Python Based Physiological Signal Processing for Vital Signs Monitoring

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Abstract—**Attractiveness of Python program language is partially based on availability of large number of open-source libraries. In this paper we demonstrate application of one of Python libraries (BioSPPy) on a set of physiological signals from the Physionet CEBS database. Electrocardiogram and respiratory signals are analyzed, both before and after listening of classical music (states B and P, respectively). Heart rate variability analysis is performed using functions from the toolbox and by inspection of spectral aspects of the signals. Several metrics are used for comparison, like instantaneous heart rate and ratio between the spectrum segments. The obtained results show further possibilities for developing graphical interfaces for efficient vital signal analysis, and implementations based on open-hardware platforms.**

Index Terms— **R-peak detection, heart rate variability, respiratory signal, python library, open source.**

I. INTRODUCTION

Excellent reception of the Python program language among experts led to development of numerous open-source libraries for diverse purposes. The most of them are still not widely applied or thoroughly examined. This is especially important for monitoring of vital signs. Each library is optimized for specific type of signals and files (such as image, sound, video). This further leads to optimal time consumption in case of any kind of signal processing. Python is interpreter- and object-oriented program language that is widely used among academicians for educational and research purposes. It is also used for production of commercial products [1].

Biomedical signals express wide range of distinctions in time and frequency domain. This paper demonstrates implementation of BioSPPy library on physiological signals, like cardio signals [2]. Electrocardiogram (ECG) is a common physiological reference signal, which is used in this paper. Since in medical practice individuals are often inspected from the aspect of breathing, we also included respiratory signal

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(RESP) in the experiment. Signals considered in this paper are taken from the Physionet CEBS database [3]. All signals are acquired from awake and inactive subjects exposed to musical stimulus.

The fundamental physiological signals are analyzed in Python environment using modules from BiosPPy library in order to be further implemented in computer-aided expert systems. Functions within that module cover essential signal processing (filtering, signal representation), R-peak detection with various algorithms, as well as signal analysis in frequency domain.

Our focus is directed towards heart rate variability (HRV) analysis. It can be conducted in different ways and from diverse aspects [4]. From medical point of view, analysis of the signal that represents a number of heart beats per minute (HR) is crucial. Pathological states are reflected on the variability of the heart rate. In similar way, it is possible to track the influence of some other factors, such as music [5-7].

In this paper we use a method for analysis of HRV in frequency domain, in particular, power spectral density. As a result we provide the ratio between energies of spectral components within particular ranges of frequency. Analysis is executed for both states and on all subjects from the dataset. Several comparisons are made here.

The organization of this paper is as follows. In Section II, materials and methods are described. Further information on the database of signals and BioSPPy library is provided. The simulation and experimental results are given in Section III. Conclusions are summarized in Section IV.

II. MATERIALS AND METHODS

A. Dataset

Physionet CEBS database is used as the experimental dataset. It consists of electrocardiogram (ECG), breathing/respiratory signal (RESP) and seismocardiogram (SCG). The main purpose for this dataset is twofold: 1) comparing the R peak detectors with respect to the influence of breathing, and 2) examination of the R-R (heartbeat) time intervals obtained from different types of physiological signals (e.g. from specific ECG lead and by segmentation of SCG without an ECG as a reference). The CEBS dataset also provides signals related to the musical influence on subjects. In particular, three states are considered: 1) the basal state – B (before the music), 2) the music state – M (while listening to the music), and 3) the post-music state – P (after the music ended). The dataset was collected using a Biopac MP36 data

acquisition system with 5kHz frequency sampling, where two ECG channels are acquired with 0.05-150Hz bandwidth, RESP from the thoracic region by the transducer with 0.05-10Hz, and SCG using the 0.5-100Hz bandwidth accelerometer.

The signals are obtained using twenty healthy subjects while being awake in supine position. Here, we analyze only B and P states, while M state is not included in further analysis.

