Evaluation of Python HeartPy Tooklit for Heart Rate extraction from PPG

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Abstract. Handling the mass casualty emergency situations can be improved by introducing a chest patch sensor that is able to deliver the main vital parameters: Heart Rate (HR), Respiration Rate (RR), SPO2 and Blood Pressure. The START triage procedure requires both HR and RR parameters almost instantly.
In this paper we investigate the calculation of HR from a raw PPG signal, using appropriate functions from the Python HeartPy Tooklit, by comparing the calculated HR to the measured HR for the same patients, recorded at the same time as the PPG signal. By using several evaluation metrics, it was concluded that there is no significant difference between the measured and the calculated HR (MAE = 0,3, MSE=0,3, R^2 =0,99, Pearson's and the Spearman's coefficient of correlation, 0.99). This result is the same whether raw or filtered PPG signal was used for the HR calculation.

Keywords: Photoplethysmogram data · Signal processing · Heart rate analysis · Peak detection · Evaluation metrics

1 Introduction

Wearable real-time physiological status monitors constructed as patch-like devices capable to collect and analyse information on vital parameters such as respiration (respiration rate - RR), heartbeat (heart rate – HR), SPO2, ECG (electrocardiography), blood pressure (BP) or body temperature, can help first responders and remote personnel to rapidly intervene in time of critical events - military and civil scenarios as a result of terrorist attacks, IEDs' explosions or during rescue operations. A real-time analysis of the health status of a person in action (e.g. rescuers, emergency crews) and its prompt communication to a team leader can have critical impact on the outcome of crisis events. The mobile patch device is to be placed by emergency crews on the victims' chests as soon as possible.

PythonHeartPyTooklit用于PPG心率提取的评价

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抽象的。通过引入能够提供主要生命参数的胸部贴片传感器，可以改善大规模伤亡紧急情况的处理：心率（HR），呼吸率（RR），SPO2和血压。START分诊程序几乎立即需要HR和RR参数。

在本文中，我们使用Python HeartPy Tooklit中的适当函数，通过将计算的HR与相同患者的测量HR（与PPG信号同时记录）进行比较，研究了根据原始PPG信号计算HR。通过使用几种评价指标，得出的结论是，测量和计算的HR之间没有显著差异（MAE＝0.3，MSE＝0.3，R＝0.99，Pearson 和斯皮尔曼相关系数，0.99）。无论使用原始PPG信号还是滤波PPG信号进行HR计算，该结果均相同。

关键词：光电容积描记图数据·信号处理·心率分析·峰值检测·评估指标

1 介绍

可穿戴实时生理状态监测器，构造为贴片式设备，能够收集和分析呼吸等生命参数的信息（呼吸率- RR），心跳（心率- HR）、SPO 2、ECG（心电图）、血压（BP）或体温，可以帮助第一响应者和远程人员在关键事件发生时快速干预- 由于恐怖袭击导致的军事和民事场景，或者在救援行动中。对行动中人员（例如救援人员、紧急救援人员）的健康状况进行实时分析，并将其及时传达给团队领导，可以对危机事件的结果产生关键影响。紧急救援人员将尽快将移动的补丁设备放置在受害者的胸部。

One of the objectives of the ongoing project ("Smart Patch for Life Support Systems" - NATO project G5825) is to build a prototype for a patch sensor containing aforementioned vital parameters. In order to achieve this goal, the patch will contain ECG [1], PPG [13] and body temperature sensors. According to the START triage procedure [11], in order to assign the health status label (green, yellow, or red) to the injured person almost instantly, one needs to use his/her heart rate (HR) and respiratory rate (RR) vital parameters. After the triage labelling, the paramedics need the rest of the parameters – BP, SPO2 and body temperature to follow the health status of the injured person.

Our interest in this stage is to investigate the deliverance of the HR vital parameter. There are two most important technologies for measuring the heart rate: ECG and PPG (photoplethysmography). The difference between these two signal generators is as following: 1. ECG sensors measure the bio-potential generated by electrical signals that control the expansion and contraction of heart chambers. 2. PPG sensors use a light-based technology to sense the rate of blood flow, that is determined by the heart's working.

