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MUSIC-Based Algorithm for On-Demand Heart Rate Estimation Using Photoplethysmographic (PPG) Signals on Wrist

By **Foroohar Foroozan**

Imagine a world in the next few decades where your grandchildren didn't know about the word *hospital* and all your health information was recorded and monitored remotely through sensors. Imagine your home equipped with different sensors to measure air quality, temperature, noise, light, and air pressure, and, based on your personal health information, systems adjust the relevant environmental parameters to optimize your well-being at home. Analog Devices holds a unique position to make this happen by providing sensors, software, and algorithms that complement each other, which increases its share of the digital health market.

Heart rate (HR) monitoring is a key feature in many existing wearable and clinical devices. These devices generally measure photoplethysmography (PPG) signals, which are obtained by illuminating human skin using LEDs and measuring intensity changes due to blood flow in the reflected light by a photodiode. The PPG signal morphology is similar to the arterial blood pressure (ABP) waveform, which makes this signal popular within the scientific community as a potential noninvasive HR monitoring tool. The periodicity of the PPG signal corresponds to cardiac rhythm. Therefore, HR can be estimated from the PPG signals. However, the HR estimation performance can be degraded by poor blood perfusion, ambient light, and, most importantly, motion artifacts (MA).[1] Many signal processing techniques have been proposed to remove the MA noise, including the ADI motion rejection and frequency tracking algorithm, by using a three-axis acceleration sensor placed close to the PPG sensor. When there is no motion, it is desirable to have an on-demand algorithm provide a fast and more accurate estimate of the HR to tracking algorithms. This article adapts the multiple signal classification (MUSIC) frequency estimation algorithm for high precision, on-demand HR estimation using the PPG signals from the wrist, using the ADI healthcare watch platform using the block diagram in Figure 1. The details of the figure will be explained in later sections.

What Does a PPG Signal from ADI's Healthcare Watch Look Like?

As light is emitted by the LED, blood levels and tissues absorb various amounts of photons, causing different detections sensed by the photodetector. The photodetector measures the variations in blood pulsations and outputs a current that is then amplified and filtered for further analysis.

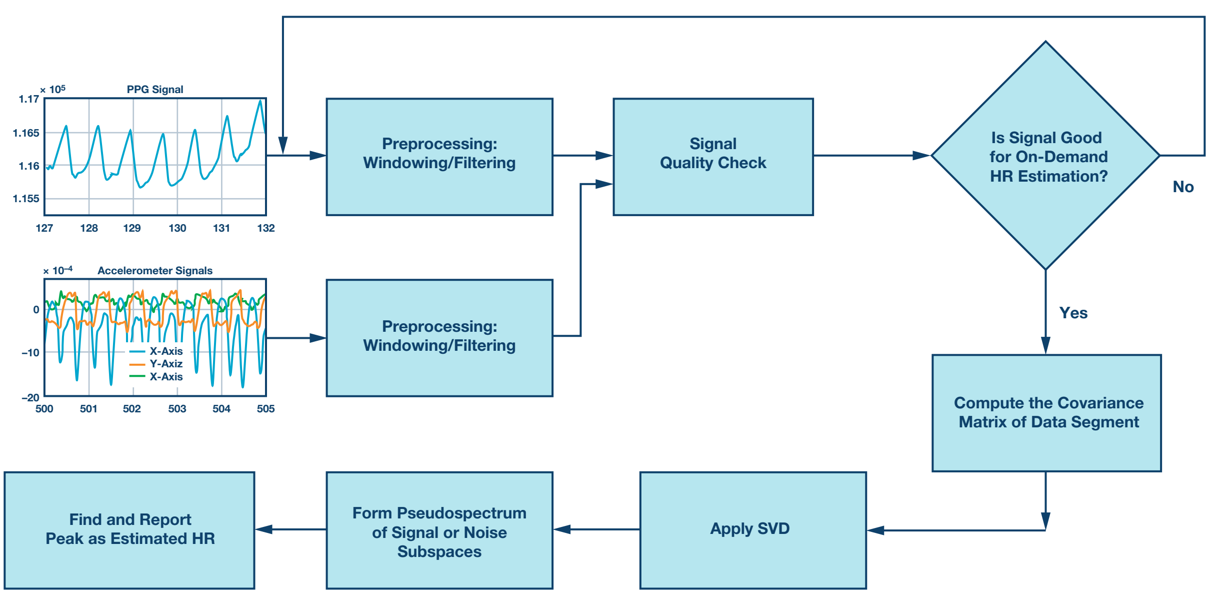

Figure 1. MUSIC-based on-demand HR estimation algorithm from PPG signals on wrist.