B. BioSPPy library

BioSPPy is a toolbox for biomedical signal processing and it is written in Python. This toolbox brings together numerous signal processing and pattern recognition algorithms specialized for the analysis of biomedical signals. The library is open-source and it is accessible both for academic and commercial purposes. It covers a range of functions adapted to biomedical signal processing. Syntax of these functions is considerably simplified with respect to optimal manipulation over biomedical signals. The library is called from the Python environment using command "import" as shown in Fig.1.

```
In [4]: from biosppy.signals import ecg

In [5]: from biosppy.signals import resp

In [6]: from biosppy import plotting

In [7]: from biosppy.signals import tools
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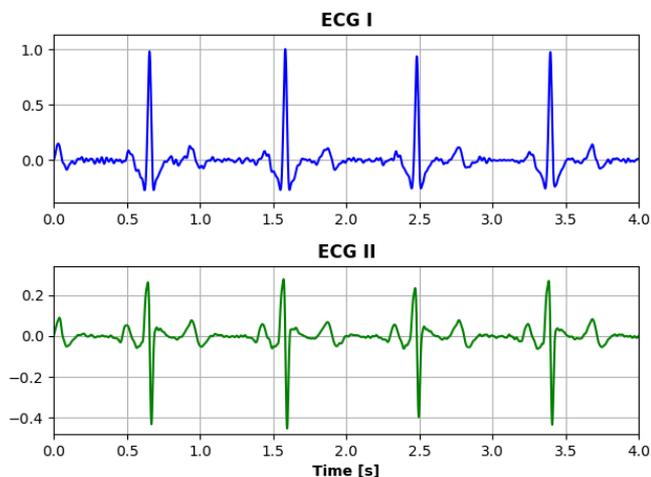Fig. 1. Import of BioSPPy library into Python environment.

Fig. 2. The first (upper panel) and the second (lower panel) ECG channel.

Toolbox is portioned into modules: biometrics, clustering, metrics, plotting, signals.bvp, signals.ecg, signals.eda, signals.eeg, signals.emg, signals.resp, signals.tools, storage and utils. In this paper we implemented modules for electrocardiogram processing ("signals.ecg"), respiratory signal processing ("signals.resp"), tools for graphical representation ("plotting"). Also, certain functions for filtering and frequency analysis are implemented within the "signals.tools" module.

Module "signals.ecg" encompasses functions for electrocardiogram signal importing, signal pre-processing (filtering interfering components from the signal, such as muscle activity, 50Hz power noise and baseline wandering), algorithms for detection of QRS complex (Gamboa, Hamilton, Slope Sum Function, etc.) [8-10]. Function for estimation of Instantaneous Heart Rate is also covered by this module.

The signals from Physionet CEBS database are grouped into .mat files. They are loaded into Python environment using the appropriate modules for import of .mat files from SciPy library (it comes with the standard distribution of programming language).

III. SIMULATION

Electrocardiogram signal is processed using signals.ecg module from BiosPPy library. There is information about two channels of electrocardiogram within the database (shown in Fig. 2 and denoted as ECG I and ECG II). The first processing step consists of signal filtering in order to suppress interferences and noise. For graphic display, functions from the plotting module are used, which significantly facilitate construction of the desired plots (built-in style, font size, line type, etc.).

The next step involves the detection of R peaks within the QRS complex (middle panel in Fig. 3). Primary algorithm is defined by Pan and Tompkins in 1985 [11]. However, as already mentioned, in the signals.ecg module there are several algorithms available that perform the R peak detection. All of them give a sequence of R peaks positions as output. One of the channels, ECG I or ECG II, can be selected as a reference channel. The time between two successive R peaks is defined as RR interval. The reciprocal value of RR interval multiplied by 60 gives a number of beats per minute. In this way, the new array is formed which represents heart rate (HR) in time. This is illustrated for raw electrocardiogram (bottom panel in Fig. 3). Parameter HR is expressed in bpm (number of beats per minute), as:

$$HR(bpm) = \frac{60}{RR(s)} \tag{1}$$

It is expected to be in the range of 60-100bmp while resting.

Here, an ECG-based R peak detection algorithm is applied. Even though, the beat variability may be measured in terms of different types of signals found in the combined set. In the first iteration, analysis of the heart variability implies analysis of HR array [12].

For twenty subjects from the database, comparison of HR values is performed in two states: B state (prior to exposure to the music stimulus) and P state (after exposure to music stimulus). As an example, plot for one of the subjects is shown in Fig. 4. Heart rate variability depends on the music type and tempo to which subjects were exposed. In the example from Fig. 4 there is an average increase for the value of heart rate.
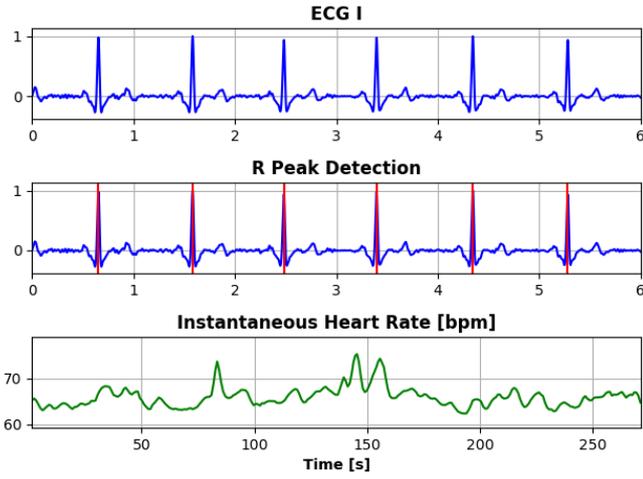
Fig. 3. Detection of R peaks for the first electrocardiogram channel. Number of beats per minute is calculated based on the detected RR intervals.
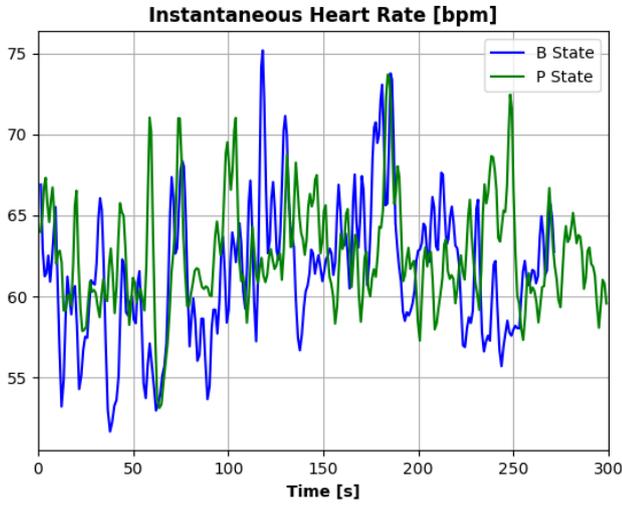

Fig. 4. Parallel display of heart variability for one subject before and after exposure to a musical stimulus (states B and P, respectively).

Visual inspection of HR signal in time domain does not provide a complete information on signal behavior. Therefore, it should be further analyzed in some of transformation domains. Most frequently used transformation domain in literature is related to Fourier transformation of HR signal [13]. Here, we use Fourier transform of HR signal, or more specifically, power spectrum density of HR signal:

$$P(f) = 10\log_{10}\left|HR(jf)\right|^2 [dB]. \qquad (2)$$

Obtained power spectrum density is then averaged using moving average filter of size of 10 samples with sliding by 1 sample. Before averaging, Hann window is applied on each segment of the signal. Fig. 5 shows two power spectrum density representations of the HR belonging to subject before and after listening to music (states B and P). Certain differences in power spectrum density curves are evident (signal power significantly drops at some frequencies).

The other type of signal which we used is respiratory signal. Again, the functions from BiosPPy are applied. It is a common practice in practical implementations to observe respiratory signal together with electrocardiogram and other cardiosignals [14]. Certain pathological states and diseases can be diagnosed and perceived following this reasoning.

Module "signals.resp" enables low-pass signal filtering as well as detection of zero-crossings of the filtered signal. Detected zero-crossing points enable estimation of the instantaneous respiration rate in time. Fig. 6 shows an example of analysis of the respiratory signal of a subject. Namely, along with originally recorded respiratory signal, filtered signal is presented with the detected zero crossings points. Moreover, estimated instantaneous respiration rate is presented in this case.
