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RapidHRV: an open-source toolbox for extracting heart rate and heart rate variability

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RapidHRV：一个用于提取心率和心率的开源工具箱变异性

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Abstract

Heart rate and heart rate variability have enabled insight into a myriad of psychophysiological phenomena. There is now an influx of research attempting using these metrics within both laboratory settings (typically derived through electrocardiography or pulse oximetry) and ecologically-rich contexts (via wearable photoplethysmography, i.e. smartwatches). However, these signals can be prone to artifacts and a low signal to noise ratio, which traditionally are detected and removed through visual inspection. Here, we developed an open-source Python package, RapidHRV, dedicated to the preprocessing, analysis, and visualization of heart rate and heart rate variability. Each of these modules can be executed with one line of code and includes automated cleaning. In simulated data, RapidHRV demonstrated excellent recovery of heart rate across most levels of noise (>= 10dB) and moderate-to-excellent recovery of heart rate variability even at relatively low signal to noise ratios (>=20dB) and sampling rates (>=20Hz). Validation in real datasets shows good-to-excellent recovery of heart rate and heart rate variability in electrocardiography and finger photoplethysmography recordings. Validation in wrist photoplethysmography demonstrated RapidHRV estimations were sensitive to heart rate and its variability under low motion conditions, but estimates were less stable under higher movement settings.

Keywords: Heart rate variability, Remote sensing, Python, Toolbox

摘要

心率和心率变异性使人们能够洞察无数的

心理生理现象现在有大量的研究试图使用这些
两种实验室环境中的指标（通常通过心电图或脉搏测量得出
血氧测量）和生态丰富的环境（经由可穿戴光电体积描记术，即，
智能手表）。然而，这些信号可能倾向于伪像和低信噪比，
传统上通过目视检查来检测和去除。在这里，我们开发了一个
开源Python包RapidHRV，致力于预处理、分析和
心率和心率变异性的可视化。这些模块中的每一个都可以用
一行代码，包括自动清理。在模拟数据中，RapidHRV证明
在大多数噪声水平下（>= 10 dB）心率恢复良好，
即使在相对较低的信噪比（>= 20 dB）下也能恢复心率变异性，
采样率（>=20Hz）。在真实的数据集中的验证显示心脏恢复良好至极佳
心电图和手指光电体积描记术中的心率和心率变异性
录音.腕部光电体积描记术的验证表明，RapidHRV估计值
在低运动条件下，对心率及其变异性敏感，但估计值较少

在更高的运动设置下保持稳定。

关键词：心率变异性，遥感，Python，Python

RapidHRV: an open-source toolbox for extracting heart rate and heart rate variability

Evidence has outlined a link between heart rate, heart rate variability, and health-related risks, ranging from cardiac mortality to mental illness (Hillebrand et al., 2013; Jandackova et al., 2016; Makovac et al., 2016a; Pham et al., 2021). Consequently, there is now an influx of research looking into whether these measures can be derived in naturalistic settings to track clinically-relevant outcomes, namely through wearable devices (Georgiou et al., 2018; Mulcahy et al., 2019). However, a key issue when opting to use the measures in naturalistic settings are the low signal to noise ratios (e.g. photoplethysmography (PPG), a typical measure for cardiac monitoring in wrist wearables, Caizzone et al., 2017). Moreover, heart rate variability measures generally require relatively longer windows for extraction compared to heart rate (Baek et al., 2015). Thus, significant noise poses a problem for out-of-laboratory applications, as point estimates can contain large errors from technological limitations and motion artifacts within windows of extraction. In experimental settings, noise has often been dealt with through visual inspection of data (Makovac et al., 2016b; Rae et al., 2020); but when approaching time courses in relatively larger-scale samples, manual outlier detection is not a pragmatic solution.

Whilst some open-source packages are already available for the analysis of heart rate and heart rate variability, these are typically modality-specific, and not targeted at wrist-worn measures (e.g. *pyVHR* for video-based estimation, Boccignone et al., 2020). Some modality-general packages do exist, but these often still require manual visual inspection and/or can require custom scripting on the users end for tailoring to e.g. noisy, wrist-worn PPG measures ('Analysing_Smartwatch_Data' in *HeartPy*, van Gent et al., 2019; *NeuroKit2*, Pham et al., 2021). As such, these are often less suited for dealing with datasets collected across large time frames. Consequently, we set out to develop a simple yet flexible toolbox for the extraction of time-domain heart rate and heart rate variability measures with automated artifact rejection applicable across recording modalities, including wrist-worn PPG. Here, we present the development and validation of an open-source Python package, 'RapidHRV'.

RapidHRV：一个用于提取心率和心率的开源工具箱

变异性

有证据表明，心率、心率变异性和与健康相关的

风险，范围从心脏死亡到精神疾病（Hillebrand 等人，2013; Jandackova 等人，2016; Makovac等人，2016 a; Pham 等人，2021年）。因此，现在有大量的研究这些措施是否可以在自然环境中得出，以跟踪临床相关的结果，即通过可穿戴设备（Georgiou等人，2018年：Mulcahy 例如，2019年）。然而，在自然环境中选择使用这些措施时的一个关键问题是低信噪比（例如，光电体积描记术（PPG），用于心脏的典型测量）手腕可穿戴设备中的监测，Caizzone等人，2017年）。此外，心率变异性测量与心率相比通常需要相对较长的提取窗口（Baek等人，2015年）。因此，显著的噪声对实验室外的应用造成问题，如点估计可能包含来自技术限制和运动伪影的大误差，提取窗口在实验环境中，噪声通常通过视觉来处理。数据检查（Makovac等人，2016 b; Rae等人，2020年）;但当接近时间课程时

在相对较大规模的样本中，手动离群值检测不是实用的解决方案。

虽然已经有一些开源软件包可用于分析心率，

心率变异性，这些通常是模态特定的，而不是针对手腕佩戴的测量（例如，用于基于视频的估计的pyVHR，Boccignone等人，2020年）。一些模态通用包确实存在，但这些通常仍然需要手动目视检查和/ 或可能需要用户端的自定义脚本，以适应例如嘈杂的腕戴式PPG measures（“Analysing_Smartwatch_Data ”in HeartPy，货货车Gent et al.，2019; NeuroKit 2，Pham 等

例如，2021年）。因此，它们通常不太适合处理跨大型数据集收集的数据集。时间框架。因此，我们着手开发一个简单而灵活的工具箱，时域心率和心率变异性测量，自动排除伪影适用于所有记录模式，包括腕戴式PPG。在这里，我们提出了

开发和验证一个开源的Python包“RapidHRV”。

Pipeline

RapidHRV was developed in Python (V 3.7.9). RapidHRV source code and tutorials are available to download through PyPi (https://pypi.org/project/rapidhrv/) and GitHub (https://github.com/peterakirk/RapidHRV). Below we provide an overview of RapidHRVs preprocessing, analysis (figure 1), and visualization. Each of the three modules only requires one function (one line of code) to run, for which we have embedded examples at the end of the relevant sections below.

–Figure 1–

Preprocessing

First, data is upsampled with cubic spline interpolation (3rd order polynomial; default = 1kHz) to increase temporal accuracy of peak detection. To mitigate potential long-term drifts in the signal, the pipeline then applies a high pass butterworth filter (0.5Hz) across the input data. Finally smoothing with a savitzky-golay filter (3rd order polynomial; default = 100ms) is applied to reduce spiking (sharp increases in the signal caused by artifacts such as motion) whilst retaining temporal precision.

