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A Comprehensive Review of rPPG Methods for Heart Rate Estimation

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Abstract

Recently, there has been an increasing interest in assessing basic health indications covering blood pressure, heartbeat, and breathing rate using remote photoplethysmography (rPPG) to obtain the results without direct contact with humans; rPPG has become essential to measuring vital signs while avoiding difficulties in many cases, such as transmission of infection through contact with persons who have serious diseases or disturbing people with sensitive skin or newborn babies. This technique can also be used for other applications, such as monitoring people's stress levels during indirect investigations and monitoring the health indications of truck drivers to send them a notification if they suffer a health crisis. This paper discusses the methods used in remote photoplethysmography (rPPG) that focus on measuring the photoplethysmography (PPG) using an RGB camera. These techniques achieved good results corresponding to the availability, cost, and ease of use.

Subject Areas

Artificial Intelligence, Image Processing

Keywords

Remote Photoplethysmography (rPPG), Heart Rate Measurement, Remote Health Monitoring, Computer Vision, Deep Learning

1. Introduction

Heart rate (HR) is a significant physiological indicator, specifically for the rapid notification of heart diseases and arrhythmias in the heart. The techniques of HR monitoring can be categorized as direct and indirect contact with the human body. For contact methods, measurement of electrocardiogram (ECG)-based heart rate detection offers dependable outcomes in a lot of clinical diagnoses, as shown in **Figure 1**. Ten sticky electrodes are required at designated locations on the body to determine the heart rate. As mentioned above, it has high accuracy and reliable results, but it restricts the patient's moving flexibility or may cause allergic issues with sensitive or burned skin to the patient [1]. However, photoplethysmography (PPG) is a commonly employed alternative method that addresses some drawbacks while providing dependable findings. In device architecture, red and near-infrared light from LEDs is typically employed, as these longer wavelengths are appropriate for assessing deep-tissue blood flow. The variation in hemoglobin concentration during the heart's cycle results in a minor change in light absorption rate. The following non-invasive optical technique utilizes a source of light and a light detector to determine the blood volume pulse (BVP) inside superficial blood arteries during flow [2]. Beer-Lambert's theory proposes that the reduction of light at certain wavelengths can be determined by dispersion and reflection as it interacts with the skin. The variation in the levels of reflected and transmitted light is captured as a PPG signal by a photodetector, as shown in **Figure 2**. This methodology is frequently included in wearable devices, including pulse oximeters, smartwatches, and smartphones [3]. Researchers began research on the feasibility of obtaining PPG signals from video recordings by analyzing subtle color changes in the skin due to blood flow; they established that heart rate could be correctly tracked using normal cameras; also, improvements in high-definition cameras, computer vision, and deep learning methods have directed

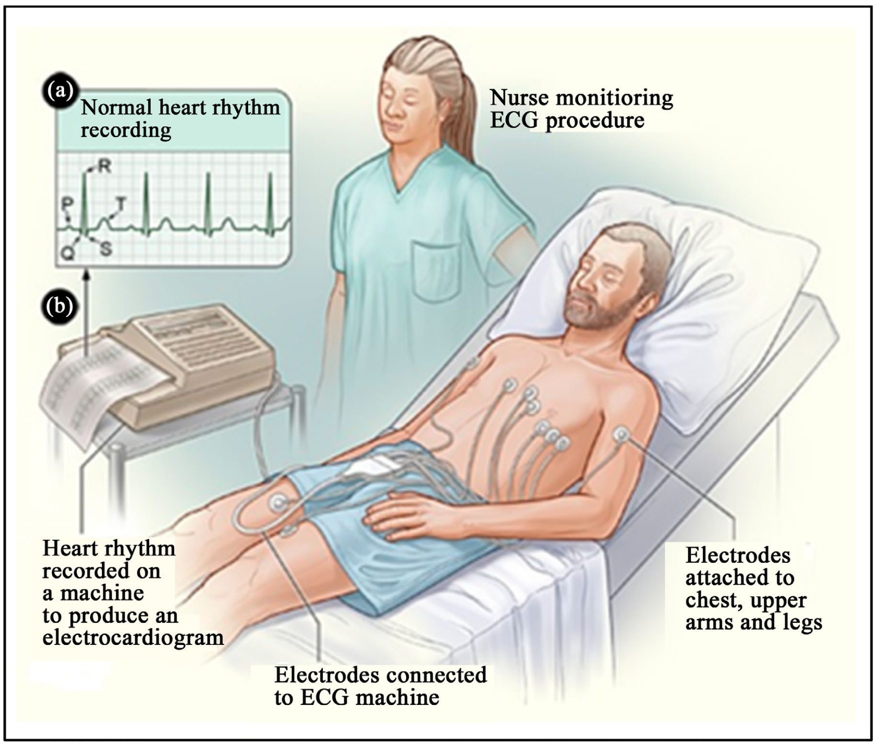

Figure 1. ECG setup and ECG trace [4].

