Paediatric Pulse Rate Measurements: a Comparison of Methods using Remote Photoplethysmography

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Abstract

Remote photoplethysmography (rPPG) is a non-invasive technique used to measure vital signs such as pulse rate. As the heart beats, blood volume changes in the microvasculature of the skin cause alterations in the light absorption pattern. As rPPG signals can be captured using most smartphone and tablet cameras, the integration of rPPG technology has the potential to streamline the triaging process within emergency department settings but also to be an invaluable tool for continuous monitoring within the home environment. This paper describes an approach for deriving pulse rate from rPPG tailored specifically towards paediatric cases with higher pulse rates than adults, demonstrating a root mean square error of 8.2 beats per minute using frequency domain analysis. Further, this work details the data collection methodology employed in a paediatric emergency department, discussing the unique challenges of the data collections process.

1. Introduction

Measuring vital signs is an important part in triaging children in hospital settings, but is also an important component of home health monitoring [12, 18]. Changes in vital signs can indicate a deterioration in health before other symptoms appear in cases of infection [3, 17]. A commonly used tool to track the vital signs in paediatrics is the Paediatric Early Warning Score (PEWS), combining vital signs into a single risk assessment score to monitor treatment urgency [11]. Persistent unexplained tachycardia is used as an early identifier of potential paediatric sepsis [13]. Sepsis, a systemic inflammatory response associated with infection, contributes to 19% of deaths across the world, and untreated infections can develop into sepsis quickly [5]. Developing sepsis is more likely in children with pre-existing conditions, and carries a mortality rate of nearly 50% in the most vulnerable group [22].

Despite the importance of monitoring vital signs in paediatric patients, it is not without challenges. Accurate measurements can be time consuming and require expensive, calibrated equipment as well as trained staff to use it. Additionally, paediatric patients can find the measuring process painful or stressful, and stress itself leads to a change in vital signs, affecting the reliability of the measurement.

To avoid stress in children when measuring their vital signs, a non-obtrusive, non-contact method can help achieve more reliable vital sign measurements, especially in the lower age range. In an effort to achieve cost-efficient vital sign monitoring, research has been focused on photoplethysmography (PPG). PPG signals represent the changes in blood volume in the skin by measuring changes in reflected light. PPG signals can be collected using a contact sensor (such as a pulse oximeter), but these sensors could still cause distress to paediatric patients.

Verkruysse *et al.* (2008) first demonstrated the feasibility of remote PPG (rPPG) to extract heart and respiration rates using ambient light and consumer-grade cameras [20]. Since then, there has been a rapid expansion of research in the use of cameras for remote patient monitoring, surveyed recently by McDuff [9]. For example, rPPG was shown to successfully compute pulse rate within 1.4bpm compared to an automatic sphygmomanometer [7]. While the use of consumer-grade cameras opens up a cost-effective monitoring method for both clinical and home use, there remain challenges. Remote PPG is sensitive to changes in ambient light, which affect signal quality, and to subject movement, a particular issue in younger children [6, 8].

Remote technologies for pulse rate monitoring have a wide range of applications in paediatric patients. rPPG methods could open up home- and tele-monitoring via a smart device, but also monitoring in NICU/PICU; contactless monitoring reduces infection risk and is also less distressing for the infants. Aarts et al studied the pulse rate in 19 infants in the NICU using a camera approximately 1 meter away from the patient [1]. Although this method worked well even in the relatively dim lighting, patient movement was a problem for signal quality and accuracy [1]. Bal also performed a study with rPPG signals from 2 healthy patients and 7 PICU patients captured using a laptop webcam [2]. Both these studies show promise for rPPG as a vital sign monitoring tool, but only use a small sample set.

In this paper, we describe the data collection process of a large quantity of high quality facial videos for rPPG extraction in a Paediatric Emergency Department (PED). We discuss the challenges with collecting data and describe the use of two different pulse rate algorithms on the recovered signals: one based on time domain analysis already in use for adult pulse rate recovery, and one based on frequency domain analysis specifically designed to recover pulse rates from noisier signals with a wider range of pulse rates.