基于MUSIC 的手腕PPG 信号按需心率估计算法

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想象一下，在接下来的几十年里，你的孙子们不知道医院这个词，你所有的健康信息都被记录下来，并通过传感器远程监控。想象一下，你的家配备了不同的传感器来测量空气质量、温度、噪音、光线和气压，并且根据你的个人健康信息，系统会调整相关的环境参数，以优化你在家里的健康状况。ADI 公司通过提供相辅相成的传感器、软件和算法，在实现这一目标方面拥有独特的地位，从而增加了其在数字医疗市场的份额。

心率（HR ）监测是许多现有可穿戴和临床设备中的关键特征。这些设备通常测量光电体积描记（PPG ）信号，其通过使用LED 照射人类皮肤并通过光电二极管测量由于反射光中的血流而引起的强度变化来获得。PPG 信号形态类似于动脉血压（ABP ）波形，这使得该信号在科学界作为潜在的无创HR 监测工具而流行。PPG 信号的周期性对应于心律。因此，可以从PPG 信号估计HR 。然而，HR 估计不良的血液灌注、环境光以及最重要的运动伪影（MA ）会降低性能。已经提出了许多信号处理技术来去除MA 噪声，包括ADI 运动抑制和频率跟踪算法，通过使用靠近PPG 传感器放置的三轴加速度传感器。当不存在运动时，期望具有按需算法来向跟踪算法提供HR 的快速且更准确的估计。本文采用多信号分类（MUSIC ）频率估计算法，使用ADI 医疗保健手表平台，使用手腕PPG 信号进行高精度按需HR 估计，如图1所示框图。该图的细节将在后面的部分中解释。

ADI 医疗保健手表的PPG 信号是什么样的?

