Establishing best practices in photoplethysmography signal acquisition and processing

Peter H Charlton, Kristjan Pilt and Panicos A Kyriacou

1 Department of Public Health and Primary Care, University of Cambridge, United Kingdom
2 Research Centre for Biomedical Engineering, City, University of London, United Kingdom
3 Department of Health Technologies, Tallinn University of Technology, Ehitajate tee 5, 19086 Tallinn, Estonia
* Author to whom any correspondence should be addressed.
E-mail: pc657@medschl.cam.ac.uk

Abstract
Photoplethysmography is now widely utilised by clinical devices such as pulse oximeters, and wearable devices such as smartwatches. It holds great promise for health monitoring in daily life. This editorial considers whether it would be possible and beneficial to establish best practices for photoplethysmography signal acquisition and processing. It reports progress made towards this, balanced with the challenges of working with a diverse range of photoplethysmography device designs and intended applications, each of which could benefit from different approaches to signal acquisition and processing. It concludes that there are several potential benefits to establishing best practices. However, it is not yet clear whether it is possible to establish best practices which hold across the range of photoplethysmography device designs and applications.

This Editorial considers whether it would be possible and beneficial to establish best practices for acquiring and processing photoplethysmography signals.

Photoplethysmography is an optical technique which provides non-invasive measurements of the arterial pulse wave, which is related to the blood volume change in the observed microvascular tissue. The photoplethysmogram (PPG) signal is already widely utilised by clinical devices such as pulse oximeters (Alian and Shelley), and wearable devices such as smartwatches (Charlton and Marozas). Photoplethysmography holds great promise for health monitoring in daily life. Indeed, several potential applications of photoplethysmography were presented in 2021 alone in Physiological Measurement, including: blood pressure monitoring (Esmaeipoor et al 2021, Xing et al 2021); detecting peripheral arterial disease (Allen et al 2021); sleep staging (Li et al 2021); screening for sleep apnea and cardiovascular disease (Behar et al 2020, Ouyang et al 2021); and detecting driver sleepiness (Hultman et al 2021).

Despite the widespread use of photoplethysmography, best practices have not yet been established for acquiring and processing photoplethysmography signals. This may in part be due to the diversity of photoplethysmography device designs, ranging from smartwatches to earbuds, and applications, ranging from oxygen saturation measurement in clinical practice to heart rate monitoring during exercise (Charlton et al 2022). Potentially, the best approach to signal acquisition and signal processing could differ between each device design and application. Nonetheless, there could be benefits to establishing best practices, such as establishing hardware configurations that consistently provide high quality signals, and establishing signal processing algorithms that can accurately derive parameters from a variety of PPG signals. This is illustrated by the findings of Liu et al in their recent article in Physiological Measurement. They found that the use of different PPG signal filtering settings can result in different measurements being obtained from PPG pulse wave analysis. Based on this, they highlighted the potential benefits of the ‘standardisation’ of PPG filtering (Liu et al 2021). In this case, establishing best practices for filtering PPG signals would have the benefit of allowing pulse wave indices to be compared between studies and between devices. However, this may not be straightforward as different filtering settings may be required for different applications, such as heart rate monitoring (which uses the fundamental frequency of the PPG, ≈0.5–3Hz) and blood pressure assessment (which uses higher frequency content).
Potential areas in which best practices could be established include factors relating to device design (hardware and software) and measurement protocols (recording setting and duration). These are summarised in figure 1, and now described.