2. Data collection

2.1. Collection method

Data collection took place in the PED at Sunderland Royal Hospital. Children were recruited with ages ranging from birth until their 18th birthday presenting to the PED and, in the opinion of the treating clinical team, able to participate in the research study. Pre-set targets were in place to ensure a spread across all age ranges and, where possible, skin tones. There were no other clinical inclusion/exclusion criteria ensuring that we achieved a broad range of health states. This encompassed febrile and afebrile children, along with those presenting with illnesses such as respiratory diseases and otherwise well children, for example those with minor physical injuries. By including all paediatric ages and multiple health states we were able to test vital sign measurements over a wide range as well as providing an opportunity to research classification algorithms able to distinguish between ill and well children. The protocol for data collection is described in detail in [10].

To extract rPPG signals, high quality (non-compressed) videos were collected using a purpose-built data collection app on an iPad 10 for a duration of 1 minute. Collecting the video instead of a derived signal allows for post-processing with different signal extraction techniques, which is needed due to the uncertainty about the best rPPG signal extraction method to use for paediatric patients. While in previous adult studies a camera sampling rate of 30 frames per second was used [23], we used the newer iPad 10 in this study to enable data capturing at 60 frames per second. This higher frame rate should help in recovering the higher pulse rates often seen in children. Videos were recorded on the data collection app, at the same time as vital signs were collected from the patient. In most cases the pulse rate was captured using a pulse oximeter, but a small subset of patients had an ECG, with the aim to time align the ECG recording to the rPPG waveform.

In an effort to overcome the problem of signal degradation associated with patient movement, we designed a game within the data collection app to motivate them to keep still. By keeping their face still, the young patient was rewarded with a giraffe animation over their face. The longer they could keep still in the same position, the more points they were given, and milestones of points were rewarded with an animation of confetti across the screen. A screenshot of this game can be seen in Figure 1. The hospital room in which data collection took place was well-lit with overhead panel lighting. No additional bright lighting was used to avoid distressing the patients. A well-lit environment is always important, but even more so when the screen is used to display the animation shown in Figure 1 to avoid the light changes causing noise in the signal.

Age (years)	Number of patients	Successful facial videos
0-5	126	116
5-11	110	203
11+	110	220
All combined	346	539

Table 1. Overview of collected dataset.

2.2. Dataset overview

In total, we had 346 paediatric patients taking part. For older participants, two facial videos per patient were recorded. For younger patients, a combination of facial videos and chest/back videos were taken. In this study we only focused on pulse rate measurements from facial videos, of which there were 539 in total. Signal extraction was successful on 78% of these videos, with 4.6% containing signals from patients with skin tone 5 or 6 on the Fitzpatrick scale. Sometimes a signal could not be detected due to too much movement or talking in the video. In Table 1 an overview of the dataset is shown split by age, and Figure 2 shows an overview of the dataset used for pulse rate analysis split by age and sex.

Some age categories were harder to recruit than others. Teenagers were commonly unwilling to take part, because they did not wish to take part in a clinical study while not feeling well. Parents/guardians of toddlers often chose to

Figure 1. Screenshot of the data collection app showing the giraffe animation and confetti as a result of reaching a score milestone as seen in the tracker on the bottom right of the screen. The top of the screen also shows a count down to the end of the recording, using a numerical count down as well as a moving progress bar.

Age (years)	Non-compliant (%)	Refusal (%)	Successful (%)
0-5	4.6	32.8	62.7
5-11	0.5	34.2	65.3
11+	0	41.2	58.8
All combined	2.3	35.4	62.3

Table 2. Overview of recruitment percentages and reasons for not taking part in different age categories. Patients were classed as non-compliant if data collection was attempted, but unsuccessful, and as a refusal if they (or their parents/guardian) did not wish to take part in the research trial.

opt out because they did not feel sitting still for a minute for the video was achievable, and some patients in this age group had to be withdrawn for non-compliance. An overview of the reasons not to participate and the recruitment success rate in each of the age categories is shown in Table 2.