The ECG sensor is very common in the biosensor industry [1]. The integration of PPG sensor into chest-based patch device is primarily for measuring the SPO2 parameter.

It is more common to extract HR using the ECG signal, due to its power consumption, accuracy, ease of integration and richness of data [4]. Nevertheless, HR parameter can be extracted from the PPG signal, as well [11]. Following the fact that the operation of data collection from the patch device can take incorrect reading due to sensor displacement while rescuing the patient and since we have both of the sensors (ECG and PPG) on the same place (chest of the injured person), we developed an idea to use both of the signals, since it is very important to have the HR measured instantly and accurately.

In this paper we investigate the extraction of HR from the PPG signal, using Python HeartPy Tooklit. Our goal is to ensure the accuracy of calculating HR with the suitable Python Toolkit functions by comparing the calculated HR from the raw PPG signals and its correlation to the measured HR for the same patients recorded at the same time. We use the publicly available BIDMC PPG and Respiration Dataset available at Physionet.

The structure of the paper is as follows. Section II presents an overview on similar papers or related researches, Section III elaborates the process of database extraction and filtering, explanation of the used HeartPy functions and the used methodology. The results of the experiment and relevant discussion are presented in Section IV. The conclusion of the paper is given in Section V.

2 Related Work/Background

The PPG sensor measures the changes in the intensity of the light that passes through or is reflected by the examined tissue. The changes in the intensity of the transmitted or reflected light correspond with the changes in blood volume in the tissue that are caused by the periodic heart activity. Therefore, the PPG

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在本文中，我们研究了使用Python HeartPy Tooklit从PPG信号中提取HR。我们的目标是通过比较从原始PPG信号计算的HR及其与同时记录的相同患者的测量HR的相关性，确保使用合适的Python Toolkit函数计算HR的准确性。我们使用Physionet 上公开提供的BIDMC PPG和呼吸数据集。

本文的结构如下。第二节介绍了类似的论文或相关研究的概述，第三节阐述了数据库提取和过滤的过程，解释了使用的HeartPy功能和使用的方法。实验结果和相关讨论见第四节。第五节是本文的结论。

2 相关工作/背景

PPG传感器测量穿过被检查组织或被检查组织反射的光的强度的变化。透射光或反射光的强度的变化对应于由周期性心脏活动引起的组织中血容量的变化。因此，PPG signal can be used to estimate the HR [2]. The HR from the PPG signal can be detected in the time or the frequency domain. In the time domain, the HR is estimated by the detection of the peaks in the PPG signal that occur with the heartbeat [20]. In the frequency domain, the HR is obtained by the analysis of the peaks in a spectrum where the most distinctive peak should correspond to the HR [12]. Wearable devices with the integrated PPG sensor placed e.g., on the wrist or a chest are used to monitor the physiological parameters of the subject in the hospital or during the emergency situations. Therefore, the recorded PPG signal can be contaminated with the artifacts caused by the subject movement and techniques for its elimination need to be implemented in order to obtain the most accurate estimate of the HR. Previously, analogue filters were used to obtain the required frequency range of the PPG signal followed by the digital filters that were used for the filtering and differentiation of the respiratory and heart signals from the measured PPG signal. Consequently, the heart signals were used to determine the HR by the zero-crossing method [15]. The results of the current research demonstrate that the signal decomposition techniques can be used to eliminate the motion artifacts in the PPG signal and thus determine the HR. An example of this approach is a general framework, named TROIKA, that is incorporating three features which are signal decomposition, sparse signal reconstruction and spectral peak tracking. The TROIKA shows a good accuracy in the determination of HR from the noisy PPG data obtained during running [21]. Another approach for the HR estimation from the noisy PPG signals involves a cascade of adaptive filters. First, the PPG signals are pre-processed and after that combination of adaptive filters is used to eliminate the moving artifacts. The HR is then estimated in the frequency domain from the periodogram. The results indicate that this method has a good result in the HR estimation for different datasets [3]. Further, the removal of motion artifacts can be done using Wiener filtering followed by a phase vocoder used for the HR estimation and its refinement. The system can be used also offline employing the Viterbi decoding algorithm [19]. Many other methods can be used for the determination of HR from the PPG signal contaminated with artifacts such as denoising using wavelets [17] or Kalman filtering [14]. At present, the use of deep learning techniques for the estimation of the HR from the PPG signal is being investigated. It was shown that a Multi-Layer Perceptron (MLP) neural network consisting of 3 layers and 22 neurons can be used to estimate the HR with acceptable accuracy and computational time [6]. The PPG signals obtained during various activities and obtained via measurements in clinical practice were used to test a framework named CorNET that uses Deep Neural Network (DNN). The DNN is composed of the Computational Neural Network (CNN) and the Long Short-Term Memory (LSTM) network, each in two layers and accompanied by a dense layer [5]. It follows from the above-mentioned information that various methods could be used for the estimation of the HR from the PPG signals from simpler to more sophisticated up to deep learning methods.