Several factors in the hardware design influence the PPG signal (Charlton and Marozas, Lemay et al.), and are therefore potential areas in which best practices could be established. Firstly, the wavelength of emitted light determines the depth of light penetration, and consequently the level of the vasculature contributing to the PPG signal (Liu et al. 2019), which influences signal quality (Fallow et al. 2013). Current best practice is to use longer wavelengths (e.g. infrared) for transmission photoplethysmography as these penetrate deeper (Anderson and Parrish 1981), and shorter wavelengths (e.g. green) for reflectance photoplethysmography as these produce higher signal quality for heart rate measurement (Matsumura et al. 2020). However, this practice may need to be revisited as the use of green light has been found to result in less accurate heart rate monitoring in subjects with darker skin tones (Fine et al.). Secondly, in reflectance photoplethysmography the signal quality is influenced by the geometry of the light emitter, light detector, and sensor casing. Current best practice is to design the surrounding casing to eliminate ambient light as far as possible (Abay and Kyriacou). In the future this may be extended to using geometries in which the LED surrounds the photo detector, as these have been found to give higher signal quality (Khan et al. 2019). Thirdly, the contact pressure applied by the device to the skin impacts the shape of the PPG pulse wave (Chandrasekhar et al. 2020) and consequently its second derivative (Grabovskis et al. 2013). Best practice in this area of contact pressure has not yet been established: higher pressures may reduce probe-tissue movement artifact, and have been found to increase the accuracy of PPG-based heart rate monitoring (Scardulla et al. 2020). However, it is not clear whether such pressures would be suitable for long-term monitoring. Ideally, the contact pressure should remain constant when analysing pulse wave shape, such as when tracking changes nocturnal changes in blood pressure (Radha et al. 2019). Fourthly, the body site chosen for PPG measurement influences pulse wave shape (Hartmann et al. 2019), and the utility of the acquired signal (Charlton and Marozas). Best practice has not yet been established in this area: in clinical devices the finger is often used (Alty et al. 2007), whereas in consumer devices the wrist is often used due to user preference (Prinable et al. 2017). In summary, the challenge of establishing best practices is not trivial, as several factors can influence the PPG signal, and it is likely that different device configurations would be best suited to different applications.

The software used in PPG devices influences the PPG signal and the parameters derived from it, and therefore presents potential areas in which to establishing best practices. Firstly, there is a compromise between increasing the sampling frequency to capture details of the shape of PPG pulse waves, and reducing it to reduce power consumption (Lee et al. 2018). Best practices differ between applications, with minimum acceptable sampling frequencies of 10, 16, and 25 Hz reported for heart rate, respiratory rate, and pulse rate variability measurements respectively (Wolling and Van Laerhoven, Charlton et al. 2017). Choi and Shin (2017). Secondly, different approaches can be used to remove motion artifact, ranging from eliminating periods of motion (Guo et al. 2021), to denoising the PPG (Zhang et al. 2015), to cancelling motion artifact using a reference accelerometer or gyroscope signal (Marozas and Charlton 2021). Here, best practices also differ between applications: in hospital monitoring it has been proposed that periods of motion should be eliminated from analyses (Orphanidou et al. 2015), whereas in exercise monitoring the alternative approaches of denoising the PPG or cancelling motion artifact are used (Zhang et al. 2015). Whilst it may be challenging to develop a universal strategy to PPG signal quality assessment, recent work has demonstrated that a single approach can perform well.
across different heart rhythms and different PPG devices (Mohagheghian et al). Thirdly, the analog and digital filtering used to pre-process signals influences both the amplitudes and timings of PPG pulse wave features (Liang et al 2018, Liu et al 2021). For instance, an optimal low-pass filter cut-off of 6 Hz has been proposed to preserve the higher harmonic components of the PPG, and minimise variability in indices calculated from its second derivative (Pilt et al 2013). Fourthly, the choice of signal processing algorithm used to estimate a physiological parameter from the signal can greatly influence the accuracy and precision of the parameter (Charlton et al 2016). Best practices for deriving pulse wave features from finger PPG signals have been proposed (Elgendi 2014, Elgendi et al 2014). However, best practices have not yet been established for signals acquired at the wrist, which differ from finger signals (Rajala et al 2018). Similarly, it could be beneficial to optimise neural network architectures for PPG analyses, building on existing architectures (Li et al 2021). Further work is also required to identify the best pulse wave features for different tasks from amongst the wide range of features proposed in the literature (Charlton et al 2018, Lin et al 2020). For instance, recent studies have investigated the best features for blood pressure estimation (Xing et al 2021) and pulse rate variability analysis (Peralta et al 2019). The best algorithm design may also depend on a subject’s characteristics, as shown by recent proposals of different blood pressure estimation algorithms for subjects of different ages (Xing et al 2020) and subjects of different blood pressure categories (Khalid et al 2020). In summary, it may be difficult to establish best practices for the software used in PPG devices, as the best approach may vary according to the sensor configuration, application, and subjects being monitored.