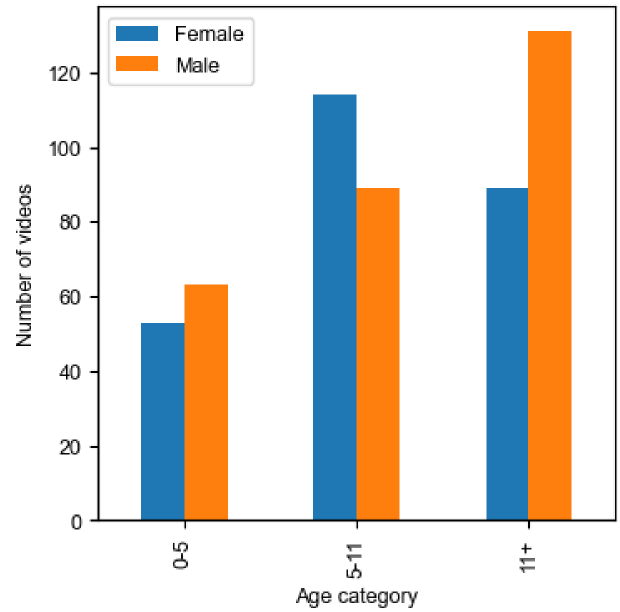

Figure 2. Histogram of number of videos collected in each age category split by sex.

2.3. Validation procedure

The performance of two different pulse rate algorithms will be compared. The performance will be compared based on the root mean square error (RMSE) from the ground truth, as well as the method's success rate in returning a result. In addition to the overall performance in the full dataset, the performance for different age categories will also be studied separately.

3. Pulse rate extraction

In this section the two different algorithms for pulse rate calculations are described. The first algorithm, time domain pulse decoding, has been used by Lifelight® in adult populations [7, 19]. We developed the second algorithm, frequency domain pulse decoding, specifically tailored to the noisier signals from children as well as to the higher pulse rates found in children. Before the pulse rate can be extracted, the rPPG signal needs to be extracted from the video. A face detection algorithm is used on each frame of the 60 second long video to determine the average face position as well as the stability of the face. The face detection algorithm from OpenCV extracts 68 facial landmarks [15], which we use to calculate the location of different regions of interest. The regions of interest only get calculated once and remain fixed for the duration of the measurement. In Figure 3 an example of the extracted facial landmarks is shown with the two regions of interest that we use for pulse

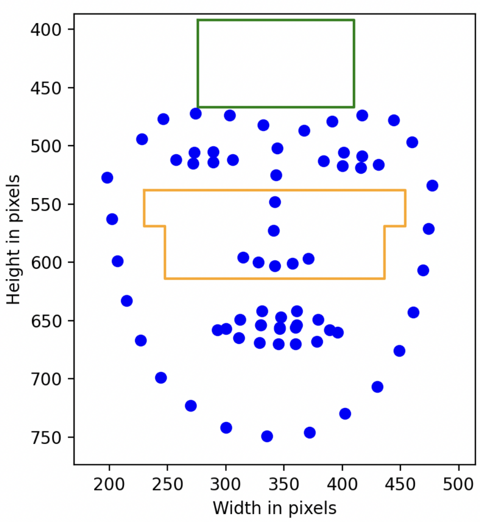

Figure 3. An example of the extracted facial landmarks from a video. The two regions used for signal derivation are shown in relation to the averaged facial landmarks.

rate calculation: the forehead and the mid-face region. The mid-face region is drawn based on the position of the eyes and width of the face, while the forehead region is based on the position of the eyebrows. On top of these two smaller regions, the signal is also collected from the full face. The average red, green and blue values for each frame in these regions is calculated and all 3600 data points (60 second recording at 60fps) for each color channel are saved as the time-domain rPPG signal for all three regions (the full face, mid-face and forehead region).

3.1. Time domain pulse rate recovery

The Lifelight® algorithm, described in detail in [19], uses the green channel for its pulse rate calculation. No changes were made to this algorithm to assess the accuracy in the paediatric population. Before the time domain data is assessed, a bandpass filter is used to remove both low-frequency disturbances from the signal (such as breathing and movement) as well as high-frequency disturbance above 4Hz. This filtered signal is used to calculate a smoothed first derivative [14]. Each peak in the first derivative corresponds with the fiducial point of a pulse, and the number of peaks and the distance between the peaks can be used to calculate the pulse rate. By calculating the distance between peaks, we can also detect when a specific part of the signal contained noise instead of pulsatile information. The difference between noise and a pulsatile signal is determined by the time domain regularity of the intervals between fiducial points. Unusually long or short intervals are discarded when calculating the pulse rate, but when too many unusual intervals are found, no pulse rate is returned as the signal quality is deemed too low. To calculate the pulse rate we use Equation 1,

$$\textit{pulse rate} = \frac{60}{\tau}, \tag{1}$$

where τ is the mean of the realistic intervals between fiducial points.