Extracting Heart Rate and Heart Rate Variability

Following preprocessing, the pipeline scales the data (between 0 and 100) and runs peak detection on every window (default width = 10s; for a methodological discussion and prior validation of using ultra-short, 10s windows in heart rate variability estimation, see Munoz et al., 2015). This outputs peaks and their properties (e.g. heights, amplitudes, width; *SciPy* 'find_peaks', Virtanen et al., 2020). For ECG data however, peak detection is vulnerable to irrelevant prominent P and T waves. Specifically, traditional amplitude-based analyses may occasionally detect non-R wave peaks that demonstrate a similar or greater amplitude than R waves. Consequently, for ECG data, RapidHRV can implement k-means clustering (k = 3) to

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管道

RapidHRV是用Python（V 3.7.9）开发的。RapidHRV源代码和教程

可通过PyPi（https：/ / pypi.org/ project/ rapidhrv / ）和GitHub 下载（https：/ / github.com/ peterakirk/ RapidHRV）.下面我们提供RapidHRV的概述预处理、分析（图1）和可视化。三个模块中的每一个都只需要一个函数（一行代码）运行，我们在

下面的相关章节。

- 图1-

预处理

首先，使用三次样条插值对数据进行上采样（三阶多项式;默认值=

1 kHz），以提高峰值检测的时间精度。为了减轻潜在的长期漂移，信号，然后管线在输入数据上应用高通巴特沃思滤波器（0.5Hz）。最后，使用savitzky-golay滤波器（3阶多项式;默认值= 100 ms）进行平滑为了减少尖峰（spiking）（由诸如运动之类的伪影引起的信号的急剧增加），

保持时间精确性。

心率和心率变异性的提取

在预处理之后，管道缩放数据（在到100之间）并运行peak

每个窗口上的检测（默认宽度= 10 s;用于方法论讨论和之前的在心率变异性估计中使用超短10秒窗口的验证，参见Munoz等人，2015 年）。这将输出峰值及其属性（例如高度、振幅、宽度; SciPy “find_peaks”，Virtanen 等人，2020年）。然而，对于ECG数据，峰值检测容易受到不相关的显著P波和T波。具体地，传统的基于幅度的分析可以偶尔检测到非R波峰值，其显示出与R波相似或更大的振幅波因此，对于ECG数据，RapidHRV可以实现k均值聚类（k = 3），以

discern R waves from P and T waves prevalent in the signal (*scikit-learn* 'KMeans', Pedregosa et al., 2011). This is implemented by reducing the minimum amplitude threshold to near-zero (i.e. 5%), running amplitude-based peak detection, then sorting peaks into three clusters using relevant properties (i.e. peak widths, heights, and prominences). R waves are then determined based on cluster centroids for peak properties, expecting R waves to hold higher prominences *and* lower widths compared to P and T waves. Figure 2 demonstrates an example (from dataset 3, see *Validation Methods*) wherein amplitude-based analyses may incorrectly identify T waves as R waves in an atypical ECG signal, and how RapidHRV's peak clustering helps mitigate this.

–Figure 2–

As RapidHRV uses fixed movements for the sliding window, a window can start or end at any point during the cardiac signal. This can occasionally result in underestimation of the first/last peak's amplitude as the baseline value may—for example—be set during the P wave. Therefore, RapidHRV recalculates amplitudes of the first/last peaks using baseline imputation from the neighboring peaks.

For extracting beats per minute (BPM) the number of peaks, k - 1, is multiplied by 60 (seconds), and divided by the difference in time between the first and last peaks, i and j:

$$\mathrm{BPM} = ((k-1) * 60)/(j-i)$$

The root mean square of successive differences is calculated by obtaining: (1) the interbeat interval, IBI_i, between neighboring peaks; (2) the successive differences in interbeat intervals, IBI_i - IBI_{i+1}; (3) the square of differences; (4) the mean of squared differences (dividing by the number peaks, N, - 1); and (5) the root of the mean square of successive differences (RMSSD):

RapidHRV可以实现k均值聚类（k = 3）到RapidHRV 5

从信号中普遍存在的P和T波中辨别R波（scikit-learn 'KMeans'，Pedregosa et
例如，2011年）。这通过将最小幅度阈值减小到接近零（即，
5%），运行基于幅度的峰值检测，然后使用
相关性质（即峰宽、峰高和峰宽）。然后确定R波
基于峰值特性的聚类质心，期望R波具有更高的连续性
与P波和T波相比，宽度更小。图2展示了一个示例（来自数据集3，
参见验证方法），其中基于振幅的分析可能会错误地将T波识别为R波

我们还讨论了非典型ECG信号中的波形，以及RapidHRV的峰值聚类如何帮助缓解这种情况。

- 图2-

由于RapidHRV对滑动窗口使用固定移动，窗口可以在
在心脏信号期间的任何点。这有时会导致低估
例如，可以在P波期间设置作为基线值的第一个/ 最后一个峰值的幅度。
因此，RapidHRV使用基线插补重新计算第一个/ 最后一个峰值的振幅

从邻近的山峰。

为了提取每分钟心跳数（BPM），峰值的数量k - 1乘以60
（秒），除以第一个和最后一个峰值之间的时间差i和j:

$$\mathrm{BPM} = ((k-1) * 60)/(j-i)$$

连续差值的均方根通过以下公式计算：（1）
相邻峰之间的心搏间期IBI;（2）心搏间期的连续差
间隔，IBI- IBI;（3）差异的平方;（4）平方差异的平均值（除以
由峰数N，-1）;和（5）连续差异的均方的根

（RMSSD）：

$$\text{RMSSD} = \sqrt[2]{\frac{\Sigma_{i=1}^{N-1}(\text{IBI}_i - \text{IBI}_{i+1})^2}{N-1}}$$

BPM and RMSSD were selected as the primary measures as they appear to be the most stable metrics when derived from ulta-short recordings (Baek et al., 2015). RapidHRV also supplements these measures with the standard deviation of N-N intervals (SDNN), standard deviation of successive differences (SDSD), proportion of successive differences greater than 20ms (PNN20), proportion of successive differences greater than 50ms (PNN50), and high-frequency power (HF; note: as this requires more data points than time-domain analyses NaN is returned if there is insufficient data).

Outlier Detection

The last phase of the pipeline is to pass measures derived from peak extraction to outlier rejection (figure 3). This is applied at the level of the sliding window. If a window is declared an outlier, heart rate and heart rate variability measures are removed from the cleaned time series. By default, RapidHRV returns both the cleaned and the uncleaned time series. In addition to default parameters listed below, the package has optional arguments embedded to allow users to override these presets. Given that not all users may be entirely comfortable manually adjusting these, RapidHRV additionally contains semantically-labeled arguments as inputs for outlier constraints (‘liberal’, ‘moderate’ [default], and ‘conservative’; corresponding parameters are parenthesized under *Biological Constraints* and *Statistical Constraints*).

Biological Constraints. RapidHRV first applies restrictions to exclude data that are highly unlikely given known physiology:

1. Screening for sufficient peaks in a window (default: number of peaks > (window width / 5) + 2), floored at 3; default at 10s = 3 peaks). This is primarily for computational applicability and efficacy, screening data prior to further processing. The minimum number of peaks required to enable calculation of RMSSD is 3. As such, this is also applied to the uncleaned time series.

$$\mathrm{RMSSD} = \sqrt[2]{\frac{\Sigma_{i=1}^{N-1}(\mathrm{IBI}_i - \mathrm{IBI}_{i+1})^2}{N-1}}$$

BPM和RMSSD被选为主要指标，因为它们似乎是

当从超短记录导出时的稳定度量（Baek等人，2015年）。RapidHRV还
用N-N间隔的标准差（SDNN）、标准偏差（SDNN）
连续差异偏差（SDSD），连续差异大于
20 ms（PNN 20），连续差异大于50 ms的比例（PNN 50），以及
高频功率（HF;注：因为这需要比时域分析更多的数据点

如果数据不足，则返回NaN ）。

离群点检测

流水线的最后一个阶段是将从峰值提取得到的度量传递给离群值

拒绝（图3）。这在滑动窗口的级别上应用。如果窗口声明为
从净化的时间序列中去除离群值、心率和心率变异性测量。
默认情况下，RapidHRV返回已清理和未清理的时间序列。除了
默认参数，包中嵌入了可选参数，允许用户
忽略这些错误。鉴于并非所有用户都可以完全舒适地手动调整
RapidHRV还包含语义标记参数作为离群值的输入
constraints （'liberal'，'moderate' [default]，and 'conservative';对应的参数是