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3 Materials and Methods

3.1 Database

In this research we used the BIDMC PPG and Respiration Dataset [16,10] available at `https://physionet.org/content/bidmc/1.0.0/`. BIDMC dataset is composed of signals extracted from the larger MIMIC II matched waveform Database, that also contains manual breath annotations. Total database size is 207.7 MB. This data was obtained from critically-ill patients at the Beth Israel Deaconess Medical Centre in Boston, MA, USA. There are total 53 patients in the dataset and for each patient the following physiological signals and physiological parameters are stored:

- Photoplethysmogram (PPG) sampled at 125 Hz;
- Electrocardiogram (ECG) sampled at 125 Hz;
- Impedance respiratory signal sampled at 125 Hz;
- Heart Rate (HR) sampled at 1 Hz;
- Respiratory Rate (HR) sampled at 1 Hz;
- Blood oxygen saturation level (SPO2) sampled at 1 Hz;

Each physiological signal is 8 minutes long. There is also information about age and gender of each patient.

The data was initially downloaded using a custom made Python script. The WFDB software package was used, in order to download the data in the wanted Python pickle format, specifically the wfdb.rdsamp function. The downloaded data was saved to a local storage.

We also performed filtering of the PPG signal, thus obtaining two databases: with raw and filtered PPG signal data. In order to filter the PPG signal, we conducted a cleaning procedure, for the waveform quality. First, the PPG signal was normalized to zero mean unit variance. Then, it was filtered with a 4th order Butterworth band-pass filter, with cutoff frequencies of 0.5 Hz and 8 Hz to remove the baseline wandering below 0.5Hz and high-frequency noise above 8Hz. Next, to remove the outliers of the PPG signal it was filtered using the Hampel filter. The choice of the filters was made according to the procedure proposed in [18].

3.2 Python HeartPy Algorithm

In order to calculate the Heart Rate from PPG, we used the Python HeartPy Toolkit [8]. The HeartPy Algorithm comes with different pre-processing options to clean up signals, including finite impulse response (FIR) filtering and outlier detection. To detect peaks, this algorithm uses an adaptive threshold to accommodate for morphology and amplitude variation in the PPG waveform, followed by outlier detection and rejection. Heartbeats identification was made by calculating the moving average using a window of 0.75 seconds on both sides of each data point. Then, the regions of interest (ROI) were computed between

3 材料和方法

3.1 数据库

在本研究中，我们使用了可在https://physionet.org/content/bidmc/1.0.0/上获得的BIDMCPPG和呼吸数据集[16，10]。BIDMC数据集由从更大的MIMICII匹配波形数据库中提取的信号组成，该数据库还包含手动呼吸注释。总数据库大小为207.7 MB。这些数据来自美国马萨诸塞州波士顿Beth Israel Deaconess 医疗中心的危重患者。数据集中总共有53 名患者，并且对于每名患者，存储以下生理信号和生理参数：