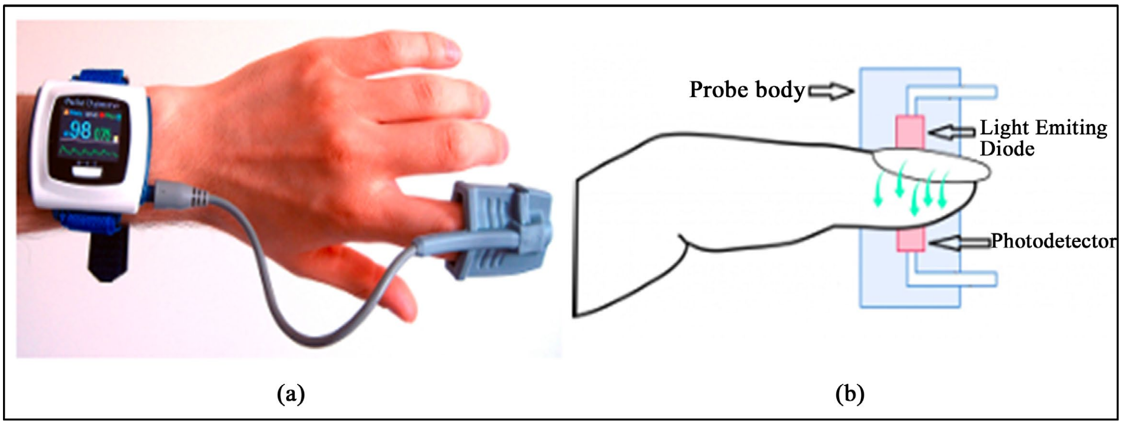

Figure 2. (a) A wrist-mounted remote sensor pulse oximeter with a probe. (b) A pulse oximeter is a tool that non-invasively evaluates oxygen saturation by transmitting light via the skin of a finger [2].

more research studies toward measuring heartbeats without contact with the body. As wearable devices gained popularity, the incorporation of rPPG into smartwatches, cellphones, and fitness trackers offers users immediate health data without the necessity for invasive sensors. Remote tracking of health has been gaining popular interest due to its offer of a more comfortable and unobtrusive method for heart rate evaluation, especially for people who have sensitive or burnt skin or require continuous vital signs measurement, as in an intensive care unit (ICU). Therefore, methods directed to replace traditional measurement techniques are based on the process known as rPPG [5] [6]. As mentioned above, rPPG is helpful in cases of epidemics and infectious diseases, such as COVID-19, where it is preferable to avoid direct contact with the patient [7]. Remote photoplethysmography (rPPG) uses a camera, including thermal, infrared spectrum, or RGB cameras, to capture video of the individual and detect small color variations in facial skin to produce the remote signal for PPG. The rPPG method operates on an idea similar to the standard PPG method, where the rapid flow of blood within the circulatory system alters the blood density within the blood vessels area below the skin surface with every heartbeat, producing regular waves. The primary distinction between the two methodologies lies in the approach employed for collecting the PPG signal; rPPG techniques obtain the signal by capturing the face of the subject without contact. Conversely, traditional PPG techniques require a physical sensor that stays in touch with the skin [8]. The principle of rPPG method is ambient light falls on the skin; part of this light will suffer from a specular reflection from the skin surface, which is devoid of physiological information, and the other parts of the light will suffer from a diffuse reflection from the blood vessels inside the skin, changes in blood volume inside the vessels corresponding to heartbeats result in minor differences in reflected light from the skin surface, from which the PPG signal is derived following processing. This diffuse signal contains physiological information that is captured using the camera, and the heart rate is calculated or estimated from this signal after filtering and processing it, as shown in Figure 3 [9]. The rPPG has become one of the most widely used methods due to