在生物学约束和统计学约束下加括号）。

生物限制。RapidHRV首先应用限制以排除以下数据：

鉴于已知生理学，极不可能：

1.在窗口中筛选足够的峰（默认值：峰数>（窗口宽度/ 5）+ 2），在3处进行筛选;默认值为10秒= 3个峰）。这主要是为了

计算的适用性和有效性，筛选数据之前，进一步
处理.计算所需的最小峰数

RMSSD为3。因此，这也适用于未清理的时间序列。

2. Minimal and maximal heart rate (‘moderate’ [default]: 30 > BPM > 190; ‘liberal’: 20 > BPM > 200; ‘conservative’: 40 BPM > 180). These boundaries were based on typical heart rate at rest and during exercise in the healthy population (Pierpont & Voth, 2004; Sandvik et al., 1995; Savonen et al., 2006).
3. Minimal and maximal heart rate variability (‘moderate’ [default]: 5 > RMSSD > 262; ‘liberal’: 0 > RMSSD > 300; ‘conservative’: 10 > RMSSD > 200). Default arguments correspond to the minimum/maximum 2nd/98th percentiles of resting RMSSD across ages 16-89 years (van den Berg et al., 2018).

Statistical constraints. RapidHRV next applies statistical constraints to account for noisy data that may otherwise appear to provide measures within the range of known physiology:

4. Median absolute deviation (MAD) of peak heights (distance from minimum value of signal in window; i.e. 0) and prominence (amplitude from baseline height; ‘moderate’ [default] = 5 MAD units; ‘liberal’ = 7; ’conservative’ = 4). Unlike Z-scoring, this quantifies each peak’s height and prominence in a given window in terms of its deviation from the median value in the same window (for a discussion of median absolute deviation see Leys et al., 2013). Applying these constraints to height and prominence helps exclude windows with noise-driven inaccuracies in peak detection.
5. Median absolute deviation of interbeat intervals (‘moderate’ [default] = 5 MAD units; ‘liberal’ = 7; ’conservative’ = 4). This was also implemented to account for inaccuracies in peak detection, either where spiking may cause detection of an irrelevant peak shortly after e.g. an R wave, or low signal to noise ratio may result in missing relevant peaks.
6. Time from the first peak to the last peak does not recede 50% of the fixed window width. This is to ensure the user that the *actual* length of time for extracting HR/HRV is not less than half of that which is specified in the window width argument. Given debates surrounding adequacy of different window lengths for HRV extraction (Baek et al., 2015; Munoz et al., 2015), this was implemented

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2.最小和最大心率（'中等' [默认]：30 > BPM > 190; '自由'：20 > BPM > 200; '保守'：40 BPM > 180）。这些界限是基于

对健康人群在休息和运动时的典型心率的影响（Pierpont

& Voth，2004; Sandvik等人，1995; Savonen等人，2006年）。

3. 最小和最大心率变异性（“中度”[默认值]：5 > RMSSD>
（2）“自由”：0> RMSSD> 300;“保守”：10> RMSSD> 200）。Default 的
参数对应于静止的最小/ 最大第2/ 98位数

16-89岁年龄段的RMSSD（货车den贝格等人，2018年）。

统计限制。RapidHRV接下来应用统计约束来解释噪声

可能以其他方式出现以提供已知生理学范围内的测量的数据：

4.峰高（与窗口中信号最小值的距离;即0）和突出度（与基线高度的振幅;

'温和' [默认] = 5 MAD单位; '自由' = 7; '保守' = 4）。不像
Z评分，这量化了给定窗口中每个峰的高度和突出度
就其与同一窗口中的中值的偏差而言（对于
中值绝对偏差的讨论参见Leys等人，2013年）。应用这些
高度和突出度的约束有助于排除噪声驱动的窗口

峰值检测不准确。

5. 心搏间期的中位绝对偏差（“中度”[默认] = 5 MAD
单位;“自由派”= 7;“保守派”= 4）。这也是为了说明
峰值检测的不准确性，其中尖峰可能导致检测到
可能导致在例如R波之后不久出现不相关的峰或低信噪比

在缺失相关峰的情况下。

6. 从第一个峰值到最后一个峰值的时间不后退固定窗口的50%
宽度.这是为了保证用户的实际提取时间长度
HR/ HRV不小于窗口宽度规定值的一半
论点考虑到围绕不同窗口长度是否足够的争论，
HRV提取（Baek等人，2015; Munoz等人，2015年），这一点得到了落实。

primarily as a theoretical constraint (rather than for just cleaning per se) to ensure the user is not provided data that deviated significantly from their specified window.

Analysis can be executed with one line of code, which returns a pandas DataFrame (McKinney, 2012; Reback et al., 2022) containing the analyzed data.

–Figure 3–

Visualization

To allow for selected manual inspection, we have also implemented optional interactive visualizations via matplotlib (Hunter, 2007) which allow the user to plot the time course of heart rate and heart rate variability. The user can then select and view specific data points to see the window of extraction (figure 4). We have provided an example pipeline below:

```
import rapidhrv as rhv
example_signal = rhv.get_example_data()  # Load example data
preprocessed = rhv.preprocess(example_signal)  # Preprocess data
analyzed = rhv.analyze(preprocessed)  # Analyze data
rhv.visualize(analyzed)  # Visualize data
```

–Figure 4–

Validation Methods

Datasets

这是RapidHRV 8实施的

主要作为理论约束（而不仅仅是清洁本身），以确保
不向用户提供显著偏离其指定的

窗口

分析可以通过一行代码执行，这将返回一个pandas DataFrame（McKinney，2012; Reback等人，#20202;分析数据。

- 图3-

可视化

为了允许有选择的人工检查，我们还实现了可选的交互式检查。通过matplotlib 可视化（Hunter，2007），允许用户绘制心脏的时间过程心率和心率变异性然后，用户可以选择并查看特定的数据点，

提取窗口（图4）。我们在下面提供了一个示例管道:

```
将rapidhrv导入为rhv

example_signal = rhv.get_example_data（）#加载示例数据

preprocessed = rhv.preprocess（example_signal）#预处理数据

analyzed = rhv.analyze（preprocessed）#分析数据

rhv.visualize（已分析）#可视化数据
```

- 图4-

验证方法

数据集

To validate the above pipeline we subjected it to a series of tests across both simulated and real data (table 1). We first started by testing RapidHRV's estimations in two sets of simulated data (PPGSynth; Tang et al., 2020). Next, we ran validation in real data across successively noisier modalities: electrocardiography (ECG), finger infrared photoplethysmography (IR PPG), and wrist PPG data. Database information and code generated in validation tests are available through the open science framework (https://osf.io/7zvn9/).

–Table 1–

1. **Simulations Across Noise and Sampling Rates**. We first took the pipeline forward to validation using simulated photoplethysmography (PPG) data from PPGSynth (Tang et al., 2020) in MATLAB. This allowed us to test how well RapidHRV recovered known parameters under specified conditions, such as sampling rate and noise. We produced 5 minute long synthetic datasets (1000Hz), each of which varied according to the following cardiac features:

    - Mean heart rate (BPM range 60-120, increments of 5). These were selected to allow us to check the sensitivity of the pipeline for detecting values across typical resting heart rate, as well as elevations of these values.
    - Heart rate variability (RMSSD range 0-100, increments of 5). Again, these were selected based on typical resting heart rate variability and moderate increases/decreases.

Following simulation of the data, we introduced noise via:

- White gaussian noise filtering (signal to noise ratios = 0.01, 10, 20, 30, 40, 50, and 60dB). Here, we selected a range of values starting from near-zero to ascertain at which level of noise the pipeline could no longer recover parameters (with near-zero expected to prevent the extraction of any meaningful metrics).

