectrogram of the processed signal (dashed-dotted line), and location of the true heartbeat frequency (bullet marker).

The last step of heart rate estimation encompasses feature extraction from each time window of the PPG signal and accelerometer data. The features include statistical characteristics of signals such as mean, median, variance, skewness, and kurtosis. Other features are extracted based on the frequency of the most probable spectral bins, for instance, the frequency of peaks with the highest magnitudes and the weighted average value of spectral bins. In order to take into account the dynamic behavior of the heart rate variation, we have augmented the extracted features from three past windows to further boost the information required to estimate the heartbeat values. Before training the network, we need to employ Principal Component Analysis (PCA) dimensionality reduction techniques to reduce the dimensionality of input information to prevent the problem of overparameterization. After PCA, more than 95% variance of the original data has been preserved and the dimensionality of the dataset is reduced by 97%.

A FFN with four fully connected long-short-term memory (LSTM) layers, Rectified Linear Unit (RELU) activation function, and dropout selection training strategy is used to model the variation of the heartbeats from features. We have dedicated 75% of all samples to train the network and the rest of the data are used for validation and testing purposes. The proposed DNN incorporated with the preprocessing approach used in this study represents a robust and reliable framework to estimate the variation of the heart rate. To further assess the effectiveness of the proposed algorithm, a dataset of twelve subjects with a duration of five minutes of the experiment including three different types of physical activity is considered for this study [4].

And for each subject, the performance indexes Mean Absolute Error (MAE) and Relative Absolute Error (RAE) are calculated and compared with previous works.

Acknowledgment

Financial support from the National Institutes of Health (NIH) under the grants 1DP3DK101075-01 and 1DP3DK101077-01 and Juvenile Diabetes Research Foundation (JDRF) grant A18-0036-001 made possible through collaboration between the JDRF and The Leona M. and Harry B. Helmsley Charitable Trust is gratefully acknowledged.

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