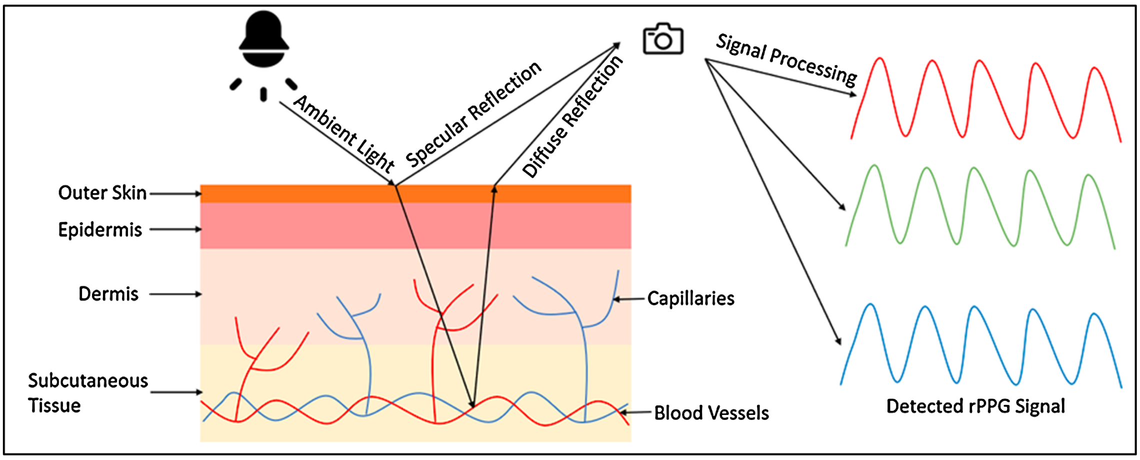

Figure 3. Mechanism of rPPG using the dichromatic reflection model (DRM). The digital camera records both specular and diffuse reflections from ambient light. Specular reflection includes surface information unrelated to signals from the body, while diffuse reflection is affected by circulation. The signal of rPPG can be generated via additional processing of signals [11].

the cheap cost of the standard camera, comfort for patients, and high accuracy of the results. This method can be used in various contexts, including Telehealth, which allows healthcare providers to monitor patients requiring continuous observation of health indicators remotely. Additionally, outside the medical domain, this method can assess individuals' stress levels during indirect investigations conducted by authorities and the possibility of using it to monitor the vital indicators of car drivers in order to alert the driver in the event of recording indicators for an upcoming health crisis. This technique enables us to take health indicators from a few meters away with standard cameras. Despite its many advantages, rPPG faces some challenges; factors like motion artifacts and varying lighting conditions can affect accuracy; performance can vary across different skin tones, requiring additional research for equitable application; the diversity of the database in the methods that use deep learning to extract the PPG signal affects the accuracy [10].

This research provides an in-depth review of rPPG monitoring utilizing computer vision and deep learning approaches to determine the heart rate. According to the work method, the review divides the heartbeat measurement into two types. Section two lists the details related to the two types. Section three lists the Potential applications. Section four lists the advantages and Limitations. Conclusions are in section five.

2. Literature Review

The main signal being worked on to obtain the heartbeats is obtained in two ways. The first method is to measure the amount of diffuse reflections light from the skin to obtain the main signal, and then different algorithms are applied to process the main signal to achieve the heart rate. The second method extracts the main signal from subtle head movements generated by heartbeats and then applies different algorithms and filters to signal processing to achieve the heart rate. Below is the previous study according to how the main signal is obtained.

2.1. Heartbeat Measurement Based on the Reflection of Light on the Skin

Thermal cameras may be useful for the collection of rPPG data, enabling the extraction of physiological information regarding heart pulse, blood flow, and respiratory rate [12]. This method tracks the region of interest (ROI), which is the blood vessel that contains different amounts of blood according to the heartbeat. After recording the thermal signal, the noise is removed, and the fast Fourier transform (FFT) is used to calculate the heartbeat, as shown in **Figure 4**. The accuracy of this approach was about 88%. The environment in which data were recorded from the samples was typical regarding lighting and movement. However, the system cannot work well in a realistic environment because of changes in illumination and difficulties in restricting a person's movement. Additionally, the body's temperature and ambient temperature can also affect the results, and the high cost of thermal equipment limits the widespread use of this method [4].