- 以125 Hz采样的光电体积描记图（PPG）; - 以125 Hz采样的心电图（ECG）; - 以125 Hz采样的阻抗呼吸信号; - 以1 Hz采样的心率（HR）; - 以1 Hz采样的呼吸率（HR）; - 以1 Hz采样的血氧饱和度水平（SPO 2）;

每个生理信号长达8 分钟。此外，还包括每位患者的年龄和性别。

数据最初是使用定制的Python脚本下载的。使用WFDB软件包，以便以所需的Python pickle 格式下载数据，特别是wfdb.rdsamp 函数。下载的数据保存到本地存储器。

我们还对PPG信号进行滤波，从而获得两个数据库：原始PPG信号数据和滤波后的PPG信号数据。为了过滤PPG信号，我们进行了波形质量的清洗程序。首先，将PPG信号归一化为零均值单位方差。然后，用截止频率为0.5 Hz和8 Hz的4阶巴特沃思带通滤波器对其进行滤波，以去除0.5 Hz以下的基线漂移和8 Hz以上的高频噪声。接下来，为了去除PPG信号的异常值，使用Hampel 滤波器对其进行滤波。根据[18]中提出的程序选择滤波器。

3.2 PythonHeartPy算法

为了从PPG计算心率，我们使用了Python HeartPy Toolkit [8]。HeartPy算法具有不同的预处理选项来清理信号，包括有限脉冲响应（FIR）滤波和离群值检测。为了检测峰值，该算法使用自适应阈值来适应PPG波形中的形态和幅度变化，然后进行离群值检测和拒绝。通过在每个数据点的两侧使用0.75 秒的窗口计算移动平均值来进行心跳识别。然后，计算感兴趣区域（ROI）， two points of intersection where the amplitude of the signal was larger than the moving average. This is a standard way of detecting peaks. This algorithms uses two methods of obtaining a peak's location. The first approach, the highest point in the marked ROI is taken as peak position. In the second approach a univariate spline is used to upsample and interpolate the ROI, which is then solved for its maximum [9].

A special case is the signal clipping that makes it difficult to find the accurate placement of a peak's position. This can happen due to different reasons. HeartPy algorithm detects the onset and end of these clipping segments, and uses spline interpolation to make a reconstruction of the waveform. The best solution is decided by lowering the standard deviation of peak-peak intervals. The instantaneous heart rate (beats per minute - BPM) is computed and evaluated together with the standard deviation of peak-peak intervals. The BPM value must be within a predefined range which can be set by user. The default setting is: 40 <= BPM <= 180 [7] .

3.3 Methodology

The methodology for evaluating the HeartPy algorithm for our purpose starts with the calculation of the Heart Rate for each patient, by processing the PPG signal using the Python toolkit HeartPy. For each patient there are 60001 records for the PPG signal, as for the HR there are 481 values, which verifies the fact that the data for PPG signal is sampled at 125 Hz frequency. Since the BIDMC database is not filtered, the HeartPy algorithm was tested on both raw and filtered data (Section 3.1). In order to process the unfiltered data more accurately, it was necessary to handle the missing data, using Python libraries Pandas and Numpy, that offer compatible data structures able to perform many kinds of data manipulation. The median from the available heart rate values of the given patient was placed in the fields where the data was missing.

After the described preprocessing part, for both of the data sets - raw and the filtered PPG signal, the HR was calculated by the HeartPy's Process function. By setting the frequency parameter at 125 Hz, we obtained the heart beats per minute (bpm) values. The second step is to compare these values with the average of 481 values, representing the measured Heart Rate for each patient available in the database.

Subsequently, the calculated HR values were compared with the measured HR values of each patient in the database, utilizing evaluation metrics for estimation of their difference - MAE (Mean Absolute Error), MSE (Mean Squared Error), RMSE (Root Mean Squared Error), RMSLE (Root Mean Squared Logarithmic Error) and R^2 (Squared Root), as well as Pearson's and Spearman's coefficient of correlation.