3.2. Frequency domain pulse rate recovery

Similar to the time domain pulse decoding algorithm, the first step of spectrally decoding the pulse rate is signal cleaning. However, instead of using bandpass filters, the plane-orthogonal-to-skin (POS) method by W. Wang et al is used [21]. This method is particularly effective in extracting the pulsatile rPPG signal from facial videos. After combining the red, green and blue channels to extract the rPPG signal for both the forehead and the midface regions, the signal is used in a spectral power density calculation. For this calculation we use Welch's method, an algorithm designed to balance the trade off between frequency-resolution and noise robustness [16].

The first step of Welch's method is to divide the signal into overlapping segments, in our case 512 frames (roughly 8.5 seconds of data). Subsequently, windowing is applied to each segment to reduce spectral leakage and the power density spectrum of each segment is calculated. An average of all calculated spectra from one video is created, and from this average the peak frequency bin within the range of age determined plausible heart rates (60-200 bpm) is selected as the calculated pulse rate for the measurement. In Figure 4 an example of a calculated spectrum is shown as well as a short segment of the POS rPPG signal that was used for the input. The ground truth pulse rate for this example was 143 beats per minute, and while the pulsatile signal is not clearly visible in the rPPG signal, it can be extracted from the averaged spectral power density, which calculates a pulse rate of 141 beats per minute.

4. Results

All successfully extracted facial signals are processed using the two pulse rate algorithms described in the previous section. The forehead region did not outperform the mid-face region, so for further comparison between the two methods the mid-face region is used for the frequency domain algorithm. In the time domain algorithm only 68% of the signals returned a result, while the frequency domain algorithms shows a much higher success rate of 90%. This is in part due to the use of POS in the frequency domain method, because POS is better than bandpass filters at separating rPPG components from movement artifacts, but also in part due to the time domain redundancy utilized by the Welch periodogram to concentrate the peak energy at the mean pulse rate. In Figure 5 scatter plots showing the calculated value

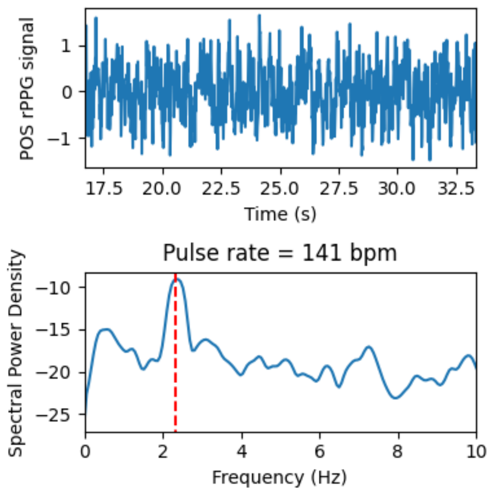

Figure 4. A section of POS rPPG signal and the calculated averaged spectral power density, showing a peak at 2.35 Hz corresponding to a pulse rate of 141 beats per minute.

Age (years)	Time domain RMSE (bpm)	Frequency domain RMSE (bpm)
0-5	27.5	15.4
5-11	13.7	7.5
11+	8.7	5.4
All combined	14.6	8.2

Table 3. Calculated RMSE in beats per minute for both algorithms separated by age category.