当LED 发出光时，血液水平和组织吸收不同数量的光子，导致光电检测器感测到不同的检测。光电探测器测量血液脉动的变化，并输出电流，然后放大和滤波以进行进一步分析。

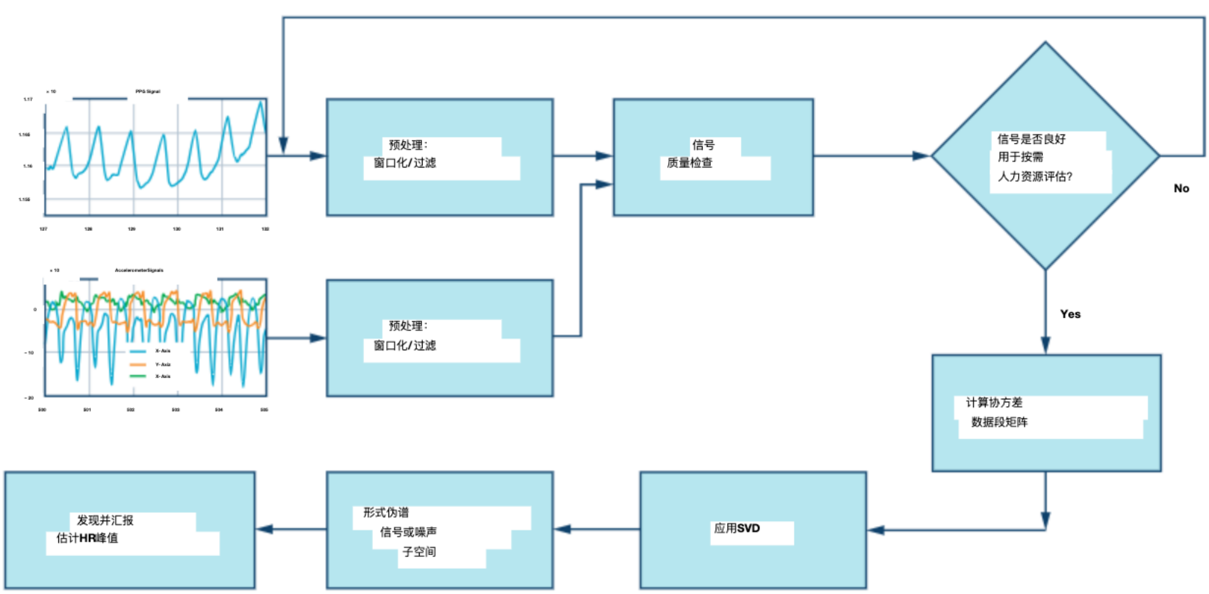

图1.基于*MUSIC* 的按需心率估计算法，从手腕上的*PPG* 信号。

Figure 2a shows a general PPG signal consisting of alternating current (ac) and direct current (dc) components. The dc component of the PPG waveform detects the optical signal reflected from the tissue, bone, and muscle, and also the average blood volume of both arterial and venous blood. The ac component, on the other hand, demonstrates changes in the blood volume that occurs between the systolic and diastolic phases of the cardiac cycle, where the fundamental frequency of the ac component depends on the HR. Figure 2b is the PPG signal from the ADPD107 watch, which was introduced in previous *Analog Dialogue* articles. The goal of the ADI multisensory watch is to measure multiple vital signs on the human wrist. The ADI watch has PPG, an electrocardiogram (ECG), electrodermal activity (EDA), an accelerometer (ACC), and temperature sensors. This article focuses only on the PPG and ACC sensors.

Now let's have a close look into the similarity of the PPG and ABP waveforms. The ABP waveform is created due to the ejection of blood from the left ventricle. The main pressure travels down the systemic vascular network and reaches several sites, causing reflection due to significant changes in arterial resistance and compliance. The first site is the juncture between the thoracic and abdominal aorta, which causes the first reflection, commonly known as the late systolic wave. The second reflection site is the juncture between the abdominal aorta and common iliac arteries. The main wave is reflected back once again, which makes a small dip, called the dicrotic notch, which can be observed between the first and second reflections. There are other additional minor reflections, which are smoothed in the PPG signals.[2] The focus of this article is on the HR estimation, which only depends on the periodicity of the PPG signals and the exact morphology of the PPG is not taken into consideration for the purpose of this algorithm.

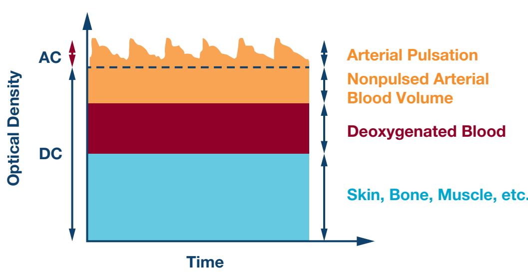

Figure 2a. Typical PPG signal with ac and dc parts.

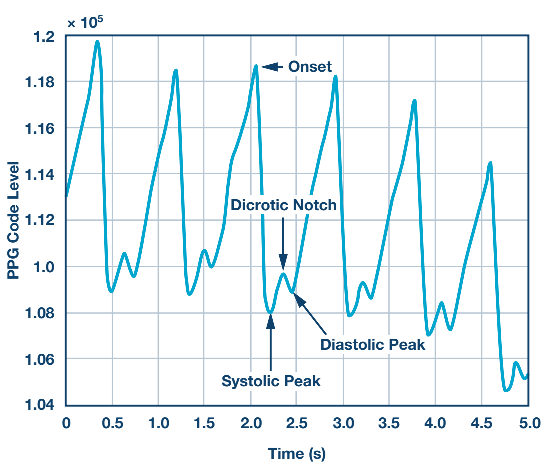

Figure 2b. ADI healthcare watch PPG signal.

Preprocessing of PPG Signals

The susceptibility of the PPG signal to poor blood perfusion of the peripheral tissues and motion artifact is well known.[1] In order to minimize the influence of these factors in the subsequent phases of the PPG analysis for HR estimation, a preprocessing stage is required. A band-pass filter is required to remove both high frequency component (such as power sources) of the PPG signals, as well as low frequency components, such as changes in capillary density and venous blood volume, temperature variations, and so on. Figure 3a shows a PPG signal after filtering. A set of signal quality metrics is used to find the first window of PPG signal appropriate for the on-demand algorithm. The first check involves the ACC data and the PPG signal to determine whether a segment of motion free data can be detected—then, the other signal quality metrics are measured. Estimates from such a window of data are rejected by the on-demand algorithm if there is motion above a certain threshold of the absolute value of the ACC data in three directions. The next signal quality check is based on certain autocorrelation having features of the data segment. One example of the autocorrelation of the filtered PPG signal is shown in Figure 3b. Autocorrelation of acceptable signal segments exhibits properties such as having at least one local peak and not more than a certain number of peaks corresponding to the highest possible HR; having the local peaks in a descending order with increasing lags; and a few others. Autocorrelation is only computed for lags that correspond to meaningful heart rates within a margin of range, from 30 bpm to 220 bpm.