为了验证上述管道，我们对它进行了一系列测试，

和真实的数据（表1）。我们首先在两组数据中测试RapidHRV的估计，
模拟数据（PPGSynth; Tang等人，2020年）。接下来，我们在真实的数据中运行验证，
依次噪声更大的模态：心电图（ECG）、手指红外线
光电体积描记法（IR PPG）和腕部PPG数据。生成的数据库信息和代码

验证测试可通过开放科学框架（https：/ / osf.io/ 7zvn9/ ）获得。

- 表1-

1.模拟噪声和采样率。我们首先使用来自PPGSynth的模拟光电体积描记（PPG）数据（Tang et

例如，2020年，在MATLAB？这使我们能够测试RapidHRV恢复的情况
在特定条件下的参数，如采样率和噪声。我们生产了5
分钟长的合成数据集（1000 Hz），每个数据集根据以下内容变化

心脏特征：

- 平均心率（BPM范围60-120，增量为5）。这些被选中，
  允许我们检查管道的灵敏度，以检测典型的

  静息心率，以及这些值的升高。
- 心率变异性（RMSSD范围0-100，增量为5）。同样，
  根据典型的静息心率变异性和中度

  增加/ 减少。

在数据模拟之后，我们通过以下方式引入噪声：

- 白色高斯噪声滤波（信噪比= 0.01，10，20，30，40，50，
  60dB）。在这里，我们选择了从接近零到
  确定在何种噪声水平下管道不再能够恢复参数

  (with期望接近零以防止提取任何有意义的度量）。

- Downsampling (frequencies = 20, 50, 100, and 250Hz). These were selected: A) to capture the range of sampling rates currently used in photoplethysmography studies (typically >= 20Hz); and B) because prior work has suggested sensitivity to RMSSD deteriorates dramatically between 20-100Hz (Choi & Shin, 2017). This offered the opportunity to test the effects of cleaning on what would otherwise be considered poor quality data.

2. Simulated 'Anxiety'. Again, we simulated data using PPGSynth. However, simulations were based on prior anxiety literature to emulate experiment-specific effects. We wanted to validate the sensitivity of the pipeline across specified sampling rates and levels of noise but in the context of a known psychophysiological effect. For this, we used an estimated Cohen's *d* of .384, which was derived from a previous within-subjects threat-of-shock study (RMSSD, t_{25} = 1.96, polarity flipped for readability; Gold et al., 2015). To reflect decisions in experimental design, we ran a power calculation using the 'pwr' package (Champely et al., 2017) in R, leading us to simulate a sample of N = 171 (α=.001, 1-β=.95). These 'experiments' were simulated 10 times to ascertain confidence intervals around estimated effect sizes.

For each 'subject', we generated a 5 minute simulated time series (1kHz) using typical resting heart rate and heart rate variability (BPM: μ = 74, σ = 13, Savonen et al., 2006; RMSSD: μ = 23, σ = 7, bounded between 5-262, Nunan et al., 2010). These simulations were intended to emulate the 'safe' condition (no anxiety induction) in a threat-of-shock study. Next, we simulated another time series for each subject that deviated from their 'safe' RMSSD (heart rate held constant) based on our effect size estimate (*d* = .384). This emulated our 'threat' (anxiety induction) condition and contained general reductions in heart rate variability. Each time series was finally submitted to downsampling and noise filtering using the same parameters as in the previous simulations (white gaussian noise filtering to 0.01, 10, 20, 30, 40, 50, 60dB; downsampling to 20, 50, 100, and 250Hz).

- 下采样（频率= 20、50、100和250 Hz）。这些被选中：A）为了捕获当前在光电体积描记术中使用的采样率的范围研究（通常>= 20 Hz）;和B），因为之前的研究表明灵敏度RMSSD在20 - 100 Hz之间急剧恶化（Choi & Shin，2017）。这提供了一个机会，以测试清洁的影响，

  否则被认为是质量差的数据。

2.模拟“死亡”。同样，我们使用PPGSynth模拟数据。然而，在这方面，模拟基于先前的焦虑文献以模拟实验特异性效应。我们希望验证管道在指定采样率和噪声，但在已知的心理生理效应的背景下。为此，我们使用了估计的科恩的d为.384，这是从之前的受试者内休克威胁研究中得出的（RMSSD，t = 1.96，极性翻转以便于阅读; Gold等人，2015年）。以反映决定，在实验设计中，我们使用“BIGER”包进行功效计算（Champely等人，（2017年）在R中，我们模拟了N = 171（α= 0.001，1-β= 0.95）的样本。这些“实验”是

模拟10次，以确定估计效应量的置信区间。

对于每个“受试者”，我们使用典型的静息心率和心率变异性（BPM：μ = 74，σ = 13，Savonen等人，2006年;农村社会发展委员会：μ = 23，σ = 7，介于5-262之间，Nunan 等人，2010年）。这些模拟旨在在电击威胁研究中模拟“安全”条件（无焦虑诱导）。接下来我们模拟每个受试者的另一个时间序列，偏离他们的“安全”RMSSD（心率保持不变）基于我们的效应量估计（d = .384）。这模仿了我们的“威胁”（焦虑诱导）条件，并包含心率变异性的总体降低。每个时间序列最后使用与图1中相同的参数进行下采样和噪声滤波。先前的模拟（白色高斯噪声滤波到0.01、10、20、30、40、50、60 dB;

下采样到20、50、100和250 Hz）。

3. Estimation via ECG. Following simulations, we wanted to clarify that our package was able to adequately extract measures from one of the highest standards for heart rate variability recordings, ECG. Here, we tested whether our package was able to recapitulate known age-related effects of heart rate variability. For this, we used the *Fantasia* database (Iyengar et al., 1996). This consisted of 40 subjects (20 'Young' Age Range = 21-34 years; 20 'Old' Age Range = 68-81 years) watching the movie 'Fantasia' (duration ≈ 2 hours) whilst undergoing ECG recordings. Automated peak detection was previously run on this dataset, with every beat annotation verified by visual inspection. The full dataset and description is available on PhysioNet (https://physionet.org/content/fantasia/1.0.0/; Goldberger et al. 2000).

4. Estimation via Wrist Photoplethysmography. We next took the pipeline forward to validation in a modality considered relatively noisier than ECG, wrist photoplethysmography. Here, we used a dataset of 39 subjects (Age: Mean = 22.67; Range = 18–38 years; demographics reported prior to N=1 exclusion) watching 2 x 28 minute blocks of documentary and horror video clips undergoing finger IR PPG recording (1000Hz, de Groot et al., 2020). This allowed us to contrast psychological conditions of the experiment, testing whether RapidHRV was able to detect effects of anxiety. Moreover, in the original study, data had been preprocessed and analyzed using a commercially available software (Labchart; ADInstruments, Sydney, Australia; analyzed using built-in 'Peak Analysis' module). This allowed us to benchmark RapidHRV against another software. The full dataset and description is available via the Open Science Framework (https://osf.io/y76p2/).

