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Adaptive physiology-informed correction for reliable remote photoplethysmography heart-rate monitoring

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Contactless heart rate (HR) monitoring demonstrates significant potential for mobile health and telemedicine, but current remote photoplethysmography (rPPG) approaches remain vulnerable to various noise sources. While existing research has emphasized signal-level enhancement, correcting erroneous HR estimates remains underexplored. We present a plug-and-play adaptive correction algorithm that leverages cardiac dynamics constraints, adjusting HR estimates based on physiological priors of HR elevation and recovery. By mapping HR frequencies to indices and applying adaptive corrections, our method significantly reduces measurement errors with minimal computational load, even under challenging conditions. Across three public datasets, the algorithm increased the proportion of accurate measurements (mean absolute error ≤ 10 beats per minute) from 46.26% to 84.14% (LGI-PPGI), 48.03% to 69.21% (BUAA-MIHR), and 92.22% to 96.67% (UBFC-rPPG), outperforming existing correction techniques. The lightweight design facilitates seamless edge-side integration, providing a scalable solution for enhancing the reliability of contactless HR monitoring in mobile and remote healthcare settings.

Personal health is closely linked to cardiac function. Heart rate (HR) is a fundamental physiological indicator that carries valuable information about cardiovascular, physical, and mental health^{1–3}. It is routinely leveraged by clinicians to evaluate cardiac rhythm and to support diagnoses such as coronary artery disease^{4,5}, heart failure⁶, and autonomic dysfunction⁷. In sports medicine, resting HR and heart rate variability (HRV) are used to infer training load and autonomic nervous system status, thereby supporting personalized training plans⁸.

Historically, HR monitoring techniques have evolved from ancient palpation-based diagnosis⁹ to electrocardiography (ECG), which is the current gold standard and an indispensable tool in clinical practice^{10,11}. However, reliable ECG acquisition (e.g., standard 12-lead ECG) generally requires specialized equipment and professional operators. To address these limitations, researchers developed the photoplethysmography (PPG) technique to measure periodic changes in blood volume pulse (BVP). Contact-based photoplethysmography (cPPG) couples a light source and photoelectric sensor on the skin to detect transmitted or reflected optical signals at specific wavelengths^{12,13}. As a result, cPPG is widely commercialized in contemporary applications, particularly in fingertip oximeters and consumer-grade wearable devices such as smartwatches and smart rings.

Although cPPG is widely adopted in practice, its reliance on continuous skin contact reduces user comfort and applicability in scenarios such as sleep monitoring, surgery, or for patients with skin injuries. This has driven growing interest in contactless HR monitoring methods as alternative modalities, including WiFi sensing, millimeter-wave (mmWave) radar, radio-frequency identification (RFID), mechanical vibration detection, thermal infrared imaging, and visible-light optical imaging^{14,15}. WiFi sensing generally relies on channel state information (CSI) available on specific commodity devices; by contrast, time-of-flight (ToF) approaches typically require ultra-wideband systems and thus fall beyond everyday WiFi capabilities. While WiFi-based HR sensing benefits from deployment flexibility, its practicability is constrained by spatial layout, accessibility of low-level wireless signals, and multipath effects^{16,17}. In comparison, mmWave radar achieves higher resolution and better anti-interference performance, though its application scope is restricted by increased cost and hardware complexity^{18,19}. RFID-based methods provide a low-cost HR measurement solution but typically require specialized passive tags^{20,21}. Some studies explored the use of geophones²² and fiber Bragg grating (FBG) sensors²³ to detect subtle mechanical vibrations induced by heartbeats. However, these approaches are generally constrained to bed-based monitoring scenarios. Additionally, thermal infrared imaging operates in dark

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environments and can offer privacy advantages, but remains constrained by resolution and accuracy bottlenecks²⁴.

Among non-contact approaches, remote photoplethysmography (rPPG) based on visible-light imaging has gained prominence due to its simplicity and versatility. Compared with other contactless techniques, rPPG requires only a normal camera for facial video recording and a simple software application to extract HR estimates. Therefore, it enables low-cost application across clinical, at-home, and mobile settings, without relying on specialized devices. Nevertheless, rPPG signals are susceptible to motion artifacts, illumination noise, and facial region selection²⁵, potentially yielding unreliable HR estimates. Recent studies have systematically compared different color channels for rPPG signal extraction, confirming the green channel as the most reliable across multiple public datasets²⁶. Furthermore, a variety of rPPG algorithms—ranging from blind source separation^{27–29} and color model-based methods^{30–32} to recent machine learning approaches^{33,34}—have been designed to enhance signal quality. However, these methods generally rely on signal-level enhancement and often fail to maintain high measurement accuracy when environmental noise dominates the frequency spectrum. Additionally, the local deployment of deep learning (DL) models on resource-constrained edge devices is limited by hardware capabilities. Complex models sometimes necessitate uploading video data to the cloud for processing, thereby raising potential privacy concerns^{35,36}.

To address these conflicting demands—robustness against noise versus computational efficiency for edge deployment—shifting the focus from signal reconstruction to outcome correction provides a promising yet underexplored avenue. As shown in Fig. 1, pseudo peaks that are potentially induced by motion and illumination artifacts in the frequency domain can result in erroneous HR outputs. Prior research in cPPG has attempted to address this problem through statistical smoothing (e.g., moving average^{37,38}), model-based correction (e.g., Kalman filtering³⁹), and sensor fusion (e.g., acceleration-assisted correction^{40–42}). In rPPG, dedicated HR

correction algorithms remain underexplored. Zhu et al.⁴³ proposed the adaptive multi-track carving (AMTC) method, which tracks the dominant frequency trajectory with maximum cumulative energy, thereby reducing HR fluctuations caused by pseudo peaks. Li et al.⁴⁴ developed a head motion-aware random forest (HMA-RF) model by incorporating head motion trajectories as the input, which is utilized to determine the per-window reliability of estimated HR values. However, these approaches typically suffer from drawbacks such as dependence on extra signal sources, sensitivity to parameter settings, restricted generalization performance, and high computational burdens.

In this study, we present a lightweight, adaptive HR correction algorithm designed to be seamlessly integrated as a plug-and-play module for existing rPPG-based HR estimation pipelines. Specifically, unlike prior data-driven or accelerometer-based methods, our approach explicitly leverages physiological constraints on cardiac dynamics to adaptively adjust implausible HR estimates. This physiologically-informed strategy eliminates the need for extensive pre-training or additional sensor inputs, ensuring computational efficiency suitable for edge deployment. Extensive experiments on three diverse public datasets (LGI-PPGI, BUAA-MIHR, and UBFC-rPPG) demonstrate that our method significantly improves measurement reliability, particularly under challenging motion and low-light conditions, while outperforming existing state-of-the-art correction techniques.

Results

Performance evaluation

The correction performance of different algorithms was compared against the original HR measurements on the LGI-PPGI⁴⁵, BUAA-MIHR⁴⁶, and UBFC-rPPG⁴⁷ databases. The results are visualized as box plots in Fig. 2, where each data point represents a single HR measurement, evaluated using either MAE or DTW and averaged over the entire duration of a facial video sequence. Overall, it can be observed that all HR correction algorithms

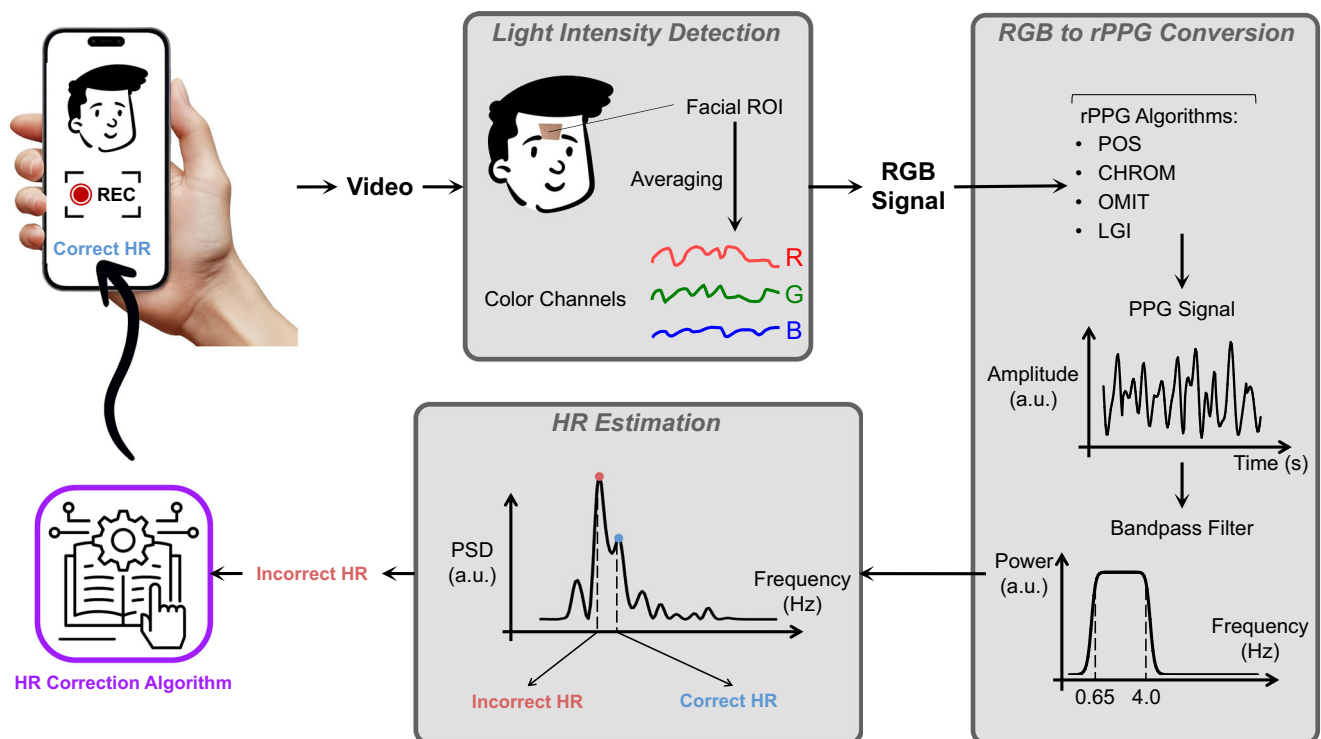


Fig. 1 | The overall workflow of remote heart rate (HR) measurement in this study. This workflow is comprised of five parts: video recording; light intensity detection; red, green, and blue color channels (RGB) to remote photoplethysmography (rPPG) signal conversion; HR estimation; and HR correction. The facial ROI refers to the region of interest for skin pixel intensity extraction. Four