A further area in which best practices could be established is the protocols used to obtain PPG measurements, where best practices could be used to obtain repeatable and reproducible measurements. Measurement protocols can be tightly controlled in clinical settings, where consideration can be given to room temperature, subject position, and the duration of rest prior to measurement (Allen and Hedley 2019). However, protocols cannot be so tightly controlled when obtaining measurements from consumer devices in daily life. Nevertheless, measurements can be obtained in a repeatable manner during periods of rest, such as resting and night-time resting heart rates (Mishra et al 2020, Radin et al 2020). Future work may consider the required recording durations and acceptable levels of signal quality to estimate different physiological parameters from the PPG (Huthart et al 2020). Whilst it is possible to obtain some parameters during exercise (e.g. heart rate) (Zhang et al 2015), it may only be possible to obtain other parameters accurately whilst at rest (e.g. those derived from the second derivative of the PPG, such as the aging index) (Takahama et al 1998).

It is clear that there are several potential areas in which best practices could be established for the acquisition and processing of PPG signals. However, it is not yet clear whether it would be possible and beneficial to establish best practices. On the one hand: it may not be possible to establish best practices as they may vary greatly between device designs and applications; it may not be possible to use them widely if they are patented; and, they may not be beneficial if they don’t substantially improve device performance. On the other hand, establishing best practices could: reduce the time taken to design and manufacture devices; ensure PPG-based measurements are as accurate and reproducible as possible; and, help advance the field as researchers and developers could build on existing best practices when making novel developments.

Several advances could aid research into determining whether it would be possible and beneficial to establish best practices for PPG signal acquisition and processing. Firstly, wearable devices which provide the raw PPG signal are invaluable for such research, as demonstrated through the use of the Empatica E4 wristband in many research studies (McCarthy et al). Whilst several research devices can provide the raw PPG signal (Charlton et al 2022), large-scale studies could be conducted more easily in daily life if consumer devices were similarly able to provide raw PPG signals. Secondly, freely available datasets allow researchers to benchmark their own PPG signal processing algorithms against others on a common dataset. Several such datasets are available (Charlton et al 2022), including: the WeSAD and PPG-DaLiA datasets, acquired using an Empatica E4 device in healthy subjects (Schmidt et al, Reiss et al 2019); and the VitalDB and the MIMIC Waveform databases, acquired from critically-ill patients (Johnson et al 2016, Lee and Jung 2018). However, there are limitations to current datasets: they are often collected from either healthy volunteers or a particular patient population, rather than a broad cross-section of society; they often contain PPG signals acquired by only one device, rather than signals acquired using different hardware configurations; and they are often recorded in either laboratory or clinical settings, but few are recorded in daily life. Thirdly, there is a need for widely accepted validation protocols with which to assess the performance of PPG-based devices. Such protocols already exist for devices measuring blood pressure and heart rate (Stergiou et al 2018, Mühlen et al 2021). However, different standards may be required for different applications, such as varying the accuracy and data availability thresholds according to the intended use case and measurement scenario (Consumer Technology Association 2018, Mukkamala et al 2021).

To conclude, there are several potential benefits to establishing best practices for acquiring and processing PPG signals. However, it is not yet clear whether it is possible to establish best practices which hold across the range of PPG device designs and applications. Therefore, much further work is required to investigate whether it
would be possible and beneficial to establish best practices, and to understand how they may differ between device designs and intended applications.

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ORCID iDs

Peter H Charlton https://orcid.org/0000-0003-8386-8655
Kristjan Pilt https://orcid.org/0000-0003-2422-0430
Panicos A Kyriacou https://orcid.org/0000-0002-2868-485X