5. Estimation via PPG. Finally, we analyzed the *PPG-DaLiA* dataset, which consists of 15 subjects (Age: Mean = 30.60 years; Range = 21-55) completing various activities whilst having wrist PPG recorded with an Empatica E4 device (Hz = 64) and simultaneous ECG measures with a RespiBAN (Hz = 700, Reiss et al., 2019). Over the course of 2.5 hours, participants engaged in a range of activities designed to elicit low and high motion. These were: sitting and reading; ascending/descending stairs; 1 v 1 table soccer; cycling on pavements and gravel; driving a car; lunch break (queuing, purchasing, and eating food in a cafeteria); walking;

3.通过ECG进行估计。在模拟之后，我们想澄清一下，

能够从心率的最高标准之一充分提取测量值
变异性记录心电图在这里，我们测试了我们的软件包是否能够概括已知的
心率变异性的年龄相关影响。为此，我们使用了幻想曲数据库（Iyengar et
例如，1996年）。这包括40例受试者（20例“年轻”年龄范围= 21-34岁; 20例“老年”年龄
范围= 68-81岁）观看电影'幻想曲'（持续时间约2小时），同时进行
ECG记录。之前在此数据集上运行了自动峰值检测，
通过目视检查验证注释。完整的数据集和描述可在

PhysioNet（https：/ / physionet.org/ content / fantasia / 1.0.0/ ; Goldberger et al. 2000）。

4.通过腕部光电体积描记法进行估计。接下来，我们将管道向前推进，

在被认为比ECG、腕部光电体积描记术噪声相对更大的模态中进行验证。
在这里，我们使用了39名受试者的数据集（年龄：平均值= 22.67;范围= 18-38岁;人口统计学
在N=1排除之前报告）观看2 x 28分钟的纪录片和恐怖片
经历手指IR PPG记录的视频剪辑（1000Hz，de Groot 等人，2020年）。这让我们
对比实验的心理条件，测试RapidHRV是否能够
检测焦虑的影响。此外，在最初的研究中，数据已经过预处理，
使用市售软件（Labchart ; ADInstruments， Sydney，Australia ;
使用内置的“峰值分析”模块进行分析）。这使我们能够对RapidHRV进行基准测试
另一个软件。完整的数据集和描述可通过开放科学

框架（https：/ / osf.io/ y76p2/ ）。

5.通过PPG估计。最后，我们分析了PPG-DaLiA数据集，该数据集包括：

15例受试者（年龄：平均= 30.60岁;范围= 21-55岁）完成各种活动，同时
使用Empatica E4设备（Hz = 64）记录腕部PPG，同时进行ECG
使用RespiBAN（Hz = 700，Reiss等人，2019年）。在两个半小时的时间里，
参与者参与了一系列旨在引起低和高运动的活动。这些问题是：
坐着和阅读;上/ 下楼梯; 1对1桌上足球;在人行道上骑自行车，
砾石;开车;午休（排队，购买，并在自助餐厅吃食物）;步行;

and working at a desk (typically on a computer). This allowed us to test whether RapidHRV was able to extract heart rate and variability measures from wrist PPG and how these compared to ECG measurements. Moreover, this enabled us to highlight under what conditions estimations are optimal. For the full dataset and description, see Reiss et al. (2019).

Analyses

Unless otherwise stated, all analyses were conducted using RapidHRV's default arguments: window width = 10s; window movement = 10s; outlier method = 'moderate' (peak/height median absolute deviation = 5, interbeat interval median absolute deviation = 5, BPM range = 30-190, RMSSD range = 5-262); minimum window successful extraction = 5s, minimum amplitude for peak detection = 50, minimum distance between peaks = 250ms; for ECG data, ecg_prt_clustering = True). To assess performance across datasets, we used: visualizations; intraclass correlation coefficients (ICC; two-way mixed effects, absolute agreement, single measure); root-mean-square-error (RMSE); and sensitivity to experimental effects (Cohen's *d*). For ICC values, we used the following semantic labels for interpretation: ICC < .5 as 'poor', .5 < ICC < .75 as 'moderate'; .75 < ICC < .90 as 'good', and .90 < ICC as 'excellent' (Koo & Li, 2016).

In our PPG dataset, we also calculated motion estimates as a proxy for the severity of noise present in PPG across conditions. We derived mean jerk magnitude (square root of the sum of squared changes in acceleration; Eager et al., 2016), which aimed to pick up on oscillatory ('jerk') motions in the wrist for each condition. Across all axes (x, y, and z; m/s^2), jerk vector, j, was calculated as the change in acceleration, a, divided by the change in time, t, between samples:

$$\vec{j}\,(t) = \frac{\Delta\vec{a}(t)}{\Delta t}$$

Finally, we derived jerk magnitudes by calculating the square root of the sum of squared jerks, j, for axes x, y, and z:

和在自助餐厅吃饭）;步行; RapidHRV 12
在办公桌前工作（通常在计算机上）。这使我们能够测试RapidHRV是否
能够从腕部PPG中提取心率和变异性指标，以及这些指标与
ECG测量。此外，这使我们能够强调在什么条件下的估计

是最佳的。有关完整的数据集和描述，请参见Reiss et al.（2019）。

分析

除非另有说明，否则所有分析均使用RapidHRV的默认值进行
参数：窗口宽度= 10秒;窗口移动= 10秒;离群值方法="中等"
(peak/ 身高中位数绝对偏差= 5，心搏间期中位数绝对偏差= 5，
BPM范围= 30-190，RMSSD范围= 5-262）;最小窗口成功提取= 5s，
峰值检测的最小幅度= 50，峰值之间的最小距离= 250 ms;对于
ECG数据，ecg_prt_clustering = True）。为了评估跨数据集的性能，我们使用了：
可视化;组内相关系数;双向混合效应，绝对值
一致性，单次测量）;均方根误差（RMSE）;和实验灵敏度
影响（Cohen's D）。对于ICC值，我们使用以下语义标签进行解释：
ICC <0.5为"差"，0.5< ICC <0.75为"中等"，0.75< ICC <0.90为"好"，0.90< ICC

"优秀"（Koo & Li，2016）。

在我们的PPG数据集中，我们还计算了运动估计值，作为
各种条件下PPG中存在噪声。我们推导出平均加加速度幅值（和的平方根
加速度的平方变化; Eager等人，2016年），旨在提高振荡
（"挺举"）运动的手腕为每一个条件。在所有轴（x、y和z; m/ s^2）上，加加速度矢量j，
计算为加速度变化a除以时间变化t，

样品：

$$\vec{j}\,(t) = \frac{\Delta \vec{a}(t)}{\Delta t}$$

最后，通过计算加速度的平方和的平方根，
轴x、y和z的加速度j：

$$\left|\vec{\dot{j}}\right| = \sqrt{\dot{j}_x^2 + \dot{j}_y^2 + \dot{j}_z^2}$$

For each subject, jerk magnitudes were averaged across time for each condition.

Validation Results

1. Parameter Recovery in Simulated PPG

RapidHRV was able to accurately recover heart rate across most sampling frequencies and noise in our initial simulations. Accurate detection of BPM primarily started to degrade when signal to noise ratios were less than 10dB (figure 5; table 2). RapidHRV cleaning provided improvements in simulations with a signal to noise ratio of 10dB.

–Table 2–

Performance in recovery of heart rate variability was again primarily based on signal to noise ratio. At 20dB RapidHRV recovery of RMSSD was good-to-excellent for higher sampling rates (>=100Hz), whereas lower sampling rates (<100Hz) required slightly lower levels of noise (>30dB) for excellent recovery. RapidHRV cleaning provided clear improvements when signal to noise ratio was below 30dB (figure 3).

–Figure 5–

Key points

- RapidHRV's estimation of simulated BPM was good-to-excellent when signal to noise ratio was 10dB or above.

RapidHRV 13号

$$\left|\vec{j}\right| = \sqrt{j_x^2 + j_y^2 + j_z^2}$$

对于每个受试者，每种条件下的加加速度幅度在时间上取平均值。

验证结果

1.模拟PPG RapidHRV中的参数恢复能够在大多数采样频率下准确恢复心率
和噪声的影响BPM的准确检测主要开始下降
当信噪比小于10 dB时（图5;表2）。提供RapidHRV清洁

在模拟中的改进，信噪比为10 dB。

- 表2-

心率变异性恢复的性能再次主要基于信号，
噪声比在20 dB RapidHRV恢复RMSSD是良好到优秀的更高的采样
采样率（>= 100 Hz），而较低的采样率（<100 Hz）需要略低的噪声水平
（> 30 dB），恢复良好。RapidHRV清洁在以下情况下提供了明显的改善:

噪声比低于30 dB（图3）。

- 图5-

重点

- RapidHRV对模拟BPM的估计在信噪比时为良好到优秀
  比率为10dB或以上。

- RapidHRV's estimation of simulated RMSSD was good-to-excellent when signal to noise ratio was 20dB and sampling rate was 100Hz or higher. Across all sampling rates, RMSSD recovery was excellent at 30dB or above.
- Cleaning appeared particularly helpful when noise was high and/or sampling rate was low.