rPPG algorithms are included in this research: plane-orthogonal-to-skin (POS)³², orthogonal matrix image transformation (OMIT)⁶², the chrominance-based method (CHROM)³⁰, and local group invariance (LGI)⁴⁵. Icons were adapted from the Microsoft 365 non-copyrighted icon library.

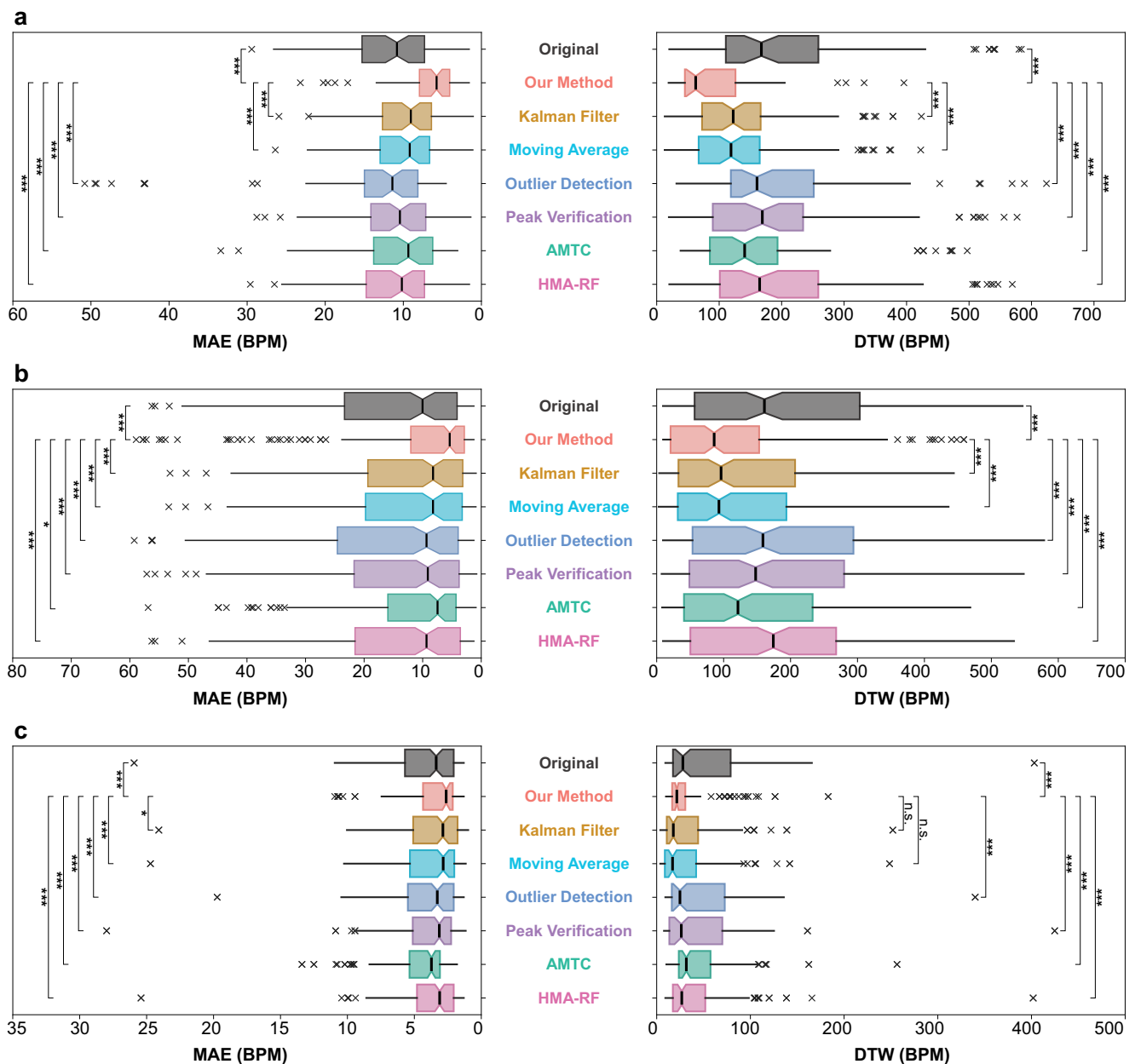


Fig. 2 | Overall performance comparison on different measurement scenarios. **a** LGI-PPGI dataset⁴⁵. **b** BUAA-MIHR dataset⁴⁶. **c** UBFC-rPPG dataset⁴⁷. The evaluation metrics of mean absolute error (MAE) and dynamic time warping (DTW) measured by beats per minute (BPM) were applied to evaluate the performance of

our method and other methods for comparison. The notches of the box plots correspond to the median values. Statistical significance was obtained using bootstrap tests. Significance levels are indicated as (* $p < 0.05$), (** $p < 0.01$), (***) $p < 0.001$), and n.s. (not significant).

included in the evaluation improved the overall accuracy of the initial HR measurements, though the effectiveness varied across different algorithms and datasets. In the LGI-PPGI dataset, which includes three types of movements, our proposed algorithm achieved the lowest median, upper quartile, and lower quartile values for both MAE and DTW. The other six algorithms for comparison had different levels of improvement. However, the outlier detection algorithm yielded many HR measurement results with worse MAE performance compared with those before correction, showing limited robustness when subjects exhibited large-scale HR variations during exercise. In the BUAA-MIHR dataset, which contains four levels of low-light conditions, the proposed algorithm consistently outperformed other methods, maintaining the best accuracy and demonstrating strong resilience to illumination noise. While the median MAE in challenging scenarios was reduced from approximately 10 beats per minute (BPM) to 5 BPM, results presented in the UBFC-rPPG dataset further demonstrated

that the proposed algorithm has the potential to enhance HR estimation accuracy even under relatively simple conditions when subjects remain steady under sufficient lighting, achieving a median MAE of around 2.5 BPM.

To systematically evaluate the group-wise performance differences between the proposed method and alternative correction approaches, we used a nonparametric bootstrap resampling procedure⁴⁸. Specifically, for each comparison, we randomly generated 10,000 bootstrap samples of the same size as the original paired observations by resampling with replacement. One-tailed p-values were then derived from the empirical bootstrap distribution. Unlike significance tests such as the paired t -test or the Wilcoxon signed-rank test, the bootstrap approach is less restrictive, as it does not impose symmetry or normality assumptions. The statistical test results, denoted using (* $p < 0.05$), (** $p < 0.01$), (***) $p < 0.001$), and n.s. (not significant), are shown in Fig. 2. Significant performance advantages of the