When enough data segments pass the quality checks consecutively, the second stage of the algorithm extracts an accurate HR using the MUSIC-based algorithm.

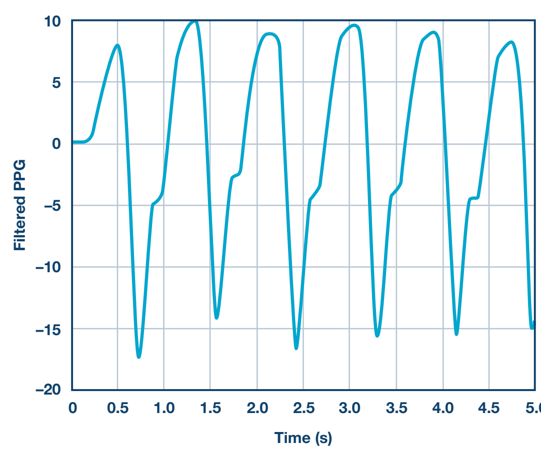

Figure 3a. Band-pass filtered PPG signal from Figure 1b.

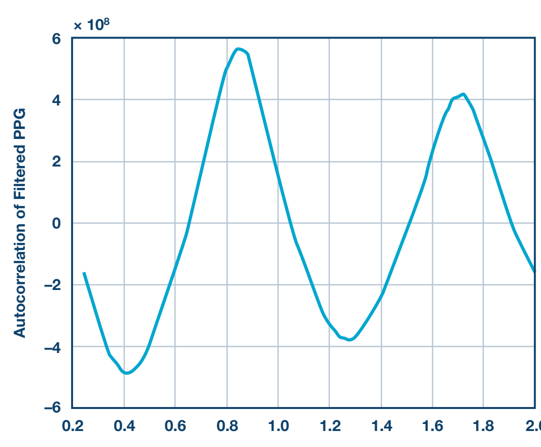

Figure 3b. Autocorrelation of the signal plot from Figure 2a.

图2a 示出了由交流（ac ）和直流（dc ）分量组成的一般PPG 信号。PPG 波形的直流分量检测从组织、骨骼和肌肉反射的光学信号，以及动脉和静脉血的平均血容量。另一方面，交流分量显示了心动周期收缩期和舒张期之间的血容量变化，其中交流分量的基频取决于HR 。图2b 是ADPD 107手表的PPG 信号，在之前的Analog Dialogue 文章中介绍过。ADI 多传感器手表的目标是测量人类手腕上的多个生命体征。ADI 手表具有PPG 、心电图（ECG ）、皮肤电活动（EDA ）、加速计（ACC ）和温度传感器。本文仅关注PPG 和ACC 传感器。

现在让我们仔细研究PPG 和ABP 波形的相似性。由于血液从左心室喷射而产生ABP 波形。主压力沿全身血管网络向下传播并到达多个部位，由于动脉阻力和顺应性的显著变化而引起反射。第一个部位是胸主动脉和腹主动脉之间的接合处，这会引起第一个反射，通常称为收缩晚期波。第二个反射部位是腹主动脉和髂总动脉之间的交界处。主波再次被反射回来，这使得一个小的倾角，称为重搏切迹，可以在第一次和第二次反射之间观察到。存在其它附加的次要反射，其在PPG 信号中被平滑。 本文的重点是HR 估计，其仅取决于PPG 信号的周期性，并且该算法的目的不考虑PPG 的确切形态。