2. Sensitivity to 'Anxiety' in Simulated PPG

RapidHRV's ability to estimate simulated effects was again primarily impacted by the level of SNR, where changes in RMSSD were not reliably detected at 0.01 and 10dB (figure 6; table 3). Effects were detected at signal to noise ratios of 20dB and 30dB, but this was estimated at around half that of the true value. Maximal effect sizes plateaued following 40dB for uncleaned data and 30dB for cleaned data. Moreover, reliable detection of effects in some scenarios (e.g. 50Hz, 10dB) appeared dependent on cleaning. This was consistent with our previous validation results, in that cleaning was beneficial at lower signal to noise ratios and sampling rates, but was not necessary (or could be relaxed) in cleaner data.

–Figure 6–

–Table 3–

Key points

- RapidHRV's estimation for simulated effects of Anxiety on RMSSD was excellent when signal to noise ratio was 30dB or above. Moreover, this estimation was robust at a low sampling rate (i.e. 20Hz).
- Cleaning was beneficial when noise was high, but was not necessary when noise was low.

- RapidHRV对模拟RMSSD的估计在信噪比时为良好到优秀
  采样频率为100 Hz或更高。在所有采样率中，
  RMSSD在30 dB或以上恢复良好。
- 当噪音高和/ 或采样率低时，清洁显得特别有用。
  low.

2.模拟PPG RapidHRV对“焦虑”的敏感性估计模拟效应的能力再次主要受到SNR水平，其中RMSSD的变化在0.01和10 dB下不能可靠地检测到（图6;表3）。在信噪比为20 dB和30 dB时检测到影响，但这是估计的。大约是真实值的一半。最大效应量在40 dB后达到稳定，未清理的数据和30 dB的清理数据。此外，在某些情况下，场景（例如50 Hz，10 dB）似乎取决于清洁。这与我们的先前的验证结果表明，清洁在较低信噪比下是有益的，

采样率，但没有必要（或可以放宽）在更干净的数据。

- 图6-

- 表3-

重点

- RapidHRV对焦虑对RMSSD的模拟影响的估计非常好，
  信噪比30 dB以上。此外，该估计在低
  采样率（即20Hz）。
- 当噪音高时，清洁是有益的，但当噪音低时，没有必要。

3. Estimation via ECG

As expected, visual inspection suggested ECG data to hold a high signal to noise ratio. In line with our simulation findings, we adjusted the outlier rejection method accordingly so as not to excessively exclude data (i.e. 'liberal'). The dataset had previously been analyzed using an automated peak detection algorithm, with every beat annotation verified by visual inspection (Iyengar et al., 1996). Subject-specific heart rate estimates were not available from the original database. However, RapidHRV heart rate estimations were able to recapitulate sample-wide summary statistics (figure 7; table 4).

–Table 4–

The analytical method used for extraction of heart rate variability in the original database (power spectral density analysis) was inconsistent with RapidHRV's time-domain heart rate variability measure (RMSSD). Despite this discrepancy, RapidHRV was able to capture previously reported effects of age on heart rate variability (Iyengar et al., 1996; estimated Cohen's *d* of short-term heart rate variability (i.e. α_s) ≈ 1.32), such that—in cleaned data—younger participants demonstrated higher RMSSD (*M* = 58.94, *SD* = 28.82) than older participants (*M* = 25.54, *SD* = 13.02, Cohen's *d* = 1.49; figure 6). Effects were not apparent in the uncleaned data (Cohen's *d* = -0.31).

–Figure 7–

Key points

3.如预期的那样，目视检查表明ECG数据保持高信噪比。在
根据我们的模拟结果，我们相应地调整了离群值拒绝方法，
过度排除数据（即“自由”）。该数据集之前已使用
自动峰值检测算法，通过目视检查验证每个心跳注释
（Iyengar等人，1996年）。受试者特异性心率估计值无法从原始数据中获得
数据库然而，RapidHRV心率估计能够概括整个样本范围

汇总统计（图7;表4）。

- 表4-

在原始数据库中提取心率变异性的分析方法
（功率谱密度分析）与RapidHRV的时域心率不一致
变异性测量（RMSSD）。尽管存在这种差异，RapidHRV仍然能够捕获
先前报道的年龄对心率变异性的影响（Iyengar等人，1996年;估计数
短期心率变异性（即α）的Cohen's d = 1.32），因此，
数据-年轻受试者的RMSSD（M = 58.94，SD = 28.82）高于老年受试者
参与者（M = 25.54，SD = 13.02，Cohen’s d = 1.49;图6）。在美国，

未清理的数据（Cohen的d = -0.31）。

Figure 7—

重点

- In a movie-watching ECG dataset, RapidHRV was able to recapitulate previously reported summary statistics of BPM.
- RapidHRV was able to reproduce previously reported effects of age on RMSSD as measured by ECG.
- Cleaning was vital for detecting effects of age on RMSSD in ECG.

4. Estimation via Finger IR PPG

Sensitivity to anxiety

In our finger IR PPG data, RapidHRV was able to capture previously reported (de Groot et al., 2020) effects of anxiety on BPM (table 5). RapidHRV additionally demonstrated an influence of anxiety on RMSSD. Effects on BPM were greater following cleaning, whereas detection of effects on RMSSD was entirely dependent on cleaning.

–Table 5–

Benchmarking

Overall, there was excellent agreement between RapidHRV and previous estimates (de Groot et al., 2020; implemented using LabChart, ADInstruments, Sydney, Australia) of BPM (ICC > .99; figure 8). For heart rate variability, there was good agreement between the two when using the cleaned time series (ICC = .89), but poor agreement when using the uncleaned time series (ICC = .32).

–Figure 8–

- 在一个看电影的ECG数据集中，RapidHRV能够概括以前的情况
  报告BPM的汇总统计数据。
- RapidHRV能够重现先前报告的年龄对RMSSD的影响，
  通过ECG测量。
- 清洁对于检测年龄对ECG中RMSSD的影响至关重要。

4.通过手指**IR PPG**估计

对焦虑的敏感性

在我们的手指IR PPG数据中，RapidHRV能够捕获先前报道的（de Groot 例如，2020）焦虑对BPM的影响（表5）。RapidHRV还显示，焦虑对RMSSD影响清洁后对BPM的影响更大，而

对RMSSD影响的检测完全依赖于清洗。

- 表5-

标杆

总的来说，RapidHRV和以前的估计值之间有很好的一致性（de

Groot 等人，2020;使用LabChart，ADInstruments，Sydney，Australia 实现）(ICC> .99;图8）。对于心率变异性，当
使用清洁时间序列（ICC = .89），但使用未清洁时间时一致性较差

系列（ICC = .32）。

- 图8-

Key points

- RapidHRV was able to recapitulate previously reported effects of anxiety on BPM and RMSSD as measured by finger IR PPG.
- Cleaning was vital to the detection of effects of anxiety on RMSSD.

5. Estimation via Wrist-PPG During Activities

We first derived motion estimates (mean jerk magnitude; Eager et al., 2016) as a proxy for the severity of noise present in PPG. This enabled us to split conditions into low (Reading, Working, Lunch Break, Driving) and high motion activities (Table Soccer, Stairs, Walking, Cycling; figure 9).

–Figure 9–

In our initial analysis using default arguments, RapidHRV was not able to produce estimates across many of the activities for both cleaned and uncleaned data (conditions estimated: M = 22.5%, SD = 5.18%). Visual inspection confirmed this was due to high levels of noise and variable peak amplitude present in the signal. Therefore, we adjusted window movement to 1s (to increase the number of extraction windows in each condition), reduced minimum amplitude threshold for peak detection (30), and—in line with our simulation results above (figure 3)—tightened outlier rejection ('conservative'). Following this, RapidHRV was able to produce estimates for all conditions in the uncleaned data and across most activities for cleaned data (conditions estimated: M = 87.5%, SD = 11.57%). Missing estimates from the latter were predominantly limited to high motion activities (1 missing estimate for a single subject in the driving condition).

