Estimation of Respiratory Rate from Motion Contaminated Photoplethysmography Signals Incorporating Accelerometry

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Estimation of Respiratory Rate from Motion Contaminated Photoplethysmography Signals Incorporating Accelerometry

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1. Introduction: Respiratory rate is a key physiological measurement which can be combined with other vital signs to derive patients’ early warning scores [1]. Previous studies have shown that it is a highly informative indicator of adverse events such as clinical deterioration [2, 3, 4, 5, 6]. Common practice for monitoring patients’ respiratory rate is for nurses to count the number breaths in a minute. However, this is not always accurate or repeatable [7] and is done infrequently as part of 4 hourly manual observations. To provide more regular and accurate measurements, continuous monitoring of patients’ vital signs is possible through the use of non-obtrusive and lightweight wearable sensors. These signals are often corrupted by motion artefact, so robust signal processing and machine learning techniques are required to obtain reliable estimates. A wide range of existing algorithms have recently been introduced to estimate respiratory rate from photoplethysmography (PPG) signals using finger probes or wrist worn sensors. Other studies have also been proposed which obtain a PPG signal from standard video data [8, 9, 10]. However, the quality of the PPG data from wearable sensors (wrist-type PPG sensor or pulse oximeter with a finger/ear probe) is higher than video-based systems, so in this research wrist-type PPG sensor is used to derive respiratory rate.

Previous methods used in the estimation of respiratory rate from PPG or electrocardiogram (ECG) signals include joint time-frequency analysis [11, 12], the short time fourier transform (STFT) [13], correntropy spectral estimates [14], AR models [15, 16, 17] and sparse signal reconstruction [18]. The method in [18] has been shown to be able to estimate respiratory rate with a PPG signal sampled at 10Hz, making it a potential application for low-cost wearable sensors. Recent studies propose using respiratory induced modulations of the PPG signal, which include the variation in amplitude, intensity and frequency [19, 20]. Estimates of RR from each of these are fused to get the final RR value [21, 22, 23]. A comprehensive review of the existing algorithms to estimate respiratory rate from PPG or ECG signals have recently been introduced in [24].

Most of the mentioned methods are used to estimate respiratory rate for patients who are at rest. This is appropriate for sensors in intensive care units because there is much less movement, however for continuous in-hospital and home-based monitoring, it is necessary to estimate various vital signs from signals corrupted by motion artefact. In this work, signal processing techniques are demonstrated on a public dataset which has been used in many studies for robust estimation of heart rate under intense motion. This has particular applications for sport monitoring systems. Since the estimation of respiratory rate during motion is very much limited in the literature, the principal aim of this study is to demonstrate a novel technique for obtaining the respiratory rate of subjects undertaking physical exercise. Since the proposed signal reconstruction technique aims to reconstruct pulse peaks, part of the method can be used for estimation of heart rate variability (HRV) from motion contaminated PPG signals in future studies. With more improvements in the PPG signal reconstruction stage, more reliable estimates for HRV can be obtained.

The paper is organised as follows. Section 2 describes the methods used, it explains the proposed algorithms for reduction of motion artefact from PPG signals using simultaneous accelerometer signals, and then PPG signal reconstruction using the Hilbert transform (HT). The corresponding outputs are used to estimate the respiratory rate from an auto-regressive (AR) model [23]. In Section 3, the results for estimated respiratory rates are provided. The toolbox proposed in [21] has been used to derive a reference data for RR estimates using ECG signals, and these ECG-based estimates of respiratory rate are compared to the PPG based results. Section 4 concludes the paper by summarising the PPG and ECG-based results, as well as the main contributions of the paper, the limitations of the study and potential future work.

