Amalgamation of Signal processing and Machine Learning Techniques for ECG Signal Analysis

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I. Summary

Electrocardiogram/Elektrocardiogram (ECG) as seen in Fig.1. is time series data of the electrical activity of the heart. To record an ECG, sensors which detect the electrical signals produced by your heart each time it beats are attached to the skin. ECG shape and structure tells us if the the heart of the person is functioning properly. ECG data has been analysed by researchers to identify fiducial points in order to classify different heart conditions like arrhythmias, coronary heart disease, heart attacks and cardiomyopathy accurately.

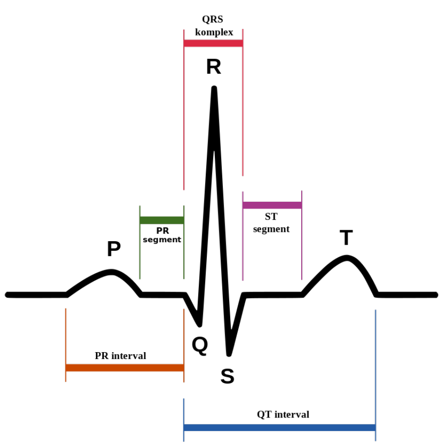

Fig. 1. A PQRST ECG waveform

There are five main stages to ECG analysis, which are summarized below.

A. Acquisition of ECG data

Datasets are important when it comes to ECG data because the attributes that are recorded with the ECG signal help in deciding which features would be extracted or explored further. The paper [1] gives a well tabulated set of ECG datasets with following specifications: 1)Name, 2)Year of acquisition, 3)Number of files, 4)Number of leads used, 5)Sampling frequency, 6)Voltage, 7)Duration of recording, 8)Method of acquisition and 9) purpose of acquisition.

B. Denoising

ECGs are recorded by attaching sensors to the body. During this process, noise gets captured along with the signal. This noise negatively affects signal quality and classification. Thus, there is a need to denoise ECG signals before feature extraction. We can use adaptive filters for this purpose. Adaptive filters are digital filters whose coefficients change with an objective to make the filter converge to an optimal state. The optimization criterion is a cost function. Paper [2] discusses several of these cost functions such as Least Mean Square, Normalized Least Mean Square, Sign Data Least Mean Square, Quantized Error Least Mean Square and their own Modified Mean Square function.

C. Feature Engineering

The QRS complex is an important wave in the ECG signal whose detection forms the basis of extraction of fiducial points such as the R-R interval, ST-segment, J-point and T-wave using feature engineering which, in turn, help in classification of the ECG signal.

1) Signal processing techniques:

Paper [1] discusses some signal processing techniques for feature engineering of ECG data. Short time Fourier transform, Wavelet transform, Discrete Wavelet transform (best sensitivity of 99.95%) and its other variations viz. Continuous Wavelet transform, Cross Wavelet transform and Dyadic Wavelet transform are used for detecting the QRS complex. Karhunen-Loeve transform and Legendre Polynomials-based transform are used for detecting the ST-segment. Phasor transform are used to detect R-peaks.

2) Machine learning techniques:

Paper [1] discusses some machine learning methods for feature engineering of ECG data. Variational Mode Decomposition (best sensitivity of 99.93% with 12-lead and 99.79% with single lead ECG) , K-Nearest Neighbours, Naive Bayes and Support Vector Machines are used for detecting QRS complex. Decision Tree and Google's Inception based 2-D Convolutional Neural Networks are used for detecting the ST-segment. Performance metrics other than Sensitivity like Specificity, Positive Predictive Value, F1-score, Mean Error, Root-Mean-Square Error and Accuracy were used as the performance metrics for the different methods listed above were also tabulated in the paper.

D. Classification

After extraction of features from the ECG signal, the detected fiducial points are used to classify the ECG signal into different classes based on the problem of interest.

1) Signal processing techniques:
Paper [1] discusses some traditional classification threshold techniques viz. Pan Tompkins based adaptive thresholding technique, Discrete Wavelet transform using Principle Component Analysis and Independent Component Analysis and Multi-modal Decision Learning (100% Sensitivity when evaluated on MIT-BIH arrhythmia dataset).

2) Machine learning techniques:
Paper [1] sources a large number of Artificial Intelligence based classification techniques wherein the computers learn the underlying classification function with(supervised learning) or without(unsupervised learning) labeled data using different types of probabilistic models. Artificial Neural Networks (ANN), a sub-domain of AI inspired by the biological neural network, has been used extensively to carry out classification of different types of arrhythmia from ECG signal analysis using Ensemble Decision Tree and particle swarm optimization based fast forward neural networks. An extensive literature survey on Support Vector Machines, a type of linear classifier, has been done to detect arrhythmia using Sequential Minimum Optimization SVM and Multi-class SVM. Another type of neural network known as the Convolutional Neural Network has been used in the form of Residual CNN, Recurrent NN and Long-short term memory NN in order to detect arrhythmia, ST-changes and normal and abnormal classification.