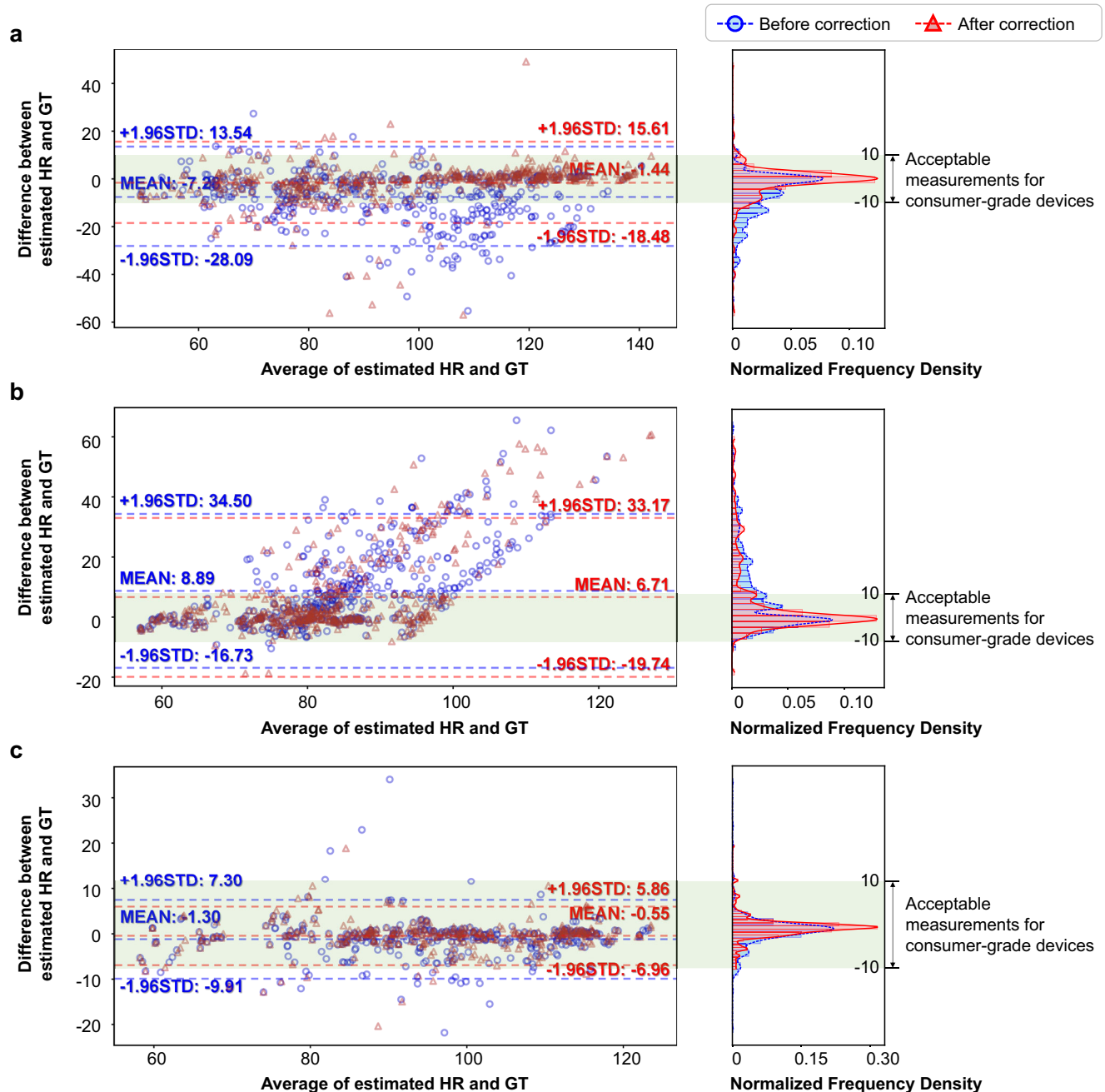


Fig. 3 | Bland–Altman analysis and the corresponding normalized frequency density of the HR estimation performance before and after being processed by our proposed correction algorithm. a LGI-PPGI dataset⁴⁵. **b** BUAA-MIHR dataset⁴⁶. **c** UBFC-rPPG dataset⁴⁷. The Bland–Altman plots on the left side are conducted between the estimated HR versus the ground truth (GT). Each data point

in the plots represents a pair of measurements within 25 seconds. The normalized frequency density on the right side is mapped from the data in the Bland–Altman plots. The acceptable range of HR measurement accuracy is set as ± 10 BPM according to the Consumer Technology Association (CTA) standards^{49,50}.

proposed method over other approaches can be observed in the LGI-PPGI and BUAA-MIHR datasets. For UBFC-rPPG, representing simple measurement scenarios with stable lighting and minimal motion, only the advantages compared with Kalman filter and moving averages are not significant.

Bland–Altman analysis was conducted to assess the agreement between the ground truth HR and estimated HR before and after being processed by the proposed correction algorithm. In Fig. 3, each point was computed based on an HR measurement result over a 25-s time window using one of the specific rPPG algorithms: POS, OMIT, CHROM, and LGI. The normalized frequency density was mapped from the left side to facilitate

intuitive visualization of the data distribution. The acceptable range of measurement was set as $\text{MAE} \leq 10$ BPM based on the requirement of consumer-grade devices according to the Consumer Technology Association standards and presented as the green shaded area in the figure^{49,50}.

In the LGI-PPGI dataset, the initial HR measurements (blue circles) were biased toward the negative direction, with a mean difference of -7.28 BPM compared to the ground truth HR. This might be due to the influence of low-frequency noise induced by subject motion. In comparison, the HR measurements after correction (red triangles) were more tightly centered around zero, providing evidence that the proposed algorithm can effectively mitigate motion artifacts and improve HR measurement accuracy. The bias

Table 1 | Quantitative analysis of the measurement acceptance rate across different HR correction algorithms under the requirement for consumer devices

Dataset	Acceptance criterion (BPM)	Before correction	Kalman filter	Moving average	Outlier detection	Peak verification	AMTC	HMA-RF	Our method
LGI-PPGI ⁴⁵	MAE $\leq$ 10	46.26%	56.12%	54.19%	47.80%	49.56%	60.57%	48.02%	84.14%
	MAE $\leq$ 5	24.89%	32.60%	31.94%	27.53%	29.96%	35.24%	27.31%	62.78%
BUAA-MIHR ⁴⁶	MAE $\leq$ 10	48.03%	55.46%	54.80%	49.34%	51.75%	60.26%	51.10%	69.21%
	MAE $\leq$ 5	28.17%	35.88%	34.28%	30.57%	31.88%	36.24%	31.00%	49.56%
UBFC-rPPG ⁴⁷	MAE $\leq$ 10	92.22%	94.17%	93.33%	92.78%	93.61%	91.94%	94.44%	96.67%
	MAE $\leq$ 5	71.67%	76.67%	76.67%	72.50%	73.89%	69.44%	74.17%	81.67%

The evaluation metric of HR measurement is the mean absolute error (MAE) in beats per minute (BPM). The acceptance criteria for HR measurement accuracy was set according to the consumer technology association (CTA) standards^{48,50}.

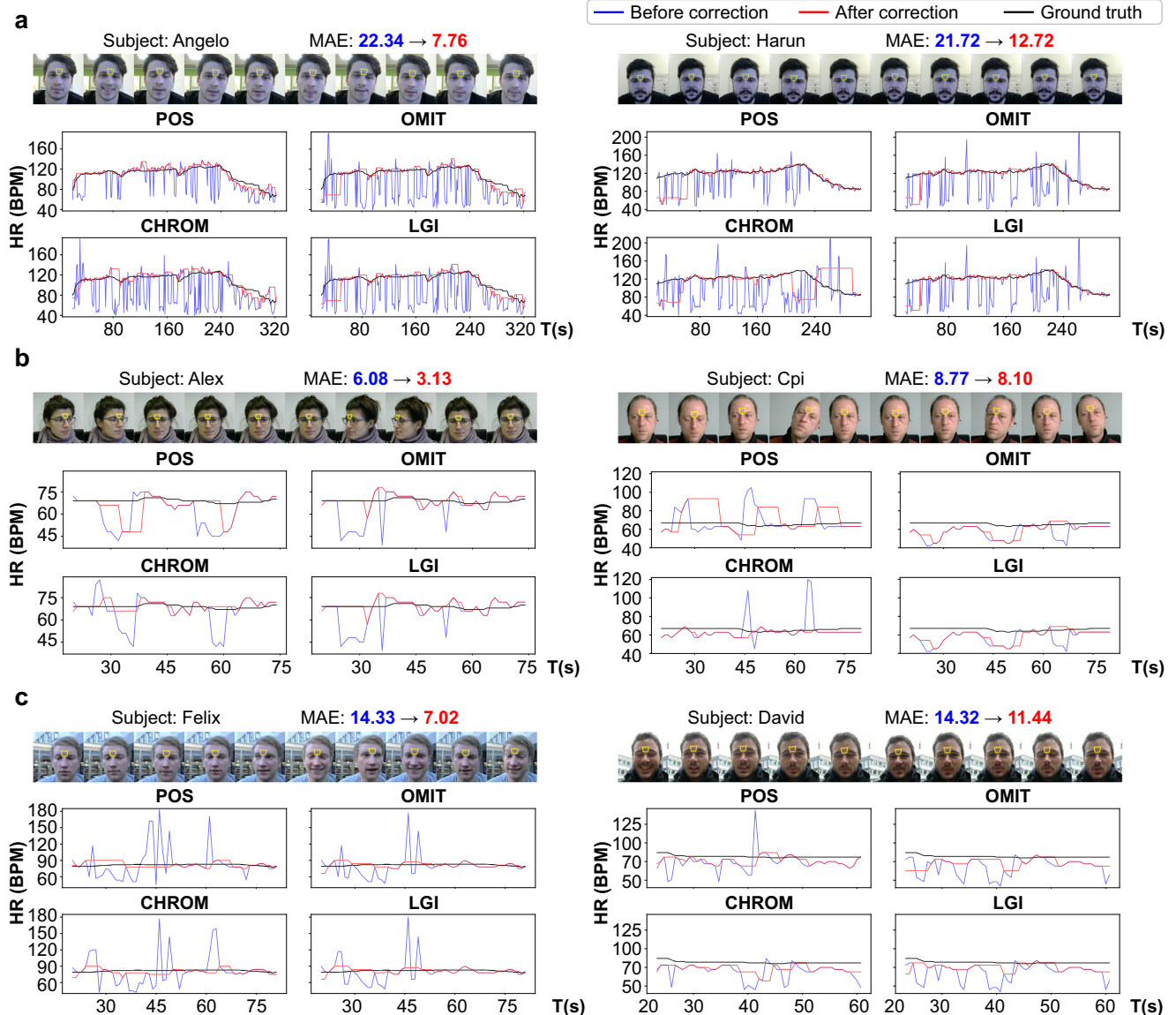


Fig. 4 | Representative examples of HR correction results produced by the proposed algorithm across different types of subject movements in the LGI-PPGI dataset⁴⁵. a Exercising. **b** Rotation. **c** Talk. The estimated HR before and after correction, as well as the ground truth HR, are shown as blue, red, and black curves, respectively. The yellow polygon on the human face represents the glabella as the ROI. Above each facial video sequence, the subject code and MAE of HR estimation

—averaged over the plane-orthogonal-to-skin (POS)³², orthogonal matrix image transformation (OMIT)⁵², chrominance-based (CHROM)³⁰, and local group invariance (LGI)⁴⁵ algorithms—are presented. The video frames of the LGI-PPGI dataset are under the Creative Commons Attribution 4.0 License (<https://creativecommons.org/licenses/by/4.0/>).