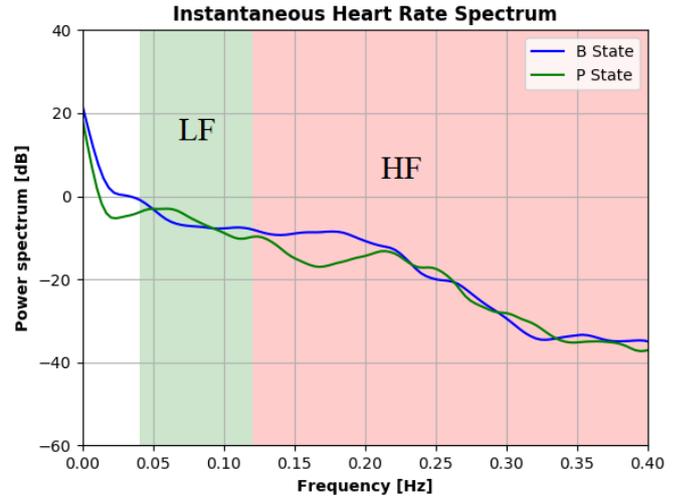

Fig. 5. Parallel display of the power spectrum density for one subject before and after listening to the music (states B and P, respectively).
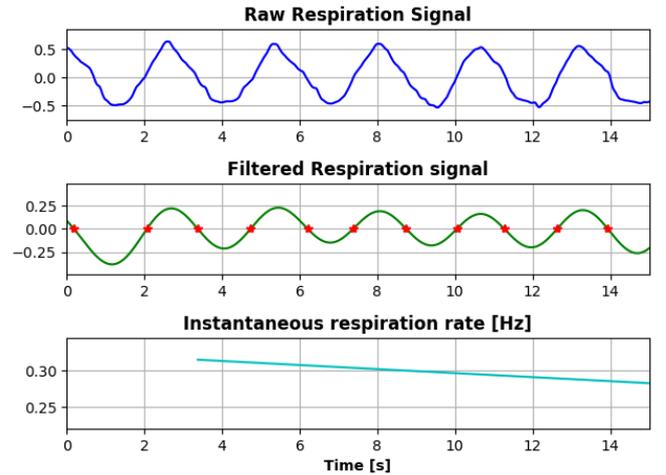

Fig. 6. Analysis of the respiratory signal (first panel), filtered signal along with the detected zero crossings (second panel), and estimated instantaneous respiration rate (third panel).

Different valuable characteristic ranges of the spectrum are introduced in literature [15]. This is applied here for differentiating the low and the high frequencies. These

segments are defined as a low-frequency part of the signal in the range from 0.04 Hz to 0.12 Hz and high-frequency part from 0.12 Hz to 0.4 Hz. Abovementioned ranges are shown in Fig. 5. Ratio of those two parts of the spectrum is denoted as a HF/LF ratio:

$$\frac{P_{HF}}{P_{LF}} = \frac{\displaystyle\sum_{0.12\,\mathrm{Hz}\leq f \leq 0.4\,\mathrm{Hz}} p(f)}{\displaystyle\sum_{0.04\,\mathrm{Hz}\leq f \leq 0.12\,\mathrm{Hz}} p(f)}. \quad (3)$$

Certain pathological states are characterized with notable maximums in HF and LF parts, and it is reflected on HF/LF ratio [15]. The HF/LF ratio is calculated for all subjects from the database and for both states (before and after listening to music).
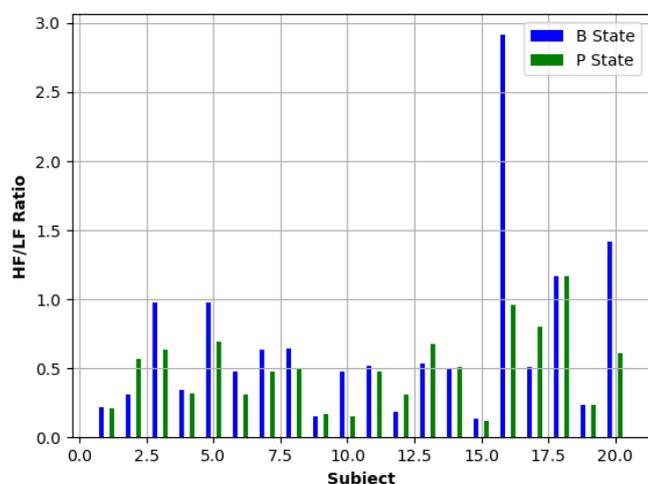

Fig. 7. Comparison of the ratio of energy contained in a high-frequency (HF) and low frequency (LF) part of the spectrum before and after listening to the music (states B and P, respectively).

Fig. 7. illustrates HF/LF ratio behavior for different subjects in two states. For most of the subjects HF/LF ratio is decreased. This is especially evident for subject number 16 which illustrates the effect of music.

IV. CONCLUSION

In this paper we demonstrated the use of open-source library from the Python 3 program environment. Functions from the library are optimized for processing of biomedical signals. The toolbox is tested on Physionet CEBS database where the signals are synchronously acquired.

We observe two groups of signals - electrocardiogram (two channels) and corresponding respiratory signal. Based on R-peak detection, we estimated the number of heart beats per minute. Analysis of heart rate variability is further examined in spectral domain, while the ratio of energies of the components on high and low frequencies is calculated for all

20 subjects in cases before and after listening to music. Influence of musical stimulus is seen as a decrease of this ratio for the most of the subjects.

Directions for future research are seen in application of Python environment and BiosPPy library for designing of graphical user interface. Further acquisition of signals in real-time will be enabled using Arduino open-hardware platform and biomedical module for acquisition of electrocardiograms and other physiological signals.

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