2. Methods:

2.1. Reduction of PPG motion artefact using simultaneous accelerometer signals: An analysis of the spectrum of simultaneous PPG and accelerometer signals recorded during physical exercise demonstrates that they have similar spectral components [25]. An adaptive filter has been used to reduce the motion interference from PPG signals, by removing these similar spectra. Motion free PPG is recovered by using the accelerometer signals as inputs to a normalised least mean squares (NLMS) filter. The measured PPG signal \( p(t) \) in the time domain can be modelled using the following...
equation:  
\[ p(t) = \hat{p}(t) + m(t) + v(t) \]  
(1)

where \( \hat{p}(t) \) is a motion free PPG signal, \( m(t) \) is the motion artefact and \( v(t) \) is the sensor noise. The NLMS filter assumes that the motion artefact in the PPG is linearly related to the accelerometer signal, \( m(t) = h^T(t)a_{acc}(t) \), \( h(t) \) is a vector of filter coefficients, with length \( L \), and \( a_{acc}(t) \) a vector of accelerometer signal at time \( t \) and the previous \( L - 1 \) time points. The error output of the filter, is therefore:

\[ e(t) = p(t) - h^T(t)a_{acc}(t) \]  
(2)

The NLMS adaptive filter modifies its coefficients in order to minimise the mean squared error, using the linear update equation:

\[ h(t + 1) = h(t) + \frac{\mu(t)}{|\|a(t)||^2}a_{acc}(t)e(t) \]  
(3)

where \( \mu(t) \) is the step size.

2.2. Reconstruction of PPG signal using the Hilbert transform: Multiple NLMS filters can be used to remove motion from the PPG signal, each using a different accelerometer axis as its input. The filters’ outputs can be combined to produce an enhanced spectrum, for example by multiplying the output spectra of the NLMS filters [25, 26]. Based on this, the final spectrum can be used to track presenting the difference between timing of consecutive pulse peaks and troughs, effectively resulting in a time-series of the height of the PPG pulse. It has been suggested in [29], to obtain pulse width in order to derive respiration from PPG pulse. The corresponding respiratory modulation based on pulse width can be explored in future studies.

To derive amplitude modulation, a time series relating to amplitudes of pulse peaks (difference between height of consecutive peak and onset) needs to be constructed while only the peak amplitudes of the pulses are required to derive the intensity modulation. To derive the frequency modulation, a time series presenting the difference between timing of consecutive pulse peaks needs to be formed. The median spectrum of these models is used to estimate the respiratory rate by finding the maximum peak in the spectrum in [23]. Based on this, a median spectrum across all respiratory modulations is calculated considering various model
orders. The AR spectra with less peakedness have a lower weight in the calculated median spectrum and, therefore, less contribution in estimation of final respiratory frequency.

This method has produced highly accurate RR estimates for PPG signals obtained from subjects at rest. Here, we apply a similar version of the method to the reconstructed PPG signals. In this work, instead of fusing respiratory frequencies from 3 different modulations, only amplitude modulations have been used in the experiment. Therefore, the amplitude modulated signal representing pulse heights is generated and resampled to a 4Hz signal and then it is subjected to the AR spectral analysis to estimate respiratory rates. These are in strong agreement with the estimates which used intensity modulations mainly for ECG signals. The block diagram of the proposed method is summarised in Figure 1.

In another recent study, a public RR toolbox has been proposed by [21] to estimate respiratory rate using 314 algorithms for ECG and PPG signals. The algorithms are divided into three stages: first the respiratory signals are extracted, then the main RR is estimated, followed by the fusing of RR estimates. The techniques for fusing RR estimates include smart fusion [22] (using baseline wander, amplitude modulation and frequency modulation as respiratory signals), spectral peak-conditioned averaging [27], pole magnitude criterion [16], pole ranking criterion [28] and temporal smoothing [29]. The toolbox has been extensively validated against reference data on various datasets. In this work, the toolbox has been used to create the reference data by combining RR estimates from ECG based methods whose outputs strongly agree. It has also been used to obtain PPG based estimates for comparison with the results of our proposed method. For pairwise comparison, the RR toolbox has been used considering only amplitude modulated signals. In the last stage temporal fusion has been performed, so that smoother results were obtained from the motion corrupted PPG/ECG signals.

2.4. Participants and data characteristics: The dataset used in this research is a publicly available dataset [30, 31] which has been recently used in a large number of studies to estimate average and instantaneous heart rate during motion [25]. The dataset provides raw signals including a single channel ECG recorded from the chest, two PPG signals using green light reflected from the wrist and accelerometer signals from three axes embedded in the same wristband sensor unit as the PPG sensors. The data was collected from 12 male subjects aged 18-35 who were walking/running on the treadmill for about 5 minutes in the following order of speeds: the speed of 1-2 km/h for 0.5 minute, the speed of 6-8 km/h for 1 minute, the speed of 12-15 km/h for 1 minute, the speed of 6-8 km/h for 1 minute, the speed of 12-15 km/h for 1 minute, and the speed of 1-2 km/h for 0.5 minute. The sampling frequency of all the signals is set to 125 Hz. Although the dataset has been extensively used for estimating heart rate, it has not been evaluated for estimation of respiratory rate. The dataset has been used in this study to estimate respiratory rate using various algorithms, and to derive the ground truth data.