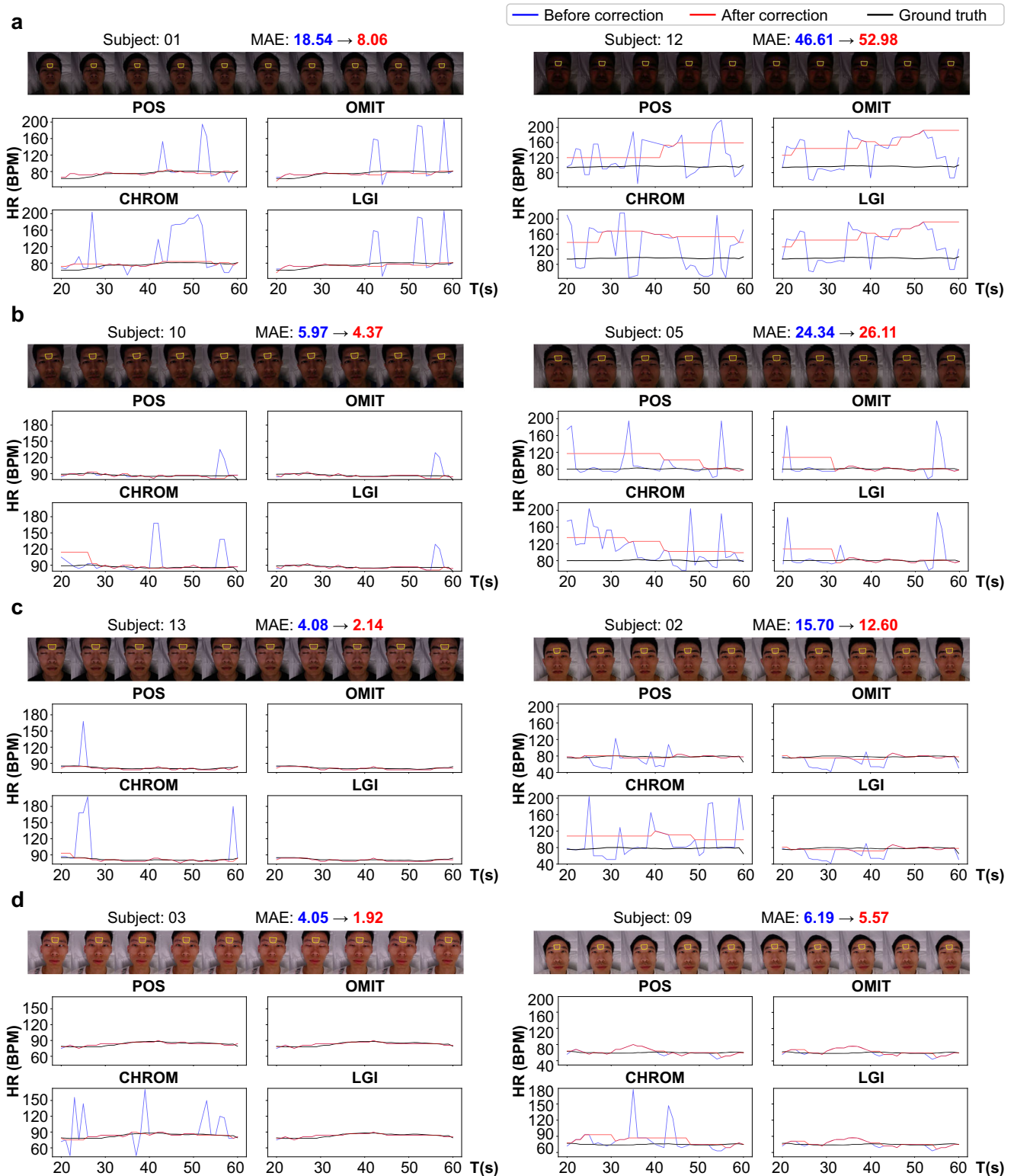


Fig. 5 | Representative examples of HR correction results produced by the proposed algorithm across different illumination levels in the BUAA-MIHR dataset⁴⁶. **a** 6.3 lux. **b** 10.0 lux. **c** 15.8 lux. **d** 25.1 lux. The estimated HR before and after correction, as well as the ground truth HR, are shown as blue, red, and black curves, respectively. The yellow polygon on the human face represents the glabella as the ROI. Above each facial video sequence, the subject code and MAE of HR

estimation—averaged over the plane-orthogonal-to-skin (POS)³², orthogonal matrix image transformation (OMIT)⁶², chrominance-based (CHROM)³⁰, and local group invariance (LGI)⁴⁵ algorithms—are presented. The video frames of the BUAA-MIHR dataset are under the Creative Commons Attribution-NonCommercial-ShareAlike 4.0 License (<https://creativecommons.org/licenses/by-nc-sa/4.0/>).

of initial HR measurements was opposite in the BUAA-MIHR dataset under low-light conditions. The mean difference between the estimated HR and ground truth HR was 8.89 BPM, suggesting greater sensitivity to high-frequency interference in dark environments. The correction algorithm reduced this bias to 6.71 BPM and produced a distribution more closely clustered around zero. For the UBFC-rPPG dataset, although most of the initial measurements already fell within the acceptable range due to the relatively simple conditions, the corrected results demonstrated that our algorithm can further enhance the measurement accuracy even when interference is minimal.

Considering the demands for short-term HR monitoring in real-world applications such as preoperative or postoperative rapid assessment⁵¹, short-term patient reaction after pharmacological intervention^{52,53}, and health screening⁵⁴, we provide a quantitative analysis of measurement acceptance rates across different HR correction algorithms in Table 1. The acceptance rate was determined by averaging absolute HR errors over non-overlapping time windows of 25 seconds and then computing the percentage of windows within the error thresholds.

For challenging datasets such as LGI-PPGI and BUAA-MIHR, the acceptance rates for MAE below 10 BPM and 5 BPM before correction were below 50% and 30%, respectively. Among baseline HR correction methods, AMTC and the Kalman filter exhibited the optimal refinement performance, but the improvements remained less than 20%. In comparison, the proposed adaptive correction algorithm achieved substantial improvements in these challenging scenarios, achieving acceptance rates of up to 84.14% (MAE ≤ 10 BPM) and 62.78% (MAE ≤ 5 BPM) on the LGI-PPGI dataset, and 69.21% and 49.56% on the BUAA-MIHR dataset, respectively.

In the UBFC-rPPG dataset, the performance of AMTC deteriorated due to the suppression effect caused by its global smoothing mechanism. HMA-RF achieved the optimal improvement of 2.22% under the MAE ≤ 10 BPM criterion among baseline methods, but failed to outperform the Kalman filter and moving average under the MAE ≤ 5 BPM criterion. By contrast, our approach achieved the most significant overall improvements of 4.45% and 10.00% for the two criteria, respectively. These results demonstrate that the proposed algorithm significantly increases the proportion of short-term measurements meeting consumer-grade standards across diverse recording scenarios.

To further illustrate the temporal behavior of our correction strategy, we present representative examples of HR refinement in challenging scenarios. Results on the LGI-PPGI dataset are shown in Fig. 4, with positive cases on the left and negative cases on the right. A key observation is that, equipped with the cardiac dynamics constraints, the proposed algorithm is robust against sudden changes in HR estimates. This advantage is more obvious during exercise, where large-scale HR variations are common. Another noteworthy regularity is the significant impact of the starting point of HR. A large deviation of the starting point from the real HR value will lead to a period of lag before the correction algorithm converges to more accurate measurements. Examples of this dilemma are shown in the HR traces of Fig. 4a (Harun), Fig. 4b (Cpi), and Fig. 4c (David) where initial deviations resulted in delays in achieving accurate corrections. Similar observations can be found in Fig. 5. When the HR starting point was close to the ground truth, the correction algorithm could effectively filter out erroneous estimates and maintain high measurement accuracy, as presented in Fig. 5a (01), Fig. 5b (10), Fig. 5c (13), and Fig. 5d (03). Conversely, typical cases of poor starting points leading to suboptimal correction results under low-light environments are shown in Fig. 5a (12) and Fig. 5b (05).