PPG 信号的预处理

PPG 信号对外周组织的不良血液灌注和运动伪影的敏感性是众所周知的。为了在用于HR 估计的PPG 分析的后续阶段中最小化这些因素的影响，需要预处理阶段。需要带通滤波器来去除PPG 信号的高频分量（例如电源）以及低频分量（例如毛细血管密度和静脉血容量的变化、温度变化等）。使用一组信号质量度量来找到适合于按需算法的PPG 信号的第一窗口。第一次检查涉及ACC 数据和PPG 信号，以确定是否可以检测到一段无运动数据，然后测量其他信号质量度量。 如果在三个方向上存在高于ACC 数据的绝对值的某个阈值的运动，则按需算法拒绝来自这样的数据窗口的估计。下一个信号质量检查基于具有数据段特征的某些自相关。在图3b 中示出了经滤波的PPG 信号的自相关的一个示例。可接受的信号段的自相关表现出诸如具有至少一个局部峰值和不超过对应于最高可能HR 的一定数量的峰值的特性;具有以递减顺序的局部峰值和增加的滞后;以及一些其他特性。自相关仅针对与范围内（从30 bpm 到220 bpm ）的有意义心率相对应的滞后进行计算。

当足够多的数据段连续通过质量检查时，算法的第二阶段使用基于MUSIC 的算法提取准确的HR 。

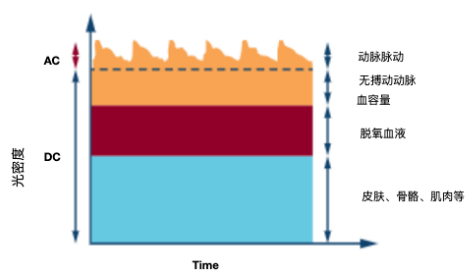

图*2a*.具有交流和直流部分的典型*PPG* 信号。

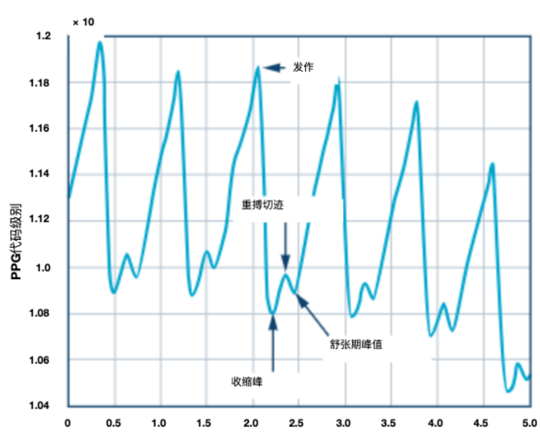

图*2b*. *ADI* 医疗保健手表*PPG* 信号。

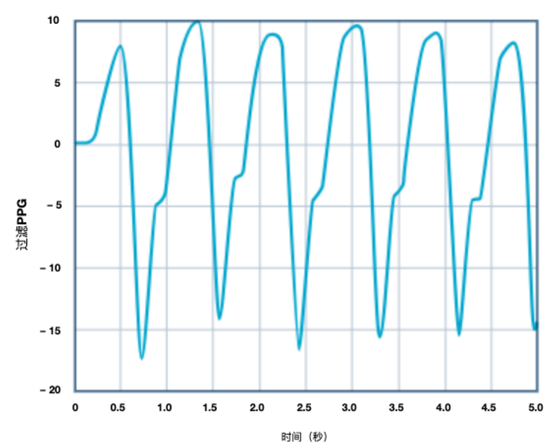

图*3a*.图*1b*中的带通滤波*PPG* 信号。

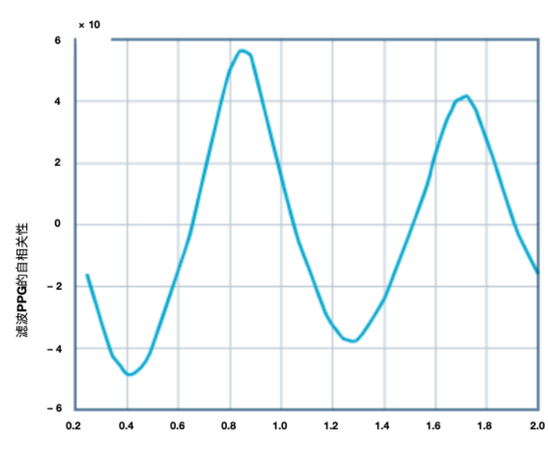

图*3b*.图*2a*中信号曲线的自相关性。

MUSIC-Based Algorithm for On-Demand HR Estimation

MUSIC is a subspace-based method using a model of harmonic signals that can estimate frequency with high precision.[3] When it comes to the PPG signals corrupted with noise, Fourier transform (FT) may not behave well, as we are seeking a high resolution HR estimation algorithm. Also, FT distributes time-domain noise uniformly throughout the frequency domain, limiting the certainty of estimation. It is difficult to observe a small peak in the vicinity of a large peak using FT.[4] Therefore, in this study, we used the MUSIC-based algorithm for frequency estimation of the HR. The key idea behind MUSIC is that the noise subspace is orthogonal to the signal subspace, so zeroes of the noise subspace will indicate signal frequencies. The following steps show a summary of this algorithm used for the HR estimation:

- Remove the mean and linear trend from the data
- Compute the covariance matrix of the data
- Apply the singular value decomposition (SVD) to the covariance matrix
- Compute the signal subspace order
- Form the pseudospectrum of the signal or noise subspaces
- Find the peaks of the MUSIC pseudospectrum as the HR estimate

MUSIC has to apply a singular value decomposition and has to search spectral peaks in the full range of frequencies. Let's look at some math in order to make the above steps more clear. Assume a window of length m of the filtered PPG signal, which is denoted as $\boldsymbol{x}_m$ and $m \leq L$ (with L being the total samples of the filtered PPG signal in a given window). Then, the first step is to form the sample covariance matrix as follows:

$$\hat{R} = \frac{1}{L-M} \sum_{m=1}^{M} x_m x_m^T$$

Then, an SVD is applied to the sample covariance matrix as given below:

$$\hat{R} = U \Lambda V = U_s \Lambda U_s^T + U_n \Lambda U_n^T$$

where U is the left eigenvectors, Λ is the diagonal matrix of the eigenvalues, and V is the right eigenvectors of the covariance matrix. The subscripts s and n stand for the signal and noise subspaces. As we mentioned before, the MUSIC-based algorithm is modified for HR estimation using prior knowledge that the signal has passed the signal quality checking stage—so the only frequency content in the signal after the preprocessing step is the HR frequency. Next, we form the signal and noise subspaces, assuming the model order only contains one single tone, as follows:

$$U_s = U(1{:}\, p, :);\; U_n = U(p+1{:}\, end, :)$$

where $p = 2$ is the model number. The frequencies within the meaningful HR limits are considered only. This reduces the computations significantly and makes it feasible for real-time implementation for embedded algorithms. The search frequency vector is defined as:

$$a(k) = [1, e^{-1 \times \frac{2\pi j(k-1)}{L}}, e^{-2 \times \frac{2\pi j(k-1)}{L}}, e^{-3 \times \frac{2\pi j(k-1)}{L}}, \ldots, e^{-(m-1) \times \frac{2\pi j(k-1)}{L}}]\,\hat{}\,T$$

where k is the frequency bin within the frequency range of interest for HR, and L is the window length for the data in $\boldsymbol{x}_m(t)$. Then, the following pseudospectrum takes the noise subspace eigenvectors to find the peaks of the MUSIC as follows.

$$\Phi(k) = \frac{1}{a^H U_n U_n^H a}$$

The word pseudospectrum is used here because it indicates the presence of sinusoidal components in the studied signal, but it is not a true power spectral density. One sample result of the MUSIC-based algorithm on a 5 second window of data is given in Figure 4, which shows a sharp peak at 1.96 Hz, and which translates to 117.6 bpm HR.

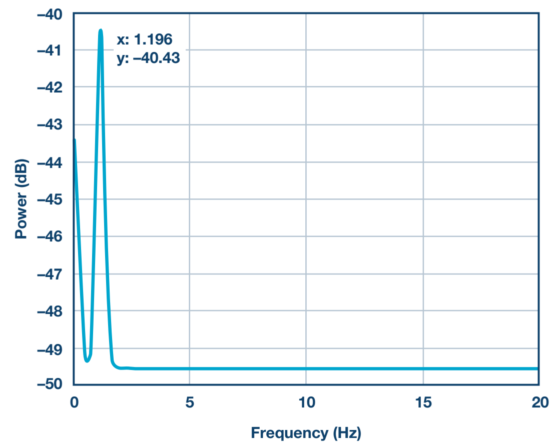

Figure 4. One sample of MUSIC-based estimation from the PPG data.