2.5. Reference Data: The dataset selected in this study includes average heart rate estimates as reference and raw signals of several simultaneous recordings from different sensors. The accelerometer sensor has been shown to be especially useful in modeling the contaminated motion artefact of PPG signals. However, one limitation in using this dataset to estimate respiratory rate is the lack of a reference data for RR estimates in order to evaluate the accuracy of the proposed technique. To obtain reference data, the public RR toolbox [21] has been used to provide a reference for RR estimates using ECG signals. The ECG signals are expected to produce more accurate RR estimates than PPGs [21]. That is the reason to select several ECG based methods in our study to derive the reference data from RR toolbox. Here, we have applied the RR toolbox using only amplitude modulated signals. In the following detailed explanations are provided to derive the reference data.

3. Results:

3.1. Reduction of Motion artefact and PPG reconstruction: To reduce motion artefact of the PPG signals, NLMS filters as explained in Section 2.1 have been applied to the two PPG signals, using each of the three accelerometer axis signals. Therefore, for each subject 6 NLMS filters are designed. For each NLMS filter, the µ and the filter order L have been set to 0.1 and 9, respectively. For subjects 8 and 9 from the dataset, the time-frequency spectrum is shown in Figure 2 and Figure 3 respectively. The time-frequency
spectra of raw PPG signals affected by motion artefact is shown in Figure 2(1) and Figure 3(1), using the Short Time Fourier Transform (STFT) with window length 6 seconds with an overlap of 2 seconds. As it can be seen from Figure 2 and 3, the motion related spectral components in Figure 2-3(1) are diminished in Figure 2-3(2) where only the dominant heart rate frequency is visible. This is crucial for PPG signal reconstruction stage.

After applying the HT to the output of each adaptive filter (using hilbert function, MATLAB, The MathWorks, Inc), the STFT of \( \varphi(t) \) in equation (7) is shown in Figures 2-3(2) and 2-3(3), before and after signal normalisation and amplification respectively. Finally, the Hilbert spectrum of the reconstructed PPG signal \( r(t) \) (see equation 7) is shown in Figure 2(4) and Figure 3(4) for subject 8 and 9 respectively. The Hilbert spectrum has been computed at each time point using instantaneous amplitude and frequency for motion reduced reconstructed PPG as a narrow band signal. The STFT has been computed for a window of 6-seconds long to present the time-frequency spectrum of motion corrupted PPG signals (as a broad band signal) and also their extracted phase modulated signals. The reconstructed PPG signal is expected to contain the main heart rate frequency. Based on the peaks detected in the reconstructed PPG signal, HRV can be measured. The reconstructed PPG signals can be used to estimate HRV using intervals between detected R peaks. Estimation of HRV from motion contaminated PPG signals [25, 32] has not been extensively studied yet. Therefore, the proposed signal reconstruction in Hilbert domain can be used to improve HRV in future studies. Here the reconstructed PPG signal is subjected to AR-based model to estimate respiratory rate.