References

Abay T Y and Kyriacou P A 2022 Photoplethysmography in oxygenation and blood volume measurements Photoplethysmography: Technology, Signal Analysis, and Applications ed P A Kyriacou and J Allen (Amsterdam: Elsevier) Ch. 5 pp 147–88
Alian A A and Shelley K H 2022 PPG in clinical monitoring Photoplethysmography: Technology, Signal Analysis and Applications ed P A Kyriacou and J Allen (Amsterdam: Elsevier) Ch. 10 pp 341–59
Allen J and Hedley S 2019 Simple photoplethysmography pulse encoding technique for communicating the detection of peripheral arterial disease - a proof of concept study Physiol. Meas. 40 08NT01
Allen J, Liu H, Isqal S, Zheng D and Stansby G 2021 Deep learning-based photoplethysmography classification for peripheral arterial disease detection: a proof-of-concept study Physiol. Meas. 42 054002
Alty S R, Angarita-Jaimes N, Millasseau S C and Chowienczyk P J 2007 Predicting arterial stiffness from the digital volume pulse waveform IEEE Trans. Biomed. Eng. 54 2268–75
Anderson R R and Parrish J A 1981 The optics of human skin J. Invest Dermatol 77 13–19
Behar J A et al 2020 Remote health diagnosis and monitoring in the time of COVID-19 Physiol. Meas. 41 10TR01
Chandrasekhar A, Yaviriamnesh M, Natarajan K, Hahn J-O and Mukkamala R 2020 PPG sensor contact pressure should be taken into account for cuff-less blood pressure measurement IEEE Trans. Biomed. Eng. 67 3134–40
Charlton P H, Bonnici T, Tarassenko L, Alastruey J, Clifton D A, Beale R and Waterkinson P J 2017 Extraction of respiratory signals from the electrocardiogram and photoplethysmogram: technical and physiological determinants Physiol. Meas. 38 669–90
Charlton P H, Bonnici T, Tarassenko L, Clifton D A, Beale R and Waterkinson P J 2016 An assessment of algorithms to estimate respiratory rate from the electrocardiogram and photoplethysmogram Physiol. Meas. 37 610–26
Charlton P H, Cellka P, Farukh B, Chowienczyk P and Alastruey J 2018 Assessing mental stress from the photoplethysmogram: a numerical study Physiol. Meas. 39 054001
Charlton P H, Kyriacou P A, Mant J, Marozas V, Chowienczyk P and Alastruey J 2022 Wearable photoplethysmography for cardiovascular monitoring Proc. IEEE 110 355–81
Charlton P H and Marozas V 2022 Wearable photoplethysmography devices Photoplethysmography: Technology, Signal Analysis and Applications ed P A Kyriacou and J Allen (Amsterdam: Elsevier) Ch. 12 pp 401–39
Choi A and Shin H 2017 Photoplethysmography sampling frequency: pilot assessment of how low can we go to analyze pulse rate variability with reliability? Physiol. Meas. 38 586–600
Consumer Technology Association 2018 Physical Activity Monitoring for Heart Rate, ANSI/CTA 2065 [Online]. (https://shop.cta.tech/collections/standards/products/physical-activity-monitoring-for-heart-rate)
Elgendi M 2014 Detection of d, d, and e waves in the acceleration photoplethysmogram Comput. Methods Programs Biomed. 117 125–36
Elgendi M, Norton I, Brerley M, Abbott D and Schuurmans D 2014 Detection of a and b waves in the acceleration photoplethysmogram Biomed. Eng. Online 13 139
Esmaelpoor J, Moradi M H and Kadkhodamohammadi A 2021 Cuffless blood pressure estimation methods: physiological model parameters versus machine-learned features Physiol. Meas. 42 035006
Fallow B A, Tarumi T and Tanaka H 2013 Influence of skin type and wavelength on light wave reflectance J. Clin. Monit. Comput. 27 313–17
Fine J, Branlan KL, Rodriguez AJ, Boonya-Ananta T, Ajmal, Ramella-Roman JC, McShane MJ and Coté GL 2021 Sources of inaccuracy in photoplethysmography for continuous cardiovascular monitoring Biosensors 11 126
Grabovskis A, Marcinkievics Z, Rubins U and Kviesis-Kigge E 2013 Effect of probe contact pressure on the photoplethysmographic assessment of conduit artery stiffness J. Biomed. Opt. 18 027004
Guo Z, Ding C, Hu X and Rudin C 2021 A supervised machine learning semantic segmentation approach for detecting artifacts in photoplethysmography signals from wearables Physiol. Meas. 42 125003
Hartmann V, Liu H, Chen F, Qiu O, Hughes S and Zheng D 2019 Quantitative comparison of photoplethysmographic waveform characteristics: effect of measurement site Front. Physiol. 10 198
Hultman M, Johansson I, Lindqvist F and Ahlström C 2021 Driver sleepiness detection with deep neural networks using electrophysiological data Physiol. Meas. 42 034001