Results of the MUSIC-Based On-Demand Algorithm for HR Estimation

We have tested the performance of this algorithm on a dataset comprising of 1289 test cases (data1) and at the beginning of the data the test subjects are asked to stand at rest. Table 1 illustrates the result of the MUSIC-based algorithm and indicates if the estimated HR is within 2 bpm and 5 bpm of the reference (ECG), as well as the 50th percentile (median) and 75th percentile of the estimation times. The second row of Table 1 shows the performance of the algorithm when there is periodic motion (such as walking, jogging, running) over a dataset of 298 test cases (data2). The algorithm is considered to be successful if either the data is rejected as unreliable by sensing the motion or by accurately estimating the HR despite the motion. In terms of memory usage, assuming a buffer size of 500 (that is, 5 sec at 100 Hz), the total memory needed is around 3.4 kB with 2.83 cycle per call for the frequency range of interest (30 bpm to 220 bpm).

Table 1. Performance Numbers for the MUSIC-Based On-Demand HR Algorithm

Metric	2 bpm Accuracy	5 bpm Accuracy	50th Percentile	75th Percentile
Accuracy (data1)	93.7%	95.2%	5.00 sec	5.00 sec
Accuracy (data2)	93.4%	94.1%	5.00 sec	5.00 sec

基于MUSIC 的按需HR 估计算法

MUSIC 是一种基于子空间的方法，利用谐波信号的模型，可以高精度地估计频率。当涉及到被噪声破坏的PPG 信号时，傅立叶变换（FT ）可能表现不佳，因为我们正在寻求高分辨率HR 估计算法。此外，FT 将时域噪声均匀地分布在整个频域中，限制了估计的确定性。使用FT 难以观察到大峰附近的小峰。因此，在本研究中，我们使用基于MUSIC 的算法来进行HR 的频率估计。MUSIC 背后的关键思想是噪声子空间与信号子空间正交，因此噪声子空间的零将指示信号频率。以下步骤显示了用于HR 估计的该算法的总结：

- 从数据中删除平均值和线性趋势
- 计算数据的协方差矩阵
- 对协方差矩阵应用奇异值分解（SVD ）
- 计算信号子空间阶数
- 形成信号或噪声子空间的伪谱

X找到MUSIC 伪谱的峰值作为HR 估计

MUSIC 必须应用奇异值分解，并且必须在整个频率范围内搜索谱峰。让我们来看看一些数学，以便使上述步骤更清楚。假设经滤波的PPG 信号的长度为m 的窗口，其被表示为X并且m

$$R = \frac{1}{L-M} \sum_{m=1}^{M} xx$$

然后，将SVD 应用于样本协方差矩阵，如下所示：

$$R = U\lambda V = U\lambda U + U\lambda U$$

其中U 是左特征向量，Λ是特征值的对角矩阵，V 是协方差矩阵的右特征向量。下标s和n代表信号和噪声子空间。如前所述，使用信号已通过信号质量检查阶段的先验知识修改基于MUSIC 的算法以用于HR 估计，因此预处理步骤之后信号中的唯一频率内容是HR 频率。接下来，我们形成信号和噪声子空间，假设模型阶仅包含一个单音，如下所示：

$$U = U(1:p, :);\ U = U(p+1:\mathrm{end}, :)$$

其中p ＝2是型号。仅考虑有意义的HR 限值内的频率。这大大减少了计算量，使其成为可行的嵌入式算法的实时实现。搜索频率向量定义为：

$$A(k) = [1, e^{-1\times\frac{2\pi j(k-1)}{L}}, e^{\frac{2\pi j(k-1)}{L}}, e^{-3\times\frac{2\pi j(k-1)}{L}}, \ldots e^{-1)\times\frac{2\pi j(k-1)}{L}}]^T$$

其中k是HR 的感兴趣频率范围内的频率仓，L是x（t）中数据的窗口长度。然后，下面的伪谱采用噪声子空间特征向量来找到MUSIC 的峰值，如下所示。

$$\Phi(k) = \frac{1}{aUUa}$$

这里使用伪谱一词是因为它表示所研究的信号中存在正弦分量，但它不是真正的功率谱密度。图4中给出了基于MUSIC 的算法在5秒数据窗口上的一个样本结果，其显示了1.96 Hz 处的尖峰，并转换为117.6 bpm HR 。