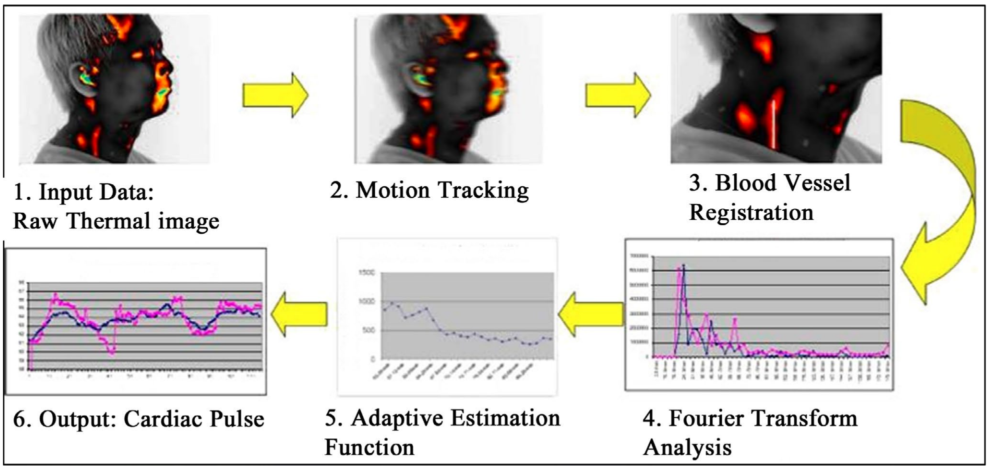

Figure 4. A description of no physical heart rate estimation using a thermal camera [4].

In 2008, Verkruysse *et al.* first studied rPPG. They used consumer-level digital cameras for HR estimation from a distance of about 1 meter, depending on the average light from the around as a source. This method focuses on taking the initial signal from the reflection of the light signal on the green channel for ROI, then applying a bandpass filter with a range of frequency (0.8, 3.5) Hz to get a heart rate range between (48, 210), then performed an FFT on the obtained signal to derive heart rate. Two primary factors constrain the spatial clarity of the PPG data (power and phase) and the level of accuracy of our existing methodology: firstly, movement objects, and secondly, decreasing signal-to-noise ratio (SNR). The first issue may be fixed by increasing the location of the volunteers. The second issue can be resolved through the use of advanced movie cameras with enhanced frame quality and better techniques for analyzing signals and processing [13].

In 2010, the author focused on blind source separation (BSS) utilizing independent component analysis (ICA). ICA is an approach for detecting independent source data generated by a collection of signals that consist of linear combinations of the fundamental sources, as seen in Figure 5. This new approach in healthcare signal analysis is fast growing. ICA has been utilized to eliminate noise from electrocardiogram (ECG) and electroencephalogram (EEG) recordings, as well as to decrease movement effect errors on the PPG signal [14]. The ICA method introduces an innovative approach for indirect heart rate evaluation from video frames via blind source separation. In this study, a laptop webcam was used for 12 participants with varying skin colors. The trials were performed indoors, utilizing different amounts of sunshine as the sole source of illumination. When recording a video of the skin on the face with a webcam, the sensor of the camera detects a mix of the reflected plethysmographic signal and various light fluctuations caused by artifacts, such as motion variations in environmental illumination, resulting in a summation of independent random parameters that exhibit greater Gaussian characteristics than the original parameters [15].