3.2. Estimation of Respiratory rate: For estimation of respiratory rate, the recent method based on the AR model [23] has been applied to the reconstructed PPG signals. Since the raw PPG signals are very noisy in the time domain, detection of pulse peaks would be impossible in most cases. Therefore, it is more reliable to detect peaks on the reconstructed PPG than on the raw signal (see Fig. 4). Thus for estimation of respiratory rate, the peaks and onsets of the reconstructed PPG are located back into the raw PPG signals using a small window size. This will help to better extract the amplitude modulated signal used to estimate respiratory rate since after PPG reconstruction low frequency information and signal amplitude could be affected (see Figure 4). Using the described dataset, subject number 11 was removed in the analysis as the ECG signals shows saturation in the recordings. For the 11 subjects remaining in the dataset, the respiratory rate has been estimated by applying the AR spectral-based method [23] to derived amplitude modulations from reconstructed PPGs. For the AR model, instead of selecting an optimal model order, AR models with varying model orders \( p = 2, ..., 19 \) are applied. Then, a median AR spectrum has been calculated that is a more enhanced spectrum and the maximal peak is used as a potential respiratory rate frequency. To do this, data segments of length 64 seconds with an overlap of 60 seconds are used to estimate RR. To smooth the RR estimates, Gaussian Process (GP) regression [33] with a Matern covariance function, has been used where the hyperparameters are set to 0.25 and 1 for the characteristic length scale and standard deviation, respectively. The constant value of the Matern covariance related to smoothness of the GP has been set to 3. In addition, the Gaussian likelihood function has been applied while the mean function has not been used. The minimise cost function that minimizes the negative log marginal likelihood in the GP allowed 50 function evaluations. To estimate respiratory rate from ECG signal, manual peak detection has been performed on the raw ECG signals, then the AR-based method has been used to estimate respiratory rate using the extracted amplitude modulated signal.

The results (mean and standard deviation of RR estimates from PPG and mean RR estimates from ECG) are shown in Figure 5, demonstrating a good agreement between ECG and PPG-based RR estimates. For each plot, consecutive window segments correspond to 4 seconds window step sizes where each window is of 64 seconds long. Similar settings have been used for Figure 6 and Figure 7. In this figure, overall trends of RR variations are preserved for most subjects motivating detailed analysis using other methods.

3.3. Deriving reference data: Because they are known to produce more accurate RR estimates, ECG signals have been used to derive the reference data. Using only amplitude modulations, the RR toolbox [21] has been applied to the ECG signals. The toolbox created the RR estimates using 12 methods. Of these 12, 5 methods which produced consistent results with a low variance in output RR estimates were selected as detailed in Figure 6. In addition, after manual peak detection of the ECG signals, the AR spectrum based method [23] has been applied using amplitude modulations, with GP applied in the final stage (see Figure 6). For many subjects, the outputs of those 5 methods from the RR toolbox are in a strong agreement with RR estimates from the AR spectrum based method in [23], as shown in Figure 6. We carefully manually labeled the ECG signals and applied AR spectrum based method to estimate RR. Therefore, as noted above, the RRs are calculated separately from manually annotated ECG signals followed by applying AR spectral analysis on resulted amplitude modulated signals.
The mean absolute error (MAE) of breaths per minute is calculated based methods from 11 subjects (Figure 6, 7), the proposed PPG based method onto the reconstructed PPG signals for subjects 1, 2, 3, 5, 9 and 12, where the similar variations in RR (see Figure 7). Considering this figure, there is a good agreement of segments), using an average of all ECG-based analysis. The subjects were running on the treadmill with varying speed in which variations in HR for almost all subjects were observed. We removed those methods from RR toolbox which produced constant RR throughout the whole experiment or values less than 10bpm for several consecutive windows.

Considering the results shown in Figure 6, a number of subjects are selected which show good agreement between RR estimates from ECG signals. The selected subjects are (1, 2, 3, 4, 5, 7, 8, 9, 10, 12). For subjects 5, 7, and 10, only the first half of the reference RRs increasing into 40bpm and then decreasing to about 20 bpm leading still relatively a low average error but it failed to produce variations observed in the reference data for the \(i^{th}\) segment. The standard error of mean is calculated as:

\[ SE = \frac{S}{\sqrt{c}} \]  

where \( S \) is the standard deviation of absolute difference between estimations and reference data \((b - \hat{b})\). The errors of RR estimates were calculated in terms of mean absolute errors and standard deviations of the errors between estimates from each PPG method and the reference data, for each subject. The PPG methods tested include the proposed method, and 8 selected methods from the RR toolbox. The MAE and 1.96 standard error are calculated for each subject and shown in Table 1. The mean error over all subjects was calculated as 5.53, 6.32, 6.70, 6.63, 6.69, 31.40, 9.34, 10.2 and 9.70 breaths per minute for the proposed PPG-based technique, PPG\(^1\), PPG\(^2\), PPG\(^3\), PPG\(^4\), PPG\(^5\), PPG\(^6\) and PPG\(^7\). The selected PPG based methods are:

\[ \text{10pg}\^{1}: \text{ppg-ELF-ELF-FMeam-FPt-PDTIMS-EHF-Ca-TPu} \]
\[ \text{ppg}\^{2}: \text{ppg-ELF-ELF-FMeam-FPt-PDTIMS-EHF-ARP-TPu} \]
\[ \text{ppg}\^{3}: \text{ppg-ELF-ELF-FMeam-FPt-PDTIMS-EHF-PZX-TPu} \]
\[ \text{ppg}\^{4}: \text{ppg-ELF-ELF-FMeam-FPt-PDTIMS-EHF-ZEX-TPu} \]
\[ \text{ppg}\^{5}: \text{ppg-ELF-ELF-FMeam-FPt-PDTIMS-EHF-ARS-TPu} \]
\[ \text{ppg}\^{6}: \text{ppg-ELF-ELF-FMeam-FPt-PDTIMS-EHF-FTS-TPu} \]
\[ \text{ppg}\^{7}: \text{ppg-ELF-ELF-FMeam-FPt-PDTIMS-EHF-WCH-TPu} \]

All abbreviations are explained and detailed in [21] and briefly noted in the caption of Figure 6. We observed that the method PPG\(^1\) has the lowest absolute error among the RR toolbox methods, but note that it does not follow the variation in RR estimates well. For many subjects there is a bias even when the average errors are still low. For example, for subject 9, PPG\(^1\) method produced almost steady respiratory rate around 20 bpm leading still relatively a low average error but it failed to produce variations observed in the reference RRs increasing into 40bpm and then decreasing to about 15bpm. In contrast, the proposed PPG method in Figure 7 matches the variation in RR estimate of the reference data much better for many subjects, although its overall mean absolute error is only 1 breath per minute less than the lowest absolute error produced by the RR toolbox.

The average runtime for each subject has been obtained as 2.8 seconds on an Intel® Xeon® Processor E5-1630 v3 (10M Cache, 3.70 GHz). The implemented code can be further optimised to be applicable in wearable devices.

\[ \text{MAE} = \frac{1}{c} \sum_{i=1}^{c} |b(i) - \hat{b}(i)| \]  

where \( c \) is the number of RR estimates for each subject (i.e. number of segments), \( b(i) \) is estimated breaths per minute and \( \hat{b}(i) \) is derived breaths per minute using reference data for the \(i^{th}\) segment.
Table 1 The error, in breaths per minute calculated as $|\text{MAE} \pm 1.96 \times \text{SE}(\text{standard error})|$ for selected subjects.

<table>
<thead>
<tr>
<th>Method (mean)</th>
<th>Subject 1</th>
<th>Subject 2</th>
<th>Subject 3</th>
<th>Subject 4</th>
<th>Subject 5</th>
<th>Subject 6</th>
<th>Subject 7</th>
<th>Subject 8</th>
<th>Subject 9</th>
<th>Subject 10</th>
<th>Subject 12</th>
</tr>
</thead>
<tbody>
<tr>
<td>PPG (5.53)</td>
<td>4.36 ± 0.87</td>
<td>4.23 ± 1.09</td>
<td>5.34 ± 2.11</td>
<td>15.03 ± 1.79</td>
<td>4.43 ± 0.76</td>
<td>4.53 ± 0.80</td>
<td>7.46 ± 1.69</td>
<td>3.02 ± 0.70</td>
<td>2.33 ± 0.94</td>
<td>4.79 ± 0.65</td>
<td></td>
</tr>
<tr>
<td>PPG (6.69)</td>
<td>6.68 ± 1.64</td>
<td>6.86 ± 0.99</td>
<td>5.50 ± 0.60</td>
<td>5.53 ± 0.39</td>
<td>2.35 ± 0.60</td>
<td>3.73 ± 0.94</td>
<td>14.84 ± 0.93</td>
<td>6.51 ± 1.02</td>
<td>8.26 ± 0.75</td>
<td>2.50 ± 0.47</td>
<td></td>
</tr>
<tr>
<td>PPG (6.32)</td>
<td>6.12 ± 0.82</td>
<td>3.94 ± 0.87</td>
<td>2.87 ± 0.57</td>
<td>5.57 ± 1.92</td>
<td>9.13 ± 0.83</td>
<td>7.66 ± 0.18</td>
<td>5.61 ± 0.62</td>
<td>5.84 ± 0.81</td>
<td>15.16 ± 1.15</td>
<td>4.66 ± 0.60</td>
<td></td>
</tr>
<tr>
<td>PPG (6.34)</td>
<td>6.98 ± 1.56</td>
<td>8.08 ± 0.99</td>
<td>6.22 ± 1.01</td>
<td>8.47 ± 0.47</td>
<td>2.89 ± 0.66</td>
<td>4.43 ± 1.12</td>
<td>12.67 ± 0.80</td>
<td>5.18 ± 1.12</td>
<td>9.48 ± 0.76</td>
<td>2.06 ± 0.39</td>
<td></td>
</tr>
<tr>
<td>PPG (6.69)</td>
<td>6.95 ± 1.56</td>
<td>8.33 ± 2.01</td>
<td>6.30 ± 0.99</td>
<td>8.49 ± 0.48</td>
<td>2.69 ± 0.64</td>
<td>4.36 ± 1.06</td>
<td>12.17 ± 0.70</td>
<td>5.27 ± 1.11</td>
<td>9.76 ± 0.89</td>
<td>4.99 ± 0.38</td>
<td></td>
</tr>
</tbody>
</table>