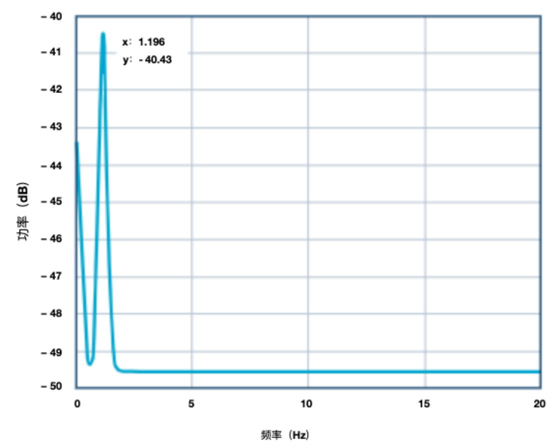

图*4. PPG* 数据中基于*MUSIC* 的估计的一个样本。

基于MUSIC 的按需HR 估计算法的结果

我们已经测试了该算法的性能，包括1289 个测试用例的数据集（data1 ），并在数据的开始，测试对象被要求站在休息。表1说明了基于MUSIC 的算法的结果，并指出估计的HR 是否在参考（ECG ）的2 bpm 和5 bpm 范围内，以及估计时间的50 百分位数（中位数）和75 百分位数。表1的第二行显示了在298 个测试用例（数据2）的数据集上存在周期性运动（例如步行、慢跑、跑步）时算法的性能。如果通过感测运动或通过准确估计HR （尽管存在运动）而将数据视为不可靠而拒绝，则该算法被认为是成功的。在内存使用方面，假设缓冲区大小为500（即，100 Hz 时为5秒），则对于感兴趣的频率范围（30 bpm 至220 bpm ），每次调用需要2.83 个周期的总内存约为3.4 kB 。

表1 基于MUSIC 的按需HR 算法的性能数字

度量	2 bpm 精度	5 bpm 精度	50 %	75 %
精度（date 1）	93.7 %	95.2 %	5.00 sec	5.00 sec
精度（date 2）	93.4 %	94.1 %	5.00 sec	5.00 sec

Final Discussion

The MUSIC-based on-demand algorithm is one of the many algorithms proposed in the vital signs monitoring segment of the ADI healthcare business unit. The on-demand algorithm used in our healthcare watch is a different algorithm than the MUSIC-based method discussed here, because it is less computationally expensive. ADI delivers software and algorithm capabilities at both sensor (embedded) and edge nodes that distill data to extract valuable information by sending only the most important data to the cloud and allowing local decision making for our customers and partners. We choose applications where outcomes really matter for our customers and where we have unique measurement expertise. This article just provides a flavor of the algorithms we are working on at ADI. With our existing expertise in sensor design, and our efforts in biomedical algorithm development (both embedded and cloud), ADI will have a unique position to provide state-of-the-art algorithms and software to the global healthcare market.

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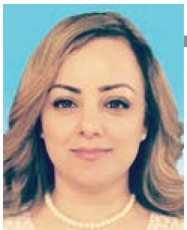

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最后讨论

基于MUSIC 的按需算法是ADI 医疗保健业务部门生命体征监测部分提出的众多算法之一。我们的医疗保健手表中使用的按需算法与这里讨论的基于MUSIC 的方法不同，因为它的计算成本更低。ADI 公司在传感器（嵌入式）和边缘节点上提供软件和算法功能，通过仅将最重要的数据发送到云端并允许客户和合作伙伴进行本地决策，从而提取数据以提取有价值的信息。我们选择的应用程序的结果确实对我们的客户很重要，我们有独特的测量专业知识。本文仅介绍ADI 公司正在研究的一些算法。 凭借我们在传感器设计方面的现有专业知识，以及在生物医学算法开发（嵌入式和云）方面的努力，ADI 将在为全球医疗保健市场提供最先进的算法和软件方面占据独特的地位。

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确认

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福鲁哈尔·福鲁赞

Foroohar Foroozan [foroohar. analog.com]是一位信号处理科学家。Foroohar 于2015年8月加入ADI公司，领导多伦多算法团队，负责医疗保健业务部门的生命体征和家庭监护系统。她还与ADI成像团队合作开发床旁超声成像系统。在加入ADI之前，她是Geotech Ltd.的研发科学家，加拿大，致力于为下一代机载、电磁地球物理测量系统她是Sunnybrook 研究所的博士后研究员，2012年至2013年致力于脑血管映射的3D超分辨率超声成像，PCT 专利正在申请中。她获得了博士学位。2011年在加拿大多伦多的约克大学Lassonde 工程学院获得计算机科学学位。她感兴趣的领域是生物医学系统中的信号处理和算法，重点是重要的信号系统和生物医学成像。她是安大略专业工程学会（P.Eng.）的成员。也是IEEE 的资深成员