在信号幅度大于移动平均值的两个交点之间计算感兴趣区域（ROI）。这是检测峰值的标准方法。该算法使用两种方法来获得峰值的位置。第一种方法，将标记的ROI中的最高点作为峰值位置。在第二种方法中，使用单变量样条对ROI进行上采样和插值，然后求解其最大值[9]。

一个特殊的情况是信号削波，这使得很难找到峰值位置的准确位置。这可能是由于不同的原因而发生的。HeartPy算法检测这些剪切段的开始和结束，并使用样条插值来重建波形。通过降低峰- 峰间隔的标准差来确定最佳解。计算瞬时心率（每分钟心跳次数-BPM），并与峰- 峰间期的标准差一起进行评估。BPM值必须在用户可设置的预定义范围内。默认设置为：40 <= BPM <= 180 [7]。

3.3 方法

用于评估HeartPy算法的方法从计算每位患者的心率开始，通过使用Python工具包HeartPy处理PPG信号。对于每名患者，PPG信号有60001 个记录，HR有481个值，这验证了PPG信号数据以125 Hz频率采样的事实。由于未过滤BIDMC数据库，因此在原始数据和过滤数据上检测了HeartPy算法（第3.1节）。为了更准确地处理未过滤的数据，有必要使用Python库Pandas 和Numpy来处理丢失的数据，这些库提供了能够执行多种数据操作的兼容数据结构。将给定患者的可用心率值的中位数置于数据缺失的字段中。

在所描述的预处理部分之后，对于两个数据集- 原始PPG信号和经滤波的PPG信号，通过HeartPy的处理功能计算HR。通过将频率参数设置为125 Hz，我们获得了每分钟心跳次数（bpm）值。第二步是将这些值与481个值的平均值进行比较，这些值代表数据库中可用的每个患者的测量心率。

随后，将计算的HR值与数据库中每例患者的测量HR值进行比较，使用评估指标估计其差异- MAE（平均绝对误差）、MSE（均方误差）、RMSE（均方根误差）、RMSLE（均方根对数误差）和R（平方根）以及Pearson 和斯皮尔曼相关系数。

4 Results

4.1 Evaluation metrics

In this section, the used evaluation metrics are presented in more details. In the following formulas, HR parameters are presented as:

HRMi - measured HR for the i-th patient;

HRCi - calculated HR for the i-th patient;

n - number of data points (patients).

MAE is a simple metric - the absolute difference between measured HR and calculated HR, and is most robust to outliers.

$$MAE = \frac{\sum_{n=1}^{n}(|HRMi - HRCi|)}{n}$$

MSE - mean squared error, represents the squared difference between the measured HR and calculated HR.

$$MSE = \frac{1}{n}\sum_{n=1}^{n}(HRMi - HRCi)^2$$

This metric can be used as a loss function, but is sensitive to outliers and then the penalization is bigger that leads to calculating bigger MSE, decreasing the robustness compared to MAE. Another evaluation metric that can be used as a loss function as well, that is more frequently used with deep learning techniques, is RMSE.

$$RMSE = \sqrt{\frac{1}{n}\sum_{n=1}^{n}(HRMi - HRCi)^2}$$

By taking the log of the RMSE metric, another evaluation metric - RMSLE (Root Mean Squared Log Error) is produced. RMSLE value will only consider the relative error between the measured HR and calculated HR value, neglecting the scale of data.

$$RMSLE = \sqrt{\frac{1}{n}\sum_{n=1}^{n}\log\left(HRCi + 1\right) - \log\left(HRMi - 1\right))^2}$$

In contrast to the previously described metrics that depend on the context of the problem, we decided to use R squared metrics. This statistical measure represents the proportion of the variance for a dependent variable that is extracted by an independent variable. In this case, it is the variation between the measured HR and the calculated HR with HeartPy.

$$R^2 = 1 - \frac{\text{Variance expained by the HeartPy function}}{\text{Total variance}}$$

Table 1 presents the results obtained from the applied evaluation metrics on the raw PPG signal and Table 2 - on the improved, cleaned, i.e. filtered PPG signal. There is no difference between the pairwise elements.