Huthart S, Eldemdi M, Zheng D, Stanby G and Allen J 2020 Advancing PPG signal quality and know-how through knowledge translation—from students to expert and researcher Front. Digit. Health 2 619692

Johnson A E W, Pollard T J, Shen L, Lehman L. H, Feng M, Ghassemi M, Moody B, Szolovits P, Anthony Celi L and Mark R G 2016 MIMIC-III, a freely accessible critical care database Sci. Data 3 160035

Khalid S G, Liu H, Zia T, Zhang J, Chen F and Zheng D 2020 Cuffless blood pressure estimation using single channel photoplethysmography: a two-step method IEEE Access 8 58146–54

Khan Y, Han D, Ting J, Ahmed M, Nagisetty R and Arias A C 2019 Organic multi-channel optoelectronic sensors for wearable health monitoring IEEE Access 7 128114–24

Lee H C and Jung C W 2018 Vital recorder - a free research tool for automatic recording of high-resolution time-synchronised physiological data from multiple anesthesiology devices Sci. Rep. 8 1–8

Lee J, Jang D H, Park S and Cho S H 2018 A low-power photoplethysmogram-based heart rate sensor using heartbeat locked loop IEEE Trans. Biomed. Circuits Syst. 12 1220–9

Lemay M, Bertschi M, Sola J, Renevey P, Genzoni E, Proença M, Ferrario D, Braun F, Parak J and Korholmen L 2021 Applications of Optical Cardiovascular Monitoring Wearable Sensors: Fundamentals, Implementation and Applications (Amsterdam: Elsevier) Ch. 18 pp 487–517

Li Q, Li Q, Calmak A S, Poian G D, Blwise D L, Vazzcarrino V, Shah A J and Clifford G D 2021 Transfer learning from ECG to PPG for improved sleep staging from wrist-worn wearables Physiol. Meas. 42 044004

Liang Y, Eldemdi M, Chen Z and Ward R 2018 An optimal filter for short photoplethysmogram signals Sci. Data 5 1–12

Lin W H, Li X, Li Y, Li G and Chen F 2020 Investigating the physiological mechanisms of the photoplethysmogram features for blood pressure estimation Physiol. Meas. 41 044003

Liu H, Allen J, Khalid S G, Chen F and Zheng D 2021 Filtering-induced time shifts in photoplethysmography pulse features measured at different body sites: the importance of filter definition and standardization Physiol. Meas. 42 074001

Liu J, Yan B P, Zhang Y, Ding X, Su P and Zhao N 2019 Multi-wavelength photoplethysmography enabling continuous blood pressure measurement with compact wearable electronics IEEE Trans. Biomed. Eng. 66 1514–23

Marozas V and Charlton P H 2021 Wearable Photoplethysmography Devices (Zenodo) (https://doi.org/10.5281/zenodo.4601547)

Matsmuruma K, Toda S and Kato Y 2020 RGB and near-infrared light reflectance/transmittance photoplethysmography for measuring heart rate during motion IEEE Access 8 80233–42

McCarthy C, Pradhan N, Redpath C and Adler A 2016 Validation of the empatia E4 wristband IEEE EMBS International Student Conference (ISC) (Ottawa, ON, Canada, 29–31 May 2016) (IEEE) (https://doi.org/10.1109/EMBISISC.2016.7508621)

Mishra T et al. 2020 Pre-symptomatic detection of COVID-19 from smartwatch data Nat. Biomed. Eng. 4 112208

Mohagheghi F et al. 2022 Optimized signal quality assessment for photoplethysmogram signals using feature selection IEEE Transactions on Biomedical Engineering In Press

Mühlen J M et al. 2021 Recommendations for determining the validity of consumer wearable heart rate devices: expert statement and conclusion of the INTERLIVE network Br. J. Sports Med. 55 767–79