Computational load

Estimating initial HR from facial videos typically consumes considerable computational cost. Given the limited computing power of chips used in practical edge-side applications (e.g., wearable or embedded devices), a crucial requirement for correction algorithms is a fast processing speed. We denote the total number of HR measurements extracted from a video as M . For the moving average and outlier detection algorithms, a sliding window of length N needs to be considered. The peak verification algorithm involves

Table 2 | Comparison of time complexity and execution time across different HR correction algorithms

HR correction algorithm	Time complexity	Execution time (ms)
Kalman filter	$O(M)$	3.16
Moving average	$O(MN)$	92.75
Outlier detection	$O(MN)$	428.42
Peak verification	$O(MK \log K)$	4310.96
AMTC	$O(M(L \log L + NK))$	Not feasible
HMA-RF	$O(M(L \log L + TDF))$	Not feasible
Our method	$O(M)$	3.04

M represents the number of frames of the input facial video. For the moving average and outlier detection methods, N refers to the number of sample points in the sliding window of HR estimates before correction. In the peak verification method, K is the number of valid HR levels in the frequency domain. In the AMTC method, L is the segment length of input signal, N is the buffer length (number of spectrogram frames), and K is the number of candidate frequency levels. In the HMA-RF method, T is the number of trees in the random forest model, D is the maximum depth, F is the number of features, and L is the segment length (same as in AMTC). Execution times are measured in milliseconds (ms) by deploying each algorithm on an Arduino Nano single-chip microcomputer⁵⁵, performing 1000 iterations of HR correction. Methods marked as "Not feasible" are not deployable due to excessive memory or computational requirements.

sorting K candidate frequencies to identify the top three peaks, which incurs $O(K \log K)$ complexity.

The AMTC algorithm performs an FFT operation with a complexity of $O(L \log L)$, where L is the length of each input signal segment. It then carries out a dynamic programming search for the optimal trace path over a $K \times N$ energy matrix, resulting in $O(NK)$ complexity per step, where N is the buffer length representing the number of spectrogram frames used for global trace smoothing and K is the number of candidate frequency bins, consistent with the definition used in the peak verification algorithm. Thus, the total time complexity is $O(M(L \log L + NK))$.

For the HMA-RF method, the training phase includes both feature extraction and model fitting. Feature extraction from the M input segments, each of length L , requires $O(ML \log L)$ operations due to the use of FFT and statistical computations. Training the random forest classifier with T trees, maximum depth D , and F features leads to an additional $O(TFD \log M)$ complexity, as the algorithm is based on recursive partitioning of the feature space rather than iterative gradient-based optimization. During inference, feature extraction for all M HR windows again requires $O(ML \log L)$ operations. The random forest prediction for all windows adds $O(MTDF)$ complexity, resulting in a total inference cost of $O(M(L \log L + TDF))$.

To practically evaluate the computational efficiency of different HR correction algorithms, we implemented and deployed them on an Arduino Nano single-chip microcomputer⁵⁵ with a flash memory of 16 KB and a clock speed of 16 MHz. Each algorithm was executed 1000 times consecutively, and the total operation time was recorded. Both AMTC and HMA-RF are infeasible to be deployed on lightweight embedded devices, as their high memory requirements induced by dynamic programming arrays or multiple decision trees and long inference cost far exceeded the limited resources available on the platform.

The results of computational load among the included HR correction algorithms are summarized in Table 2. The table reports inference time complexity together with real-case execution time. It can be observed that the proposed algorithm exhibited the fastest operating speed. This efficiency, arising from reliance on integer operations and simple arithmetic logic units, makes the proposed algorithm highly suitable for real-time deployment on resource-constrained platforms.

Discussion

In rPPG-based HR monitoring, it is essential to optimize the entire processing pipeline rather than only focusing on rPPG reconstruction algorithms. Decoding the underlying pulse information from facial videos can

Table 3 | Description of the included datasets for performance evaluation

Dataset	Number of subjects	Camera	Resolution	Frame rate (fps)	Environment	Motion
LGI-PPG ⁴⁵	6	Logitech C270 HD	640 × 480	25	Indoor, outdoor	Resting, exercising, rotation, talking
BUAA-MIHR ⁴⁶	15	Logitech C930E HD	640 × 480	30	Darkroom with different controlled illumination levels: 1.0, 1.6, 2.5, 4.0, 6.3, 10.0, 15.8, 25.1, 39.8, 63.1, 100.0 lux	Steady
UBFC-rPPG ⁴⁷	42	Logitech C920 HD Pro	640 × 480	30	Indoor	Steady

Three public datasets were included in the experiments: UBFC-rPPG (near-ideal conditions), LGI-PPG (subject movement), and BUAA-MIHR (different illumination levels).

be severely compromised by challenging recording environments such as strenuous exercise, low-light conditions, or facial occlusion. Under such circumstances, noise from different sources can obscure genuine HR frequency components, and simply selecting the dominant spectral peak may yield large estimation errors. To address this issue, applying a correction step in the post-processing stage to refine preliminary HR estimates is a promising yet underexplored solution to further improve overall accuracy.

Although several HR correction strategies have been applied in cPPG, such as moving average, Kalman filtering, and peak verification, these approaches are largely grounded in standard logic from a signal processing perspective, without explicitly incorporating physiological constraints. However, rPPG signals are generally more susceptible to environmental interference compared with cPPG, thus limiting the direct transferability of such methods. Among algorithms specifically designed for rPPG-based HR correction, AMTC, which used dynamic programming with relatively high computational resources, is sensitive to parameter tuning and often becomes trapped in incorrect frequency bands. HMA-RF depends on additional head motion data and extensive labeled training, making it resource-intensive and prone to poor generalization beyond controlled laboratory conditions.

In contrast, the proposed adaptive correction algorithm explicitly incorporates the physiological mechanisms underlying human HR variations. After an adaptation process of 15 s, it starts to use a dynamic confirmation mechanism that validates each new HR estimate against recent outputs and the directional trend of successive values. By incorporating constraints derived from cardiac dynamics, this approach preserves measurement stability when rPPG signals are obscured by noise, thereby mitigating interference, enhancing robustness, and improving accuracy across diverse scenarios. Validations on three representative datasets—LGI-PPGI (subject movement), BUAA-MIHR (low-light conditions), and UBFC-rPPG (near-ideal settings)—demonstrate that our algorithm consistently achieves significant accuracy improvement, thereby increasing the proportion of acceptable measurements for consumer-grade applications. Additional experiments presented in Supplementary Information (Note 3) further confirm these performance advantages in comparison with representative DL models.

Another advantage of the proposed algorithm is that it can be conveniently inserted into existing rPPG-based HR measurement systems with minimal modification. It can be utilized as a plug-and-play module that enhances estimation accuracy without bringing too much computational overhead. This feature is particularly valuable when there is a need to deploy rPPG algorithms on resource-constrained platforms running multiple tasks in parallel. For instance, in driving scenarios, in-vehicle chipsets are required to process data from multiple sensors and execute real-time decisions accordingly. Integrating a contactless HR monitoring function in real-time is already computationally expensive due to the deployment of an offline face detection framework. Although adding a correction algorithm may introduce significant improvement in measurement accuracy, the marginal benefits will decrease with increasing computational load. Nevertheless, the additional required computing resources of our adaptive correction algorithm are almost negligible, demonstrating its prospects in commercial applications. This cost-efficient design also holds promise for bedside monitoring, fitness equipment, healthcare kiosks, telemedicine, and other applications⁵⁶.

However, there are several limitations of the proposed algorithm. First, this correction algorithm requires an adaptation period of 15 seconds. This initialization design is to ensure the algorithm starts from a relatively reliable HR estimation as measurement conditions and rPPG algorithms vary, but restricts the robustness to shorter recordings. Second, auxiliary information from the input video and other sub-peaks is not effectively leveraged. When computational resources are relatively abundant, incorporating these additional features to construct a collaborative decision-making process could potentially improve precision. However, an underlying drift problem may be introduced to ultimately degrade HR estimation accuracy. Third, this method is designed based on the prior assumption that healthy

individuals exhibit dynamically stable and regular HR patterns. Notably, for patients with arrhythmias or cardiac rhythm disorders, abnormal HR variations may occur, and the imposed constraints could potentially induce over-smoothing or prediction biases, thereby increasing errors.

In conclusion, we present a cost-efficient adaptive correction algorithm that improves the measurement accuracy of rPPG-based HR monitoring. This algorithm can be seamlessly integrated into existing rPPG systems without requiring additional parameter tuning. The design logic of this algorithm is to leverage the constraints of cardiac dynamics and filter out unreliable HR estimates. With minimal computational overhead, this algorithm has been shown to be capable of substantially increasing the proportion of acceptable measurements across both challenging and near-ideal scenarios. As developing HR correction algorithms remains an underexplored topic in rPPG, this work highlights the potential to refine final HR estimates in the post-processing stage, supporting collaborative optimization for remote HR monitoring techniques. Future efforts should extend the evaluation on datasets with higher demographic representativeness⁵⁷. Moreover, as illustrated by the ground truth HR trajectories summarized in Supplementary Information (Note 2), most subjects in LGI-PPGI, BUAA-MIHR, and UBFC-rPPG datasets maintain relatively steady HR within moderate-intensity ranges, with few instances of large-scale or periodic HR fluctuations. Future studies may expand the evaluation on datasets of high-intensity interval training (HIIT) or pathological HR dynamics and incorporate auxiliary features to establish a more comprehensive framework. Future studies may expand the evaluation on datasets of high-intensity interval training (HIIT) to further test robustness under dynamically varying HR conditions. Integrating signal quality indices such as the NSQI⁵⁸ could enable real-time filtering of low-quality frames, complementing our adaptive correction mechanism and further improving reliability under diverse measurement conditions.