Across low motion activities, RapidHRV PPG-based estimates converged with simultaneous (visually verified) ECG measures (Reiss et al., 2019). Agreement with low motion

重点

- RapidHRV能够概括先前报道的焦虑对BPM的影响，
  通过手指IR PPG测量的RMSSD。
- 清洁对于检测焦虑对RMSSD的影响至关重要。

5.我们首先导出运动估计（平均加加速度幅度; Eager等人，（2016）代理PPG中存在噪声的严重程度。这使我们能够将条件分为低（阅读，工作，午休，驾驶）和高运动活动（桌上足球，楼梯，散步，

循环;图9）。

- 图9-

在我们使用默认参数的初始分析中，RapidHRV无法产生在许多活动中对已清理和未清理数据的估计（条件估计值：M = 22.5%，SD = 5.18%）。目视检查证实，这是由于高水平的噪声和信号中存在的可变峰值幅度。因此，我们调整了窗口移动到1 s（以增加每个条件下的提取窗口数量），减少峰值检测的最小幅度阈值（30），并且与我们的模拟结果一致上图（图3）-收紧离群值拒绝（“保守”）。在此之后，RapidHRV能够为未清理数据中的所有条件和大多数活动生成估计，清洁数据（估计条件：M = 87.5%，SD = 11.57%）。后者的缺失估计数主要限于高运动活动（1例受试者的估计值缺失，

驾驶条件）。

在低运动活动中，基于RapidHRV PPG的估计值与同时（视觉验证）ECG测量（Reiss等人，2019年）。低运动一致性

activities was excellent for BPM (ICC > .90) and agreement with RMSSD was moderate-to-good (.57 < ICC < .82; table 6; figure 10). Under high motion conditions, heart rate and heart rate variability estimates showed poor agreement (ICC < .32), except for heart rate within the cycling condition (ICC = .75).

–Table 6–

–Figure 10–

Key point

- Following calibration to the data, cleaned RapidHRV wrist PPG-based estimates demonstrated moderate-to-excellent convergence with a simultaneous ECG-based analysis whilst under low motion conditions. Agreement was generally poor under high motion conditions.

Discussion

RapidHRV is an open-source toolbox for extracting heart rate and heart rate variability measures. RapidHRV was developed in response to the need for software dedicated to dealing with extensive cardiac data collected across large time frames, such as out-of-laboratory PPG recordings, which may require point estimates from very short time windows (~10 seconds). Python packages currently exist which can analyze cardiac data (e.g. *Systole*, Legrand & Allen, 2020; *NeuroKit2,* Pham et al., 2021; *pyHRV*, Gomes et al., 2019). However, outlier rejection algorithms often require visual inspection and/or extensive scripting on the user's end. While suitable for the cardiac data collected during laboratory experiments, this may not be feasible when dealing with data collected across large time-scales, such as weeks or months. Here, we

活动对于BPM是极好的（ICC > .90），与RMSSD的一致性是中等至良好的
(.57< ICC < .82;表6;图10）。在高运动条件下，心率和心率
变异性估计显示出较差的一致性（ICC < .32），除了在骑自行车的心率

条件（ICC = .75）。

- 表6-

- 图10-

关键点

- 在对数据进行校准后，清洁RapidHRV腕部PPG估计值
证明了与基于ECG的同步
在低运动条件下进行分析。在高水平下，一致性普遍较差

  运动条件

讨论情况

RapidHRV是一个用于提取心率和心率变异性的开源工具箱
措施RapidHRV的开发是为了满足对专用于处理
在大的时间范围内收集大量心脏数据，例如实验室外PPG
记录，这可能需要从非常短的时间窗口（约10秒）的点估计。
目前存在可以分析心脏数据的Python包（例如，收缩期，Legrand &艾伦，
2020; NeuroKit 2，Pham等人，2021; pyHRV，Gomes等人，2019年）。然而，离群拒绝
算法通常需要用户端的视觉检查和/ 或大量脚本。而
适用于实验室实验期间收集的心脏数据，这可能不可行
在处理跨大时间尺度（如数周或数月）收集的数据时。这里我们

have attempted to fill this gap by developing a programmatically easy-to-use toolbox which extracts HRV measures from ultra-short windows and automates artifact detection and rejection. In general, this is applied via a series of biological and statistical constraints. Moreover, for ECG data, we have also implemented a k-means clustering algorithm for delineating P, R, and T waves. Across simulated and real datasets, we scrutinized RapidHRV, testing scenarios where it was and was not able to extract meaningful metrics. We show that signal to noise ratio, sampling rate, and recording modality had a clear impact on sensitivity of estimation. Here, we summarize these validation tests and make modality-specific recommendations for users.

Simulations

Within simulated data, RapidHRV was able to recover heart rate across most levels of noise (white gaussian noise filter >=10dB), even at relatively low sampling rates (>=20Hz). RapidHRV's recovery of heart rate variability was excellent at relatively low levels of signal to noise ratio (>=20dB), though there was degradation of performance as sampling rate decreased. Additional simulations of cardiac responses to an anxiety induction demonstrated RapidHRV estimations fully captured effects at moderate levels of noise (>=30dB) even at relatively low sampling rates (i.e. 20Hz). RapidHRV was able to partially capture effects (~50% reduction in effect size) at very high levels of noise (>=10dB when Hz >50). Simulations revealed RapidHRV cleaning was particularly beneficial at lower sampling rates and higher levels of noise, but was not necessary (or could be relaxed) when signal and sampling rates were high. Moreover, these simulations were able to clarify the validity of RapidHRV's default window (10s) for estimation of heart rate variability across a longer time period (i.e. 5 minutes).

Electrocardiography

In our electrocardiography analyses, we were able to recapitulate previously reported effects of age on heart rate and heart rate variability. In line with previous analyses (Iyengar et al., 1996), RapidHRV-estimates suggested older participants had lower heart rate variability than younger participants during movie-watching. Importantly, cleaning was vital to this detection.

Finger PPG

我试图通过开发一个易于编程使用的工具箱来填补这一空白，
从超短窗口中提取HRV测量值，并自动检测和拒绝伪影。
一般来说，这是通过一系列生物学和统计学约束来应用的。此外，对于ECG
数据，我们还实现了一个k-means聚类算法来描绘P，R和T
波在模拟和真实的数据集中，我们仔细检查了RapidHRV，测试了它
was and was not able能够to extract提取measurements有意义metrics指标.我们表明，信噪比，采样
利率和记录方式对估计的敏感性有明显的影响。在此，我们总结

这些验证测试并为用户提供特定于模式的建议。

模拟

在模拟数据中，RapidHRV能够在大多数水平上恢复心率。
噪声（白色高斯噪声滤波器>= 10 dB），即使在相对较低的采样率（>= 20 Hz）。
RapidHRV的心率变异性恢复在相对低的信号水平下非常出色，
噪声比（>=20dB），尽管随着采样率降低，性能下降。
对焦虑诱导的心脏反应的额外模拟证实了RapidHRV
估计完全捕获的影响，在中等水平的噪音（>= 30分贝），即使在相对较低的
采样率（即20Hz）。RapidHRV能够部分捕获效应（约50%的
效果大小）在非常高的噪声水平（>= 10分贝，当Hz >50）。模拟显示RapidHRV
在采样率较低和噪声水平较高的情况下，清洁特别有益，但
当信号和采样率高时，不需要（或可以放松）。而且这些
模拟能够澄清RapidHRV的默认估计窗口（10 s）的有效性

心率变异性在较长的时间段（即5分钟）。

心电图

在我们的心电图分析中，我们能够概括以前报道的
年龄对心率和心率变异性的影响。与先前的分析（Iyengar et
例如，1996年），RapidHRV估计表明，老年参与者的心率变异性低于

年轻人在看电影的时候。重要的是，清洁对于这种检测至关重要。

手指**PPG**

Using RapidHRV-estimates, we noted effects of anxiety on heart rate and heart rate variability in a database of participants watching horror and documentary videos while undergoing finger infrared PPG recordings. Notably, the estimated effect size was analogous to that noted in threat-of-shock studies (Gold et al., 2015). Moreover, when contrasting subject-specific estimates, we found good-to-excellent agreement between RapidHRV and a previous analysis using a commercially available software. Effect sizes between conditions and convergence of estimates between softwares was significantly improved following RapidHRV cleaning.