Mukkamala R, Yavarimamne M, Natarajan K, Hahn J O, Kyriakoulis K G, Avolio A P and Stergiou G S 2021 Evaluation of the accuracy of cuffless blood pressure measurement devices: challenges and proposals Hypertension 78 1161–67

Orphanidou C, Bonnici T, Charlton P, Clifton D, Vallance D and Tarassenko L 2015 Signal–quality indices for the electrocardiogram and photoplethysmogram: derivation and applications to wireless monitoring IEEE J. Biomed. Health Inform. 19 83832–8

Ouyang V, Ma B, Pignatelli N, Sengupta S, Sengupta P, Mangulmare K and Fletcher R R 2021 The use of multi-site photoplethysmography (PPG) as a screening tool for coronary arterial disease and atherosclerosis Physiol. Meas. 42 064006

Peralta E, Lazaro J, Bailon R, Marozas V and Gil E 2019 Optimal fiducial points for pulse rate variability analysis from forehead and finger photoplethysmographic signals Physiol. Meas. 40 025007

Pilk K, Ferenets R, Meigas K, Lindberg L-G, Temitski K and Virgimaa M 2013 New photoplethysmographic signal analysis algorithm for arterial stiffness estimation Sci. World J. 2013 1–9

Prinable J B, Foster J M, McEwan A L, Young P M, Tovey E and Thamrin C 2017 Motivations and key features for a wearable device for continuous monitoring of breathing: a web-based survey JMIR Biomed. Eng. 3 1–4

Radha M et al. 2019 Estimating blood pressure trends and the nocturnal dip from photoplethysmography Physiol. Meas. 40 025006

Radin J M, Wineinger N E, Topol E J and Steinshub S 2020 Harnessing wearable device data to improve state-level real-time surveillance of influenza-like illness in the USA: a population-based study Lancet Digit. Health 2 e85–93

Rajala S, Lindholm H and Taipalus T 2018 Comparison of photoplethysmogram measured from wrist and finger and the effect of measurement location on pulse arrival time Physiol. Meas. 39 075010

Reiss A, Indlekofer I, Schmidt P and Van Laerhoven K 2019 Deep PPG: large-scale heart rate estimation with convolutional neural networks Sensors 19 3079

Scardulla F, D’acquisto L, Colomboarini R, Hu S, Pasta S and Bellavia D 2020 A study on the effect of contact pressure during physical activity on photoplethysmographic heart rate measurements Sensors 20 1–15

Schmidt P, Reiss A, Duercchen R and Van Laerhoven K 2018 Introducing WeSAD, a multimodal dataset for wearable stress and affect detection 20th ACM International Conference on Multimodal Interaction (Boulder, CO, USA, 16–20 October 2018) (New York, NY: Association for Computing Machinery) pp 400–8

Stergiou G et al. 2018 A universal standard for the validation of blood pressure measuring devices: association for the Advancement of Medical Instrumentation/European Society of Hypertension/International Organization for Standardization (AAMI/ESH/ISO) Collaboration Statement Hypertension 73 368–74

Takahara K, Tanaka N, Fujita M, Matsuoka O, Saiki T, Aikawa M, Tamura S and Ikuikijamra C 1998 Assessment of vasoactive agents and vascular aging by the second derivative of photoplethysmogram waveform Hypertension 32 265–70

Wolling F and Van Laerhoven K 2018 Fewer samples for a longer life span 5th international Workshop on Sensor-based Activity Recognition and Interaction (Berlin, Germany, 20–21 September 2018) (ACM) pp 1–10

Xing X, Ma Z, Xu S, Zhang M, Zhao W, Song M and Dong W-F 2021 Blood pressure assessment with in-ear photoplethysmography Physiol. Meas. 42 105009

Xing X, Ma Z, Zhang M, Gao X, Li Y, Song M and Dong W-F 2020 Robust blood pressure estimation from finger photoplethysmography using age-dependent linear models Physiol. Meas. 41 025007

Zhang Z, Yi Z and Liu B 2015 TROIKA: a general framework for heart rate monitoring using wrist-type photoplethysmographic signals during intensive physical exercise IEEE Trans. Biomed. Eng. 62 522–31