Methods

Data collection

Three datasets specifically collected for performance assessment of remote HR measurement were used to evaluate the proposed method: LGI-PPGI⁴⁵, BUAA-MIHR⁴⁶, and UBFC-rPPG⁴⁷. These datasets have emphases on distinct application scenarios, thus providing a comprehensive reflection of algorithmic effectiveness. The UBFC-rPPG dataset comprises controlled measurement situations with stationary subjects under normal lighting conditions. The LGI-PPGI dataset was constructed to validate rPPG algorithms in the presence of subject motion. The BUAA-MIHR dataset, released in 2020, was collected to address challenges associated with low-light environments. All the included datasets are publicly accessible to the research community. Detailed dataset characteristics are summarized in Table 3.

To ensure representativeness and fair evaluation, we conducted data screening on all three datasets. In UBFC-rPPG, data from subjects 11, 18, 20, and 24 were excluded due to missing ground truth HR values. For LGI-PPGI, only recordings of complex scenarios (e.g., exercising, head rotation, and talking) were preserved to assess robustness against motion-induced noise. Similarly, for BUAA-MIHR, we selected videos recorded under illumination levels ranging from 6.3 to 25.1 lux to represent indoor low-light conditions.

Initial heart rate estimation from facial videos

The pipeline for estimating initial HR from RGB videos is illustrated in Fig. 1. The proposed method serves as a post-correction stage applied to the initial HR estimates. Given an RGB video, the facial region of interest (ROI) was located based on the keypoints extracted using MediaPipe Face Mesh⁵⁹. In consideration of potential occlusions by hair or head movements, we set glabella as the ROI for RGB signal extraction, which has been demonstrated to be robust in a previous cross-dataset evaluation study⁶⁰. The glabella ROI was defined by following the keypoint landmarks: 151, 108, 107, 55, 8, 285, 336, and 337. The keypoint number correspondence is specified in the official documents of MediaPipe Face Mesh. Videos

are segmented into 6-second windows with 1-second steps for successive HR estimation.

As noted in the Introduction, the CHROM³⁰ and POS³² algorithms have been commonly used as representative model-based algorithms. In addition, the local group invariance (LGI) algorithm⁴⁵ has achieved the best overall performance in a previous comprehensive analysis⁶¹, and the orthogonal matrix image transformation (OMIT) algorithm⁶² has shown effectiveness against compression artifacts. Therefore, we included these four rPPG algorithms in our experiment. After obtaining the transformed rPPG signals, a Butterworth bandpass filter with a passing band of 0.65–4 Hz was applied to isolate potential HR components. The initial HR measurement result was estimated by identifying the dominant frequency component of the filtered rPPG signal. The power spectral density (PSD) estimation was conducted via Welch's method⁶³, which is more robust against noise interference than standard periodograms. The proposed physiology-informed method operates adaptively to further calibrate the initial estimated HR.

Cardiac dynamics constraints

As illustrated in Fig. 1, the impact of noises on remote HR measurement can generally be reflected as pseudo peaks in the frequency domain, which might obscure the genuine HR. Noise-induced erroneous HR estimations are often presented as large-scale variations in the time domain. However, genuine HR variations follow certain temporal regularities, which have been indicated in former studies of medicine and sports science^{64,65}. Our proposed algorithm is designed based on the regularities of cardiac dynamics to refine HR measurement results. Specifically, the acceptance range for new HR estimates was limited by setting upper bounds for HR recovery and elevation, implemented as constraints on the one-step change rate $\Delta HR/\Delta t$ (in $\text{BPM} \cdot \text{s}^{-1}$). The recovery bound was derived based on the data from a large cohort study involving 40,727 healthy subjects⁶⁶. In that dataset, mean HR recovery (HRR) values were reported at 10–50 s after exercise cessation. A cubic spline regression across these time points extrapolated to 1 s yielded an estimated recovery rate of $2.81 \text{ BPM} \cdot \text{s}^{-1}$. For HR elevation, Bellenger et al.⁶⁷ measured the maximal rate of HR increase (rHRI) among 15 male runners during transitions from rest to moderate running (8 km/h) and reported an average reference value of $5.05 \text{ BPM} \cdot \text{s}^{-1}$. In consideration of interindividual variation and to ensure a physiologically conservative yet inclusive constraint, these empirical results were rounded upward, and we adopted $3 \text{ BPM} \cdot \text{s}^{-1}$ and $6 \text{ BPM} \cdot \text{s}^{-1}$ as the upper bounds for HR recovery and elevation, respectively.

The dynamics of HRR after HR elevation can be characterized by the first-order exponential decay model^{68,69} as shown in the following equation

$$HR(t) = HR_{\text{rest}} + (HR_{\text{peak}} - HR_{\text{rest}}) e^{-t/\tau_{\text{off}}}, \quad (1)$$

where $HR(t)$ denotes the HR at time t , HR_{rest} is the steady-state HR after recovery, HR_{peak} is the peak HR during intensive exercise, and τ_{off} represents the recovery time constant.

Similar to the process of HR decrease, the HR elevation can also be modeled using the first-order exponential model^{70,71}:

$$HR(t) = HR_{\text{steady}} - (HR_{\text{steady}} - HR_{\text{start}}) e^{-t/\tau_{\text{on}}}, \quad (2)$$

where $HR(t)$ is the HR at time t , HR_{steady} is the steady-state (target) HR during exercise, HR_{start} is the HR at the onset of exercise, τ_{on} represents the time constant during the HR elevation process.

Additional background on cardiac dynamics, together with Monte Carlo simulation results that validate these parameter settings—based on the research by Stornio et al.⁷² and the exponential models in Equations (1) and (2)—are provided in Supplementary Information (Note 1).

Frequency-index mapping

Before proceeding to the HR correction process, a mapping correspondence between HR values and consecutive integer indices (starting from zero) was

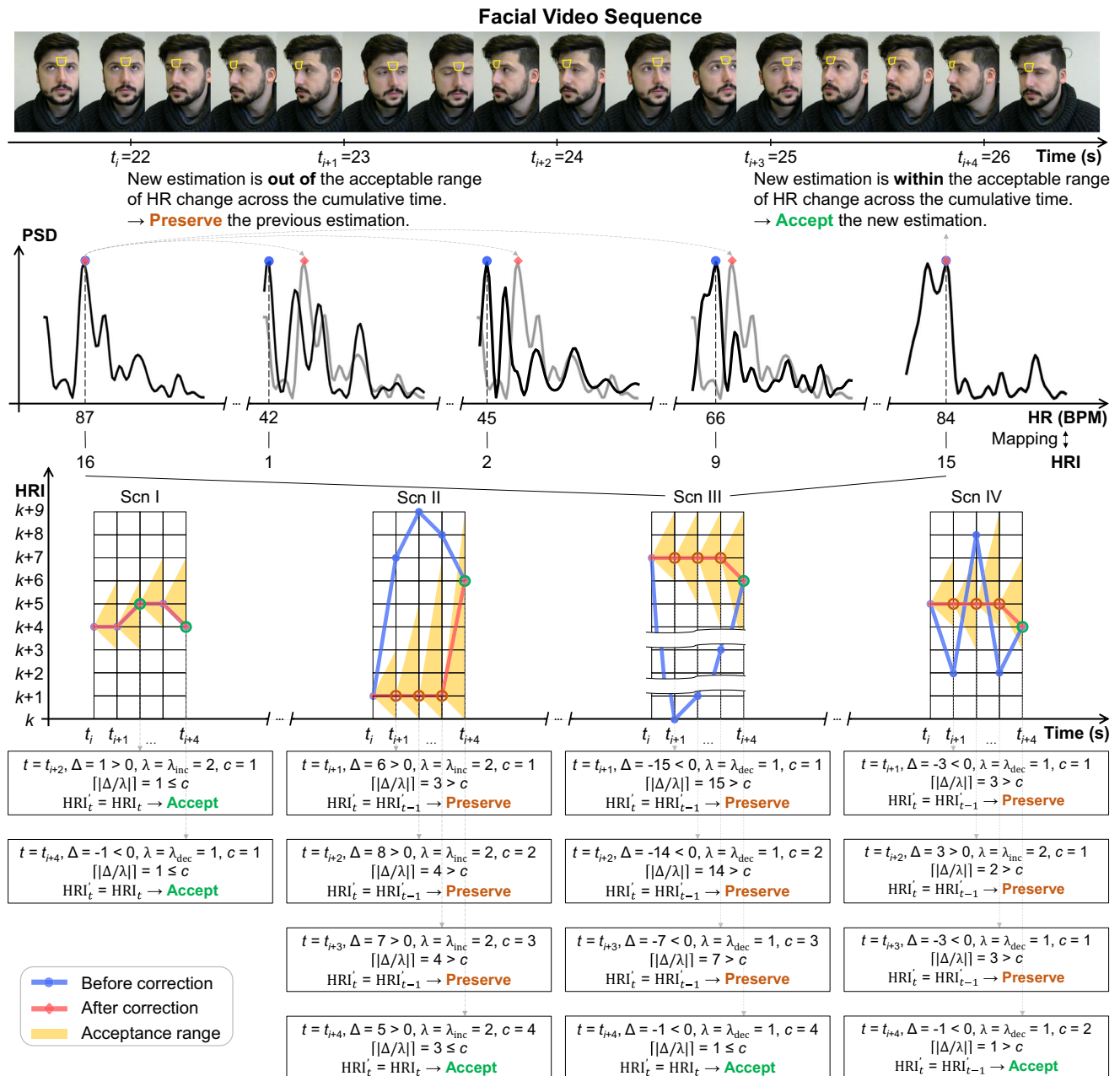


Fig. 6 | Working principle of the proposed adaptive HR correction algorithm. The facial video sequence is sampled from the LGI-PPGI dataset⁴⁵, which is under the Creative Commons Attribution 4.0 License (<https://creativecommons.org/licenses/by/4.0/>). The yellow polygon on the human face represents the glabella as the ROI. The power spectral density (PSD) of each time window is shown to further illustrate the HR estimation and correction process. HRI denotes the integer index mapped from HR. Representative scenarios I, II, III, and IV were presented using illustrative examples to further demonstrate the operation logic of the proposed HR correction algorithm. For the algorithmic notations, t_i denotes the time of the i -th