4 成果

4.1 评估指标

在本节中，更详细地介绍了所使用的评估指标。在以下公式中，HR参数表示为：HRMi - 第i例患者的测量HR; HRCi - 第i例患者的计算HR; n - 数据点（患者）数量。

MAE是一个简单的指标- 测量的HR和计算的HR之间的绝对差异，并且对离群值最稳健。

$$Ae = \frac{\sum_{n=1} (|HRMi — HRC\text{的使用}|)}{n}$$

MSE - 均方误差，表示实测HR和计算HR之间的平方差。

$$m = \frac{1}{n} \sum_{n=1}^{n} (HRM (HRC)$$

该度量可以用作损失函数，但对离群值敏感，并且惩罚更大，导致计算更大的MSE，与MAE相比降低了鲁棒性。另一个也可以用作损失函数的评估指标是RMSE，它更常用于深度学习技术。

$$rm = \sqrt{\frac{1}{n} \sum_{n=1}^{n} (HRM (HRC)}$$

通过取RMSE度量的对数，产生另一个评估度量- RMSLE（均方根对数误差）。RMSLE值将仅考虑测量的HR和计算的HR值之间的相对误差，忽略数据的规模。

$$rm\ sle) \sqrt{\frac{1}{n} \sum_{n=1}^{n} \log (HRCI + 1) - \log (HRM\ i — 1)}$$

与之前描述的依赖于问题上下文的度量相比，我们决定使用R平方度量。此统计度量表示由自变量提取的因变量方差的比例。在这种情况下，它是测量的HR和使用HeartPy计算的HR之间的变化。

$$R = 1 - \frac{\text{由HeartPy函数解释的方差}}{\text{总方差}}$$

表1呈现了从对原始PPG信号应用的评估度量获得的结果，并且表2呈现了从对改进的、清洁的、即过滤的PPG信号应用的评估度量获得的结果。成对元素之间没有区别。

Table 1. Evaluating the HeartPy performance on BIDMC database with different evaluation metrics on raw PPG signal

Evaluation metrics				
MAE	MSE	RMSE	RMSLE	R squared
0.30375	0.34617	0.58836	0.00771	0.99797

Table 2. Evaluating the HeartPy performance on BIDMC database with different evaluation metrics on filtered PPG signal

Evaluation metrics				
MAE	MSE	RMSE	RMSLE	R squared
0.30375	0.34617	0.58836	0.00771	0.99797

Another metrics that confirms the obtained results are the calculated Pearson's and the Spearman's coefficient of correlation between the same parameters, the measured and the calculated HR:

- Pearson: 0.99;
- Spearman: 0.99.

The obtained results from the evaluation metrics indicate a small difference between the measured and calculated values for HR, since normal Heart Rate for adults ranges from 60 to 100 beats per minute. Lower values of MAE, MSE, RMSE and RMSLE, imply high accuracy of the used HeartPy function. On the other hand, higher value of R^2 is considered desirable, which in our case is achieved. These results are verified by the high correlation coefficients.

This result is the same whether raw or filtered PPG signal was used for the HR calculation with the appropriate HeartPy function (Table 1 and Table 2). It can be concluded that HeartPy's algorithm is reliable for rapid and precise callculation of HR from a raw PPG signal.

5 Conclusion

Building a prototype of a chest patch sensor that can be used in mass casualty emergency situations means being able to deliver the main vital parameters: HR, RR, SPO2 and blood pressure, in real time. The START triage procedure requires both HR and RR parameters almost instantly, but to follow the hemodynamic stability of the injured person, paramedics need SPO2 and BP as well. The forementioned patch sensor will contain ECG, PPG and body temperature sensors.

The main goal of the paper was to explore the algorithms that can be used to calculate the Heart Rate only by utilizing the PPG signal from a patient, using HeartPy Toolkit [11]. It is very important to be able to rely on this fast HR calculation procedure, when trauma patient needs to be labeled in the Triage procedure (START triage system).