II. Review

A. Paper 1: Stages-Based ECG Signal Analysis From Traditional Signal Processing to Machine Learning Approaches: A Survey [1]

1) Strengths:
The paper, which consists of summary of over 100+ relevant articles from prestigious publications over the last two decades, focuses on the traditional (time/frequency domain analyses) and modern (Artificial Intelligence) methods used in different stages in ECG signal analysis: 1)Acquisition from the source, 2)De-noising, 3)Feature engineering, and 4)Classification, following a brief discussion on Electrocardiography from the perspective of physiology of the human heart like ECG acquisition setup, morphologies of the ECG waveform in ischemia and infarction, and the different types of arrhythmia.

2) Weaknesses:
This paper is extremely comprehensive and it covers almost every step required for ECG data analysis,ranging from its acquisition to its use for disease diagnosis. There is no significant additional point that this paper could have explored.

B. Paper 2: Performance analysis of adaptive algorithms for removal of low-frequency noise from ECG signal [2]

1) Strengths:
The paper compares the different algorithms to train adaptive filters, checking their performance on ECG signals. Reasoning out the results, the authors have described elaborately why the LMS had the least SNR and the fastest convergence. It also introduces the SDLMS, which has the least complex algorithm. One of the key aspects of the paper is the exposure to different and new adaptive filters that develop on the well-known LMS algorithm.

2) Weaknesses:
This paper does not explore other filters that may be used, such as HDL-based FIR filter, Kalman Filter, Wavelet Filter etc. Additionally, the paper has not explored the different kinds of noise that may be present in ECG data such as Gaussian White Noise, Equipment induced noise and Power-line interference. Different kinds of noise might require different denoising techniques.

III. Further Ideation

We propose three ideas for further work on this topic. These are summarised below:

A. Object detection based disease diagnosis using ECG data

This idea is based on a paper MusicYOLO [] in which music audio data is converted to a 2D spectrogram, and then object detection is performed on the 2D image in order to segment musical notes. After this pitch extraction is performed on the segmented note and musical transcription for the audio data is obtained.

We propose the adaptation of this idea to ECG data, which is similar to 1D audio data. However, this may lead to a large amount of data. We can use autoencoder to reduce the dimension of data. This will involve the following steps:

1) Preprocessing of Waveform:

a **Waveform Noise Reduction:** We will use the Modified Least Mean Squared Algorithm [] which to denoise the ECG waveform. It is an adaptive adaptive filtering algorithm that has been shown to give the best results.

b **Time Frequency Transformation:** The 1D ECG waveform will be converted to a 2D spectrogram. This can be done using its short time fourier transform (STFT), its Mel-Gabor transform or its constant Q-transform (CQT). The spectrogram has frequency on one axis and time on the other axis. The pixel values correspond to the amplitude of the waveform.

c **Linear Intensity Mapping:** Linear intensity mapping will be perfomed, to convert the single channel spectrogram to a 3 channel RGB image. The linear mapping will effectively quantify the spectrogram according to spectral intensities.

d **Spectrogram Cutting:** Since the spectrogram size is vry large in the time axis, breaks between heartbeats (silence) will be detected and the spectrogram will be cut into almost square slices to make it easy to perform object detection on it

2) Heartboeat Detection:

a **Heartbeat Object Detection:** The YOLOX [] model will be used to perform object detection on the spectrogram and segment and identify the different heartbeats.

b **Post Processing of the Bounding Box:** In computer vision, objects can be enclosed by other objects.However, one heartbeat cannot occur inside another heartbeat. If by mistake, one bounding box is inside another, the inner one will be discarded. Secondly, there must be a clear distinction between two heartbeats.If two bounding boxes overlap, the right edge of the left box will be considered as the single boundary between them.

c **Time Shift:** Finally, the segmented heartbeats will be shifted along the time axis to get the entire set of heartbeats.

3) Feature Extraction:

From these heartbeats, features, such as peaks and their heights and widths can be extracted easily.

4) Classification of Arrhythmias:

On extracting features from heartbeats, we can classify if the ECG data contains arrhythmias,etc, This will help doctors diagnose heart diseases and disorders.

B. ECG feature extraction from waveform snapshots

We also propose using convolutional neural networks (CNNs) to extract features from snapshots of the ECG data instead of performing time series data analysis. This is because the PQRST shape of the heartbeat waveform carries a lot of information and this information can be directly extracted from the waveform snapshot instead of needing to denoise and process the time series signal, which will require more computational power and time.

C. Exploiting the sparisty of ECG

ECG is a sparse signal. This property could be exploited to compress and store a larger amount of data in fewer bits. This falls into the study of compressive sensing. Furthermore techniques like the sparse recovery problem, and matching pursuit can be tested for their performance on the ECG signal.

References

[1] M. Wasimuddin, K. Elleithy, A. -S. Abuzneid, M. Faezipour and O. Abuzaghleh, "Stages-Based ECG Signal Analysis From Traditional Signal Processing to Machine Learning Approaches: A Survey," in IEEE Access, vol. 8, pp. 177782-177803, 2020, doi: 10.1109/ACCESS.2020.3026968

[2] R. Qureshi, S. A. R. Rizvi, S. H. A. Musavi, S. Khan and K. Khurshid, "Performance analysis of adaptive algorithms for removal of low frequency noise from ECG signal," 2017 International Conference on Innovations in Electrical Engineering and Computational Technologies (ICIEECT), Karachi, Pakistan, 2017, pp. 1-5, doi: 10.1109/ICIEECT.2017.7916551.