Wrist PPG

In our wrist PPG validation, we noted RapidHRV was not able to produce estimates for the majority of conditions due to limitations of the default arguments. Despite applying scaling (0-100) at the level of a sliding window, PPG signals showed variable peaks amplitudes. Following alterations [rhv.analyze(preprocessed, outlier_detection_settings="conservative", amplitude_threshold=30, window_overlap=9)], RapidHRV-estimates during low motion activities (e.g. reading, eating lunch) demonstrated good-to-excellent agreement with a manually-verified analysis of ECG data. During high wrist-movement activities (e.g. table soccer), estimates were generally poor-to-moderate. We do note however that in one of the high motion conditions, cycling, RapidHRV-estimation of heart rate was good (though heart rate variability estimation was poor). This may reflect our proxy for motion-related artifacts (jerk magnitude), which may not always be as good an estimator of artifacts during activities which involve changes in acceleration but relatively low movements in the wrists (i.e. cycling, as hands are gripping the handle bars). Future work should seek to correlate RapidHRV quality assurance metrics with a wider range of motion estimation methods. Overall, we found adjustments to parameter arguments beneficial to PPG data, but we also note there are contextual factors and limitations (i.e. motion-related artifacts) influencing the feasibility of accurate estimation.

Overall User Recommendations

使用RapidHRV估计，我们注意到焦虑对心率和心率的影响。
在观看恐怖和纪录片视频的参与者数据库中，
进行手指红外PPG记录。值得注意的是，估计的效应量类似于
这在休克威胁研究（Gold等，2015年）。此外，当对比
根据受试者特异性估计，我们发现RapidHRV与
使用市售软件进行先前分析。条件和条件之间的效应大小
使用RapidHRV后，软件之间的估计值收敛性显著提高

清洗.

腕部**PPG**

In our wrist PPG validation , we noted RapidHRV was not able to produce estimates for the majority of conditions due to limitations of the default arguments. Despite applying scaling

(0-100) at the level of a sliding window, PPG signals showed variable peaks amplitudes.

Following alterations [rhv.analyze(preprocessed, outlier_detection_settings = "conservative",

amplitude_threshold = 30，window_overlap=9）]，低运动期间的RapidHRV估计
活动（如阅读、吃午餐）表现出良好至极好的一致性，
手动验证的ECG数据分析。在高手腕运动活动期间（例如，桌子
足球），估计一般是差到中等。然而，我们注意到，
运动条件，骑自行车，心率的RapidHRV估计良好（尽管心率
变异性估计较差）。这可能反映了我们对运动相关伪影（jerk）的代理
幅度），这可能并不总是作为活动期间工件的良好估计器，
涉及加速度的变化，但手腕的运动相对较低（即骑自行车，如手
正在抓紧把手）。未来的工作应寻求与RapidHRV质量保证相关
度量与更广泛的运动估计方法。总的来说，我们发现
参数有利于PPG数据，但我们也注意到有上下文因素，

限制（即运动相关的伪影）影响准确估计的可行性。

总体用户建议

For ECG data, users may find traditional, amplitude-based analyses will not work for subjects who demonstrate atypical signal morphologies (e.g. particularly prominent P and T waves). RapidHRV includes the use of k-means clustering to help discern these components of the ECG signal, though this is not enabled by default (ecg_prt_clustering = False). Additionally, the cleanliness of signal, namely the stability of peak prominences, means the data may be low in artifacts, and that minor deviations could be detected as outliers. As such, when dealing with already-clean data, users may find that outlier rejection can be omitted or relaxed (e.g. outlier method = 'liberal').

Results from the finger IR PPG data used in the present study did not suggest the need for alterations to default RapidHRV arguments, but did suggest that automated cleaning should be used.

Lastly, PPG data collected from naturalistic settings is typically low in signal to noise ratio, which can constrain peak detection. Consequently, lowering the minimum amplitude threshold for peak detection and decreasing window movement may help improve extraction. Furthermore, given the large amount of motion-related artifacts and the results from our simulation analyses, we recommend: a) the use of relatively conservative cleaning (e.g. outlier method = 'conservative'), and b) inspection of motion across conditions as an indicator of estimation accuracy (table 7).

–Table 7–

Conclusion

In the present paper, we have outlined RapidHRV: an open-source Python pipeline for the estimation of heart rate and heart rate variability. Across simulated datasets, RapidHRV showed good-to-excellent recovery of heart rate and heart rate variability at relatively high levels of noise. Estimates in electrocardiography and finger IR PPG demonstrated RapidHRV was able to

对于ECG数据，用户可能会发现传统的基于幅度的分析不适用于
表现出非典型信号形态（例如，特别突出的P和T）的受试者
waves）。RapidHRV包括使用k-means聚类来帮助辨别
ECG信号，但默认情况下未启用（ecg_prt_clustering = False）。此外，本发明还
信号的清洁度，即峰比的稳定性，意味着数据可能较低，
伪影，并且微小的偏差可以被检测为离群值。因此，在处理
对于已经干净的数据，用户可能会发现可以省略或放松离群值拒绝（例如，离群值

method = 'liberal'）。

本研究中使用的手指IR PPG数据的结果并不表明需要
默认RapidHRV参数的更改，但确实建议自动清洗应该
采用

最后，从自然环境收集的PPG数据通常信噪比低
比率，其可约束峰值检测。因此，降低最小振幅
用于峰值检测的阈值和减小窗口移动可以帮助改进提取。
此外，考虑到大量的运动相关伪影和我们的结果，
模拟分析，我们建议：a）使用相对保守的清洗（例如离群值
方法= '保守'），以及B）检查跨条件的运动作为

估计准确度（表7）。

- 表7-

结论

在本文中，我们概述了RapidHRV：用于
心率和心率变异性的估计。在模拟数据集中，RapidHRV显示
心率和心率变异性在相对较高水平下恢复良好至极好，
噪声心电图和手指IR PPG的估计值表明RapidHRV能够

recapitulate known effects of age and anxiety, and showed excellent agreement with visually-inspected analyses and commercial software. Lastly, performance in wrist photoplethysmography data was good-to-excellent when participants were engaged in low motion activities, but we noted poor-to-moderate estimations when motion was high. Given the increased interest in the use of wearable measures of heart rate metrics and how they relate to other domains such as mental health, we hope that this toolbox will be of wide use to the community, and that the simulation and benchmarking tests provided may help inform the design and analysis of such studies.

RapidHRV 22号

概括了已知的年龄和焦虑的影响，并表现出良好的一致性，
目视检查分析和商业软件。最后，手腕的表现
当参与者进行低水平运动时，光电体积描记术数据为良好至极好。
运动活动，但我们注意到，当运动是高的差到中等的估计。鉴于
对心率指标的可穿戴测量的使用以及它们如何与
其他领域，如心理健康，我们希望这个工具箱将广泛使用，
社区，提供的模拟和基准测试可能有助于为设计提供信息

并对这些研究进行分析。

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确认

感谢卡里纳阿霍提供的统计咨询;感谢尼古拉斯 · 勒格朗允许我们使用心脏收缩的代码来推导高频功率;和罗素柯克帮助推导智能手表数据的运动估计。感谢其他开源分析软件，即心脏收缩（Legrand &艾伦，2020）和心脏Py（货车Gent等人，2019），其中

帮助激发了RapidHRV的发展。

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