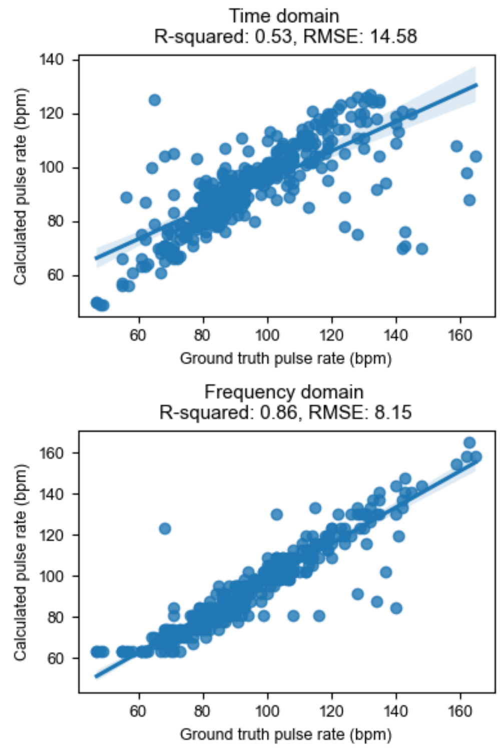

Figure 5. Scatter plots of time domain algorithm (top) and frequency domain algorithm in the mid-face region (bottom) results against ground truth.

against the collected ground truth data are shown for both algorithms on the same dataset. It can be seen that the correlation is higher for the frequency domain method with an r^2 of 0.86 compared to an r^2 of 0.53 for the time domain method.

The RMSE for the frequency domain method is also better. In Table 3 an overview of the RMSE is shown for the different age categories as well as the full dataset. It can be seen that the frequency domain method outperforms the time domain method in all age categories, but also that accurate pulse rate calculation in younger categories is more challenging.

5. Conclusion

In this paper we described the data collection study to collect rPPG signals from paediatric patients in the PED. We collected two 60-second facial videos on 346 patients, and were able to use 78% of these videos in our newly proposed pulse rate recovery algorithm aimed at paediatric patients. Remote monitoring of vital signs using smart devices is time efficient in a setting such as the PED, but also opens up a path towards remote triaging as well as a tool for home-monitoring in long-term conditions.

The frequency domain based pulse rate recovery algorithm using POS rPPG signals was more accurate and more successful in calculating pulse rates across all age categories. On all age ranges combined when comparing the two datasets, the RMSE for the frequency domain based pulse recovery was 8.2 beats per minute, while the time domain based algorithm achieved 14.6 beats per minute. The performance for both algorithms was better in the older children, due to the better signal quality but also due to the possible confusion of harmonics of breathing rate and pulse rate in the younger, especially febrile, children.

Although initial results are promising, further work is needed before the frequency domain based pulse recovery algorithm can be deployed for clinical use. A more accurate result could be achieved by using a finer FFT resolution, which is currently limited to 2.5 beats per minute. Further work is also required on improving the robustness of rPPG signal extraction from the noisiest videos with movement in the younger children, as well as a more in-depth analysis into the different age categories. We may need to explore different settings for the Welch Method for different age categories to optimise both the success rate and the accuracy for different ranges of pulse rate, or explore a combination method where multiple algorithms are combined to reach more confidence in the calculated pulse rate.

In addition to these changes for improving the pulse rate extraction, for complete remote monitoring other vital signs, such as respiration rate and SpO2 also need to be extracted from the signal.

While there are still challenges to be solved in using rPPG signals for vital sign monitoring in paediatric patients, signal cleaning methods and vital sign extraction are improving continuously. The growing attention to remote monitoring for hospitalized (paediatric) patients and the interest in applying these technologies to a broad range of patients indicate the potential for future advancements in this field. However, this study can be used to inform future research designed to establish the safety and accuracy of novel wireless monitoring devices in hospitalized paediatric patients. Future investigations would benefit from larger sample sizes, longer monitoring duration, inclusion of clinical outcomes, and standardized reporting methods [4].

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Ethics approval

The study is being performed in accordance with the spirit and the letter of the declaration of Helsinki, the Good Clinical Practice Guidelines, the protocol and applicable local regulatory requirements and laws. The VISION-Junior protocol was approved by the Health Research Authority (IRAS reference 321956) and Newcastle North Tyneside Research Ethics Committee on 30 March 2023 .

Data availability statement

The data generated and analyzed during this study are commercially sensitive and are therefore not publicly available, as mandated by Xim's contractual obligations with its grant funders and investors. Furthermore, the informed consent provided by study participants only allows access to individual data, including in anonymized form, by authorized individuals of the research team based at the study sites, Xim, and Xim's authorized partners. Reasonable requests for access to the study data within these limitations will be considered by the corresponding author.

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