The measured HR from the used BIDMC database was compared to the calculated HR from the raw PPG signal for the same subject (patient), measured

表1.使用原始PPG信号的不同评价指标评价BIDMC数据库上的HeartPy性能

评估指标				
MAE	MSE	RMSE	RMSLE	R平方
0.30375	0.34617	0.58836	0.00771	0.99797

表2.使用滤波PPG信号的不同评价指标评价BIDMC数据库上的HeartPy性能

评估指标				
MAE	MSE	RMSE	RMSLE	R平方
0.30375	0.34617	0.58836	0.00771	0.99797

确认所获得的结果的另一个度量是相同参数之间的计算的Pearson 和斯皮尔曼相关系数，测量的和计算的HR：- Pearson ：0.99 ; - 斯皮尔曼：0.99 。

从评估指标获得的结果表明HR的测量值和计算值之间存在微小差异，因为成人的正常心率范围为每分钟60 至100次。MAE、MSE、RMSE和RMSLE的较低值意味着所使用的HeartPy函数的高精度。另一方面，更高的R值被认为是可取的，在我们的情况下实现了。这些结果被高相关系数所证实。

无论使用原始还是滤波PPG信号进行HR计算，该结果均与适当HeartPy函数相同（表1和表2）。可以得出结论，HeartPy算法对于从原始PPG信号快速精确计算HR是可靠的。

5 结论

构建可用于大规模伤亡紧急情况的胸部贴片传感器原型意味着能够真实的实时提供主要生命参数：HR、RR、SPO2和血压。START分诊程序几乎立即需要HR和RR参数，但为了跟踪受伤人员的血流动力学稳定性，护理人员还需要SPO2和BP。上述贴片传感器将包含ECG、PPG和体温传感器。

本文的主要目标是探索仅通过使用HeartPy Toolkit [11]，利用患者的PPG信号计算心率的算法。当创伤患者需要在分诊程序（START分诊系统）中被标记时，能够依靠这种快速HR计算程序是非常重要的。

将来自所用BIDMC数据库的测量HR与来自相同受试者（患者）的原始PPG信号的计算HR进行比较，测量

at the same time, utilizing the HeartPy Toolkit. In order to compare if the difference between the measured and calculated HR differs when the PPG signal is filtered, we conducted a cleaning procedure, taking into account the waveform quality. By using several evaluation metrics, it was concluded that there is no significant difference between the measured and the calculated HR (MAE = 0,3, MSE=0,3, R squared=0,99, Pearson's and the Spearman's coefficient of correlation, 0.99). This result is the same whether raw or the filtered PPG signal was used for the HR calculation with the appropriate HeartPy function. This is very important conclusion that enables us to use the unfiltered PPG signal directly from the sensor in order to get the HR value almost immediately with the help of the HeartPy function.

The success of this investigation leads us to an idea to verify the use of HeartPy as a tool to extract the Respiratory Rate and SPO2 from the raw PPG signal, as well. Another step is to compare these results with the reliability, accuracy and velocity when using ECG signal for calculating HR and RR using Python libraries.

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与此同时，使用HeartPy Toolkit。为了比较当PPG信号被滤波时测量的和计算的HR之间的差异是否不同，我们考虑波形质量进行了清理程序。通过使用几个评价指标，得出结论，测量的HR和计算的HR之间没有显著差异（MAE＝0.3，MSE＝0.3，R平方＝0.99，Pearson 和斯皮尔曼相关系数，0.99）。无论原始PPG信号还是滤波PPG信号用于HR计算（使用适当的HeartPy函数），该结果均相同。这是一个非常重要的结论，它使我们能够直接使用来自传感器的未经滤波的PPG信号，以便在HeartPy功能的帮助下几乎立即获得HR值。

这项研究的成功使我们产生了一个想法，即验证将HeartPy用作从原始PPG信号中提取呼吸率和SPO2的工具。另一个步骤是将这些结果与使用Python库使用ECG信号计算HR和RR时的可靠性，准确性和速度进行比较。

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