estimated HR, and HRI_t and HRI'_t denote the current HRI at time t before and after correction. Since the time interval between two adjacent HR estimations was set as 1 s, HRI_{t-1} and HRI'_{t-1} can represent the previous HRI before and after correction. For simplicity, Δ is used to represent $HRI_t - HRI'_{t-1}$, λ refers to the maximum acceptable HRI increase and decrease ($\Delta > 0, \lambda = \lambda_{inc} = 2; \Delta < 0, \lambda = \lambda_{dec} = 1$), c denotes the uninterrupted cumulative count of inspections of HR variations in the same direction, and the ceiling function $\lceil \cdot \rceil$ maps the input variable to the least integer greater than or equal to it. Note SCN means scenario.

constructed. Within the normal HR range of 0.65–4 Hz (39–240 BPM), each increment of 3 BPM was assigned to a single HR index (HRI), reflecting the one-second HRR of 3 BPM. We define this 3 BPM incremental step as one HRI unit (sHRI), meaning one HRI unit corresponds to 3 BPM. Through

this mapping operation, an estimated HR value was transformed into the corresponding index. A real-case illustrative example of mapping between HR and HRI is shown in Fig. 6. Subsequent correction operations were performed on the HRI instead of raw HR values.

Adaptive heart rate correction mechanism

Algorithm 1. Adaptive HR Correction

Input: $HRI_{current}$ (incoming HR index)
Output: HRI_{filter} (filtered HR index)
Initialize: $HRI_{cache} \leftarrow \emptyset$, $HRI_{filter} \leftarrow \emptyset$, $HRI_{last} \leftarrow \emptyset$
for each $HRI_{current}$ **do**
 if $HRI_{filter} = \emptyset$ **then**
 $HRI_{filter} \leftarrow HRI_{current}$
 $HRI_{last} \leftarrow HRI_{filter}$
 output HRI_{filter} {Initialize filter with first index}
 continue
 end if
 Compute $\Delta = |HRI_{last} - HRI_{current}|$
 if $\Delta \leq 1$ **then**
 $HRI_{filter} \leftarrow HRI_{current}$; $HRI_{cache} \leftarrow \emptyset$
 else
 if HRI_{cache} is empty **or** $HRI_{current} = HRI_{cache}[-1]$ **or**
 $sign(HRI_{cache}[-1] - HRI_{last}) = sign(HRI_{current} - HRI_{last})$ **then**
 Append $HRI_{current}$ to HRI_{cache}
 else
 Reset $HRI_{cache} \leftarrow \{HRI_{current}\}$
 end if
 if $|HRI_{cache}| \geq \Delta$ **then**
 $HRI_{filter} \leftarrow HRI_{current}$; $HRI_{cache} \leftarrow \emptyset$
 end if
 end if
 Update $HRI_{last} \leftarrow HRI_{filter}$
 output HRI_{filter}
end for

The implementation process of the proposed adaptive correction algorithm is depicted in Fig. 6. Here, we use an example-based approach to more intuitively illustrate the algorithm decision logic through four representative scenarios (Scn I–IV). The horizontal axis of the grid diagram denotes the time of each HR measurement result, and the vertical axis represents the HRI. We denote the difference between the estimated HRI before correction at the current time step (HRI_t) and the estimated HRI after correction at the previous time step (HRI'_{t-1}) as $\Delta = HRI_t - HRI'_{t-1}$. The parameter λ refers to the maximum acceptable HRI increase or decrease and is direction-dependent: for an increase ($\Delta > 0$), $\lambda = \lambda_{inc} = 2$, and for a decrease ($\Delta < 0$), $\lambda = \lambda_{dec} = 1$. Additionally, c denotes the uninterrupted cumulative count of inspections of HR variations in the same direction. The pseudocode is provided in Algorithm 1. The correction algorithm was initiated 15 seconds after the HR estimation pipeline began, using the average of all prior measurements as the initial reference point.

Scenario I shows how the algorithm handles slight HR increases and decreases. This represents the fundamental and most common state in HR estimation. At $t = t_{i+2}$, the HRI_t was greater than the HRI'_{t-1} by 1 sHRI ($\Delta = 1$). The maximum acceptable increase in HRI within one second was set to 2 sHRI ($\Delta > 0 \rightarrow \lambda = 2$), as illustrated in the previous section of cardiac dynamics constraints. In addition, the uninterrupted cumulative inspection times in the same direction of HR variations before accepting a new estimation was 1 sHRI ($c = 1$). Similarly, when $t = t_{i+4}$, the HRI_t decreased by 1 sHRI ($\Delta = -1$) than the HRI'_{t-1} . The cumulative number of inspection times on HR decrease before accepting a new estimation was 1 sHRI ($c = 1$). The maximum acceptable HRI decrease within 1 second was set to 1 sHRI ($\Delta < 0 \rightarrow \lambda = 1$). Both of these new estimations were accepted by the algorithm since they meet the acceptance criterion of HR variations ($|\Delta/\lambda| \leq c$).

Scenario II and III illustrate the decision process when the algorithm filters out sudden fluctuations of HR estimates. In Scenario II, at $t = t_{i+1}$, there was a sudden increase in the estimated HR before correction, resulting in $\Delta = 6$. Since $|\Delta/\lambda| = 3 > c = 1$, this estimation at t_{i+1} was not accepted. At the next time point $t = t_{i+2}$, $\Delta = 8$ still exceeded the acceptance criterion, and

the cumulative number of inspection times c was 2. Thus, the acceptance criterion was still not satisfied ($|\Delta/\lambda| = 4 > c = 2$). Until $t = t_{i+4}$, the new estimation was within the acceptance range and accepted ($|\Delta/\lambda| = 3 \leq c = 4$). This example demonstrates that when large-scale variation persists, the algorithm continuously evaluates the credibility of the new estimate on a per-time-point basis. In Scenario III, we present similar situations of HR decrease using an empirical example: The sudden decreases at $t = t_{i+1}$, $t = t_{i+2}$, and $t = t_{i+3}$ were not accepted by the algorithm. At $t = t_{i+4}$, the HRI decreased by 1 sHRI ($\Delta = -1$), and the cumulative number of inspection times for HRI decrease was 4 sHRI ($c = 4$). Thus, the algorithm chose to accept this new measurement ($|\Delta/\lambda| = 1 \leq c = 4$), thereby filtering out abnormal HR decreases induced by low-frequency motion noise caused by head rotation.

Scenario IV demonstrates the decision logic of direction reversals in HR estimates. Compared with the initial value at $t = t_i$, the changing directions at $t = t_{i+1}$ and $t = t_{i+3}$ were positive, while the changing direction at $t = t_{i+2}$ was negative. Under this situation, the algorithm would set c as 1 instead of gradually increasing the acceptance range of the same variation direction like Scenario II and III. Thus, at $t = t_{i+1}$, $t = t_{i+2}$, and $t = t_{i+3}$, the algorithm rejected the fluctuations and finally accepted the new estimate at $t = t_{i+4}$ when the acceptance criterion was met. This design enhances the algorithm robustness to random noise perturbations.

Comparable methods

The proposed algorithm was compared against six established HR correction methods: moving average^{37,38}, Kalman filter³⁹, outlier detection⁷³, peak verification⁴², AMTC⁴³, and HMA-RF⁴⁴.

The moving average approach³⁸ is a relatively simple yet broadly used method that reduces short-term noises by computing the average of the most recent N HR values. The computation can be expressed as

$$\hat{h}_t = \frac{1}{N} \sum_{i=0}^{N-1} h_{t-i}, \quad (3)$$

where h_{t-i} denotes the raw HR at time $t - i$, $\hat{h}_t$ is the smoothed HR at time t , and N is the moving window size. In our experiment, N was set as 5 to achieve its overall optimal correction performance.