4. Discussion: In this paper, a new approach is proposed to estimate respiratory rate from motion contaminated PPG signals. Estimation of respiratory rate during motion has been previously limited to ECG based analysis. The proposed method has shown to be very effective in motion reduction of PPG signals enabling estimation of respiratory rate and instantaneous heart rate.

Based on the proposed method, first, simultaneous accelerometer signals are used as inputs to adaptive filters. These are applied to raw PPG signals to reduce motion artefact and produce a clear spectrum containing the dominant heart rate frequency. Then the HT is used to reconstruct PPG signals in the time domain, using extracted phase modulations, peaks and onsets from this reconstructed signal are tracked back to the raw signal and used to derive the respiratory-induced amplitude modulation. Respiratory rate is estimated from this modulation using an AR spectrum based method. Gaussian Process regression has been applied to smooth the RR estimates.

Aside from RR estimation, the proposed technique has other potential uses, for example peaks in reconstructed PPG signals can be used to derive instantaneous heart rate from PPG, which can be used to study HRV. Here a simple window has been used to locate back peaks in the raw PPG signal, but in future studies this could be made more reliable by tracking the highest energy frequency in the time-frequency domain.

Some advantages of our method are that there are less parameters to set and the PPG signal reconstruction step provides a new insight into the analysis of HRV. It also lends itself well to extracting respiratory modulations for use in the AR model. Extraction of the respiratory signal from PPG signals during motion is a challenging task. The proposed method in this paper aimed to combine various techniques which would reduce motion artefact and better estimate respiratory rate. This can provide a basis for future studies on estimation of respiratory rate and HRV from motion contaminated PPG signals.

The limitation of this study is the lack of ground truth data. However, 6 different ECG-based methods which produced similar results are selected, with an average of these RR estimates used as the ground truth estimates. Although the PPG-based method proposed in this paper produced more accurate estimates of respiratory rate than those from the RR toolbox (when compared to ECG-derived ground truth data), the minimum difference in estimates is about 1 breath per minute. This also shows very good agreement between our proposed PPG based method and the 9 selected methods (5 using ECG-based methods and 4 using PPG-based methods). The variation of RR estimates over time has been preserved by the proposed PPG-based technique, while the final average difference between our method and the best method from the RR toolbox differs only by about 1 breath per minute.

This paper provides a new platform for processing of PPG signals recorded during motion. In future studies, large datasets of signals from wearable sensors e.g. at home environments could be recorded where the information of simultaneous accelerometer data can assist to improve the estimation of various physiological parameters. RR estimation during intense physical exercise has important applications in sport monitoring to provide athletes crucial information to manage their training levels. On the other hand, monitoring of RR for patients during walking or running can help them to control their activity levels. Since the dataset analysed in this study is publicly available, we challenge future studies to process the PPG signals exploiting new RR based methods and compare the estimation of RR during motion. Another related dataset has been provided in [34] which includes gyroscope information which can allow separation of acceleration due to gravity. Reliable ground truth data is indeed necessary for detailed validation of estimated RR which needs to be considered in future studies.

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