The Kalman filter³⁹ mainly consists of two stages: prediction and update. In the prediction stage, the state estimate and its covariance are computed based on the system model. In the update stage, the Kalman gain is calculated to determine the significance of the new measurement. The estimate is adjusted using the measurement residual, and the error covariance is refined to capture the improved certainty. Given that PPG-based HR monitoring generally lacks additional inputs from multiple PPG sensors or accelerometers, we constructed a one-dimensional Kalman filter with a unit state-transition model to enhance HR estimates. The one-step prediction and its uncertainty are given by $\hat{h}_t^- = \hat{h}_{t-1}^+$ and $P_t^- = P_{t-1}^+ + Q$, where $\hat{h}_t^-$ denotes the predicted HR at time t (in BPM), P_t^- denotes the predicted estimation error variance, P_{t-1}^+ denotes the updated variance from the previous step, and Q denotes the process-noise variance, which reflects the uncertainty of the prediction model. The Kalman gain, a dimensionless parameter that balances confidence between the prediction and the new measurement, is given by $K_t = P_t^- / (P_t^- + R)$ with R the measurement-noise variance, which indicates the level of confidence in the accuracy of the HR measurement results. The involved variances (P_t^- , P_t^+ , Q , and R) have units of BPM². The estimate is corrected using the innovation (measurement residual), and the variance is reduced accordingly

$$\hat{h}_t^+ = \hat{h}_t^- + K_t(z_t - \hat{h}_t^-), \quad (4)$$

with the variance contracting as $P_t^+ = (1 - K_t)P_t^-$. Here, $\hat{h}_t^+$ is the updated HR estimate, z_t is the measured HR at time t , and P_t^+ is the updated estimation error variance. Since HR naturally exhibits moderate fluctuations and each measurement contains a certain amount of error, we set the

process-noise variance to $Q = 1.0 \text{ BPM}^2$, the measurement-noise variance to $R = 4.0 \text{ BPM}^2$, and the initial estimation error variance to $P_0^+ = 2.0 \text{ BPM}^2$ in our experiments to achieve the optimal correction effect.

The outlier detection algorithm⁷³ maintains a sliding window that stores the most recent N HR values. It identifies values that exceed a pre-defined variation threshold or deviate by more than a set number of standard deviations. If an HR value is classified as an outlier, it is discarded and replaced with the previous valid measurement. Otherwise, the value is included in the window and returns as the current HR. This method improves data reliability by filtering out erroneous measurements. However, this algorithm relies on the historical HR range and the set variation threshold to determine whether the current prediction is abnormal. Let μ_t and σ_t denote, respectively, the mean and standard deviation of the most recent N accepted HR estimates $\{\hat{h}_{t-1}, \hat{h}_{t-2}, \dots, \hat{h}_{t-N}\}$, where $\mu_t = \frac{1}{N} \sum_{i=1}^N \hat{h}_{t-i}$ and $\sigma_t = \sqrt{\frac{1}{N} \sum_{i=1}^N (\hat{h}_{t-i} - \mu_t)^2}$. Then the outlier replacement is

$$\hat{h}_t = \begin{cases} \hat{h}_{t-1}, & \text{if } |h_t - \hat{h}_{t-1}| > \Delta_{\max} \text{ or } |h_t - \mu_t| > \kappa \sigma_t, \\ h_t, & \text{otherwise.} \end{cases} \quad (5)$$

Here, h_t is the current measured HR, $\hat{h}_t$ is the final (filtered) HR, $\Delta_{\max}$ is the fluctuation threshold in BPM (e.g., 30 BPM), and κ is a unitless standard-deviation factor (e.g., 2). If the historical window is set too short, an effective and reasonable range cannot be established, which is likely to result in many data points being identified as abnormal points or failing to detect abnormal points. Moreover, for different scenarios, the size of the maintenance window has a significant impact on the effect of abnormal point detection. Therefore, based on comprehensive experiments, we set the maintenance window size to 100 for the LGI-PPGI dataset and 50 for the UBFC-rPPG and BUAA-MIHR datasets. We set the HR fluctuation threshold to 30 BPM and a threshold of two times the standard deviation to achieve the optimal effect.

The peak verification method⁴² first identifies the three strongest spectral peaks. These frequencies are converted into HR candidates and then each candidate's power is penalized based on its distance from the previous HR. The final HR output is selected based on the candidate with the highest weighted power after the penalty. This algorithm operates in the frequency domain and selects the candidate with the highest weighted power to yield a stable, history-aware HR estimate. Let (f_i, P_i) , $i = 1, 2, 3$, be the frequencies (in Hz) and powers of the three strongest spectral peaks. We convert each frequency to an HR candidate as $h_i = 60 f_i$, where the factor 60 converts Hz to BPM. With a distance penalty relative to the previous estimate $\hat{h}_{t-1}$, we select the candidate by

$$i_t^* = \arg \max_{i \in \{1, 2, 3\}} \frac{P_i}{|h_i - \hat{h}_{t-1}| + \varepsilon}, \quad (6)$$

where $\varepsilon > 0$ (e.g., 10^{-6}) avoids division by zero. The final HR estimate is then taken as the selected candidate: $\hat{h}_t = h_{i_t^*}$.

The AMTC method is a dynamic programming-based frequency tracking algorithm that aims to suppress noise-induced HR fluctuations by searching for a globally smooth and energy-maximizing frequency trajectory in the time-frequency spectrogram. It jointly considers a sequence of consecutive spectrogram frames, identifying the path with the largest total energy while enforcing continuity constraints on the trace. Following the original description of Zhu et al.⁴³, we retain the notation where k denotes the frequency transition constraint controlling the allowable bin-to-bin shift between consecutive frames, and k_2 represents the delay (look-ahead) window used in the online-AMTC version. In our implementation, the spectrogram buffer maintains the most recent 30 frames for global trajectory

optimization. The trace path is computed via dynamic programming with a frequency transition constraint ($k = 2.0$ in our experiments), allowing at most two frequency bins of shift between consecutive frames. The regularization coefficient λ (set to 2.0) balances the trade-off between maximizing total energy and enforcing path smoothness. Following the online-AMTC approach, the estimated HR is taken from the trace with a fixed delay of $k_2 = 5$ frames, which helps to achieve stable quasi-real-time output by looking ahead a few frames. These parameter settings were empirically determined to achieve optimal HR correction performance.

The HMA-RF method uses a supervised random forest classifier to identify and reject motion-contaminated HR estimates in rPPG analysis. Feature vectors include time- and frequency-domain statistics of head motion trajectories, together with signal-to-noise ratio (SNR) and raw HR predictions. The classifier is trained using ground truth HR, with predictions labeled trustworthy if the absolute error is less than or equal to 6 BPM and unreliable otherwise. We used data collected under sufficient light conditions (from 39.8 to 100 lux) from the BUAA-MIHR dataset for model training. The random forest uses 50 estimators and a maximum tree depth of 5, as empirically determined to balance generalization and overfitting. During correction, unreliable estimates are replaced by the last valid value to maintain sequence continuity.

Evaluation metrics

To evaluate HR measurement performance, we used two metrics: mean absolute error (MAE) and dynamic time warping (DTW)⁷⁴. MAE quantifies the average absolute difference between the estimated and ground truth HR values. The formula for computing MAE is defined as

$$\text{MAE} = \frac{1}{m} \sum_{i=1}^m |\hat{h}_i - h_i|, \quad (7)$$

where m is the number of sample points, $\hat{h}_i$ and h_i denote the estimated HR sequences and ground truth.

The DTW metric can effectively capture temporal variations and misalignments between two signals, making it suitable for assessing HR measurement performance across time series⁷⁴. Lower DTW values indicate closer correspondence between the estimated and ground truth HR trends. DTW evaluation was implemented using the DTAIDistance package⁷⁵.

Ethical approval and image consent

All facial images presented in Fig. 4–6 are sourced from publicly available datasets, including LGI-PPGI⁴⁵ and BUAA-MIHR⁴⁶. These datasets were collected and released under open-access Creative Commons licenses (CC BY 4.0 and CC BY-NC-SA 4.0, respectively), which permit reuse and redistribution of the datasets, including facial images, for academic research and publication with appropriate attribution. No identifiable personal information beyond the public dataset content was used. All images are displayed without artificial anonymization (e.g., black bars over the eyes).

Data availability

The LGI-PPGI dataset is under the Creative Commons Attribution 4.0 License: <https://creativecommons.org/licenses/by/4.0/>. The BUAA-MIHR dataset is under the Creative Commons Attribution-NonCommercial-ShareAlike 4.0 License: <https://creativecommons.org/licenses/by-nc-sa/4.0/>. The LGI-PPGI dataset can be accessed at <https://github.com/partofthetars/LGI-PPGI-DB>. The BUAA-MIHR dataset can be accessed at <https://xilin1991.github.io/Large-scale-Multi-illumination-HR-Database/>. The UBFC-rPPG dataset can be accessed at <https://sites.google.com/view/ybenzeth/ubfcrppg>.

Code availability

All code used for the experiments is accessible without restrictions at https://github.com/shuoli199909/rppg_adaptive_correction. The

implementations of baseline rPPG algorithms and relevant utilities are sourced from the pyVHR package^{76,77}, which is available at <https://github.com/phuselab/pyVHR>.

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Author contributions

Y.T., S.L., and Y.Z. conducted the experiments and performed the analysis. E.Y.L. and M.E. led the methodological design and provided project supervision and technical guidance. E.Y.L. and M.E. jointly supervised the project. All authors contributed to the interpretation of results and reviewed the final manuscript.

Competing interests

The authors declare no competing interests. M.E. serves as an Associate Editor for npj Biosensing and had no involvement in the review or editorial handling of this manuscript.

Additional information

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