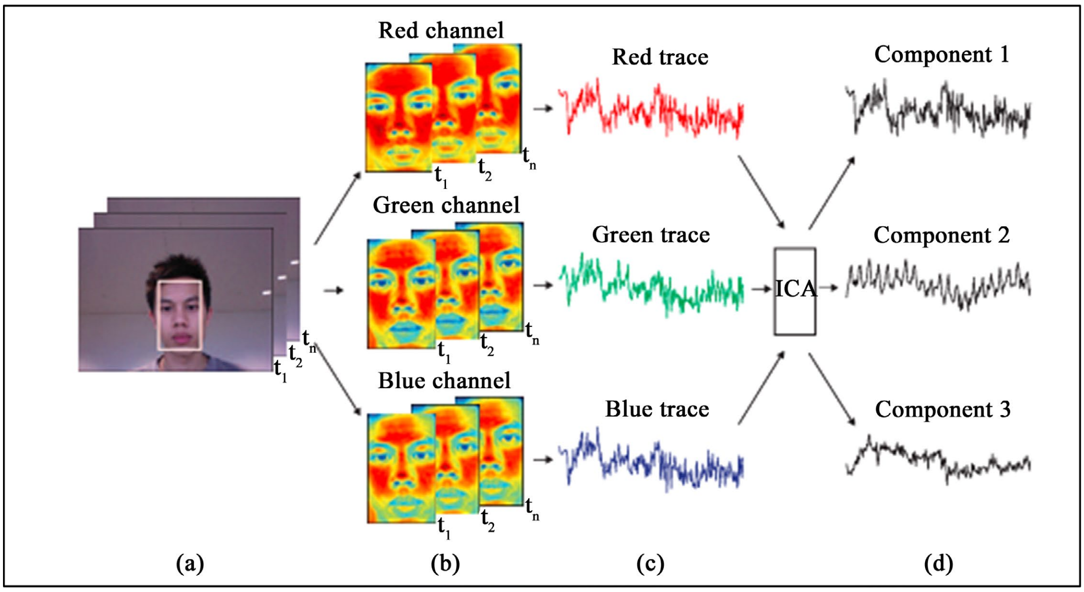

Figure 5. Methodology for heart pulse monitoring. (a) The ROI is dynamically identified with a face detector. (b) From the ROI region, extracted RGB channels and counted the averaged change to obtain (c) the unfiltered RGB signals. ICA is utilized on the normalized RGB signals for recovery (d) of three independent source signals [15].

After recording the video, face detection was performed to identify the ROI and count the average colors: red, green, and blue. The normalized raw signals are further divided into three independent source signals utilizing ICA. This method separates the extracted signal and divides it into three sources. There will be one or more sources close to the heart rate indicators, and the other source that contains noise resulting from abnormal movement and changes in lighting is ignored, then passed through a bandpass filter with a range of frequency (0.75, 4) Hz. According to this frequency range, the heart rate range must be between (45 and 240) beats per minute (bpm). The recorded videos included two statuses: the first involved no movement, and the second involved typical movement. The results were compared with a blood volume pulse (BVP). This method allows the heart rate of three people to be read simultaneously. Table 1 shows the results before and after using ICA to demonstrate this method's efficiency. There was a noticeable improvement in the accuracy of this method, but it still suffered from limitations, including being affected by changes in lighting and movement [15].

Table 1. Summary details of heart pulse measurements according to proposed methodology and reference BVP [15].

Statistic	Sitting still		With movement artifacts	
	Before ICA	After ICA	Before ICA	After ICA
No. of measurement pairs	372	327	372	372
Mean bias (bpm)	0.09	−0.05	8.16	0.64
Mean absolute bias (bpm)	2.79	0.91	10.81	2.44
SD of bias (bpm)	6.01	2.29	17.58	4.59
Upper limit (bpm)	11.86	4.44	42.62	9.64
Lower limit (bpm)	−11.68	−4.55	−26.31	−8.35
RMSE	6.00	2.29	19.36	4.63
Correlation coefficient	0.89*	0.98*	0.15*	0.95*

*Indicates significance at $p < 0.001$.

In 2012, Lewandowska *et al.* proposed principal component analysis (PCA), which is similar to the ICA method, but it operates on different principles. This method also used a webcam to record video and then employed an algorithm to detect the ROI of the face and extract the RGB signal from the ROI location on the head. The RGB signal is based on the reflections of light on the body, and these values vary according to the passage of blood in the veins. PCA is a process that determines similarities in data and represents it in a format that highlights similarities and differences, providing it a useful instrument for data analysis. The basic principle of PCA is to transform the original data into a new coordinate system in which the maximum variance by any projection lies on the first coordinate (the first principal component), the second greatest variance on the second coordinate, and so on. This method reduces the dimensionality of the data while preserving as much variance as possible, making it easier to analyze. After that, a bandpass filter is applied to the archived signal from PCA to remove unwanted frequency. To obtain the heart rate, we count the peaks of the processed signal over time. Comparing the above methods, ICA and PCA yielded almost similar results, but PCA was superior to ICA in terms of simplicity, lower complexity, and speed of calculations [16].

In 2013, Wei *et al.* used Laplacian eigenmap (LE) algorithms to extract signals from RGB channels obtained from participants' faces using an ordinary webcam to determine the HR. The LE method is distinguished from previous techniques, such as ICA and PCA, in that it processes the signal non-linearly to achieve a more accurate HR signal. The basic principle of LE is that it operates by embedding high-dimensional data into a lower-dimensional space while preserving the local geometric structure. It does this by constructing a graph representation of the data, where each data point is a node, and edges represent relationships between points based on proximity. The method seeks to minimize the distance between connected points in the new space while maximizing distances between disconnected points. The method was conducted on 20 people using a standard webcam to record a 30-second video at an average rate of 30 frames per second. The face was detected using the method described in [17]. The RGB signal was extracted, the LE algorithm was applied, and then a bandpass filter was used to delete unwanted frequencies and calculate the peaks of the final signal to obtain the heartbeats, as shown in **Figure 6**. Although the results presented showed better performance than the previous study, which used a linear process for heart rate estimation, it was more sensitive to noise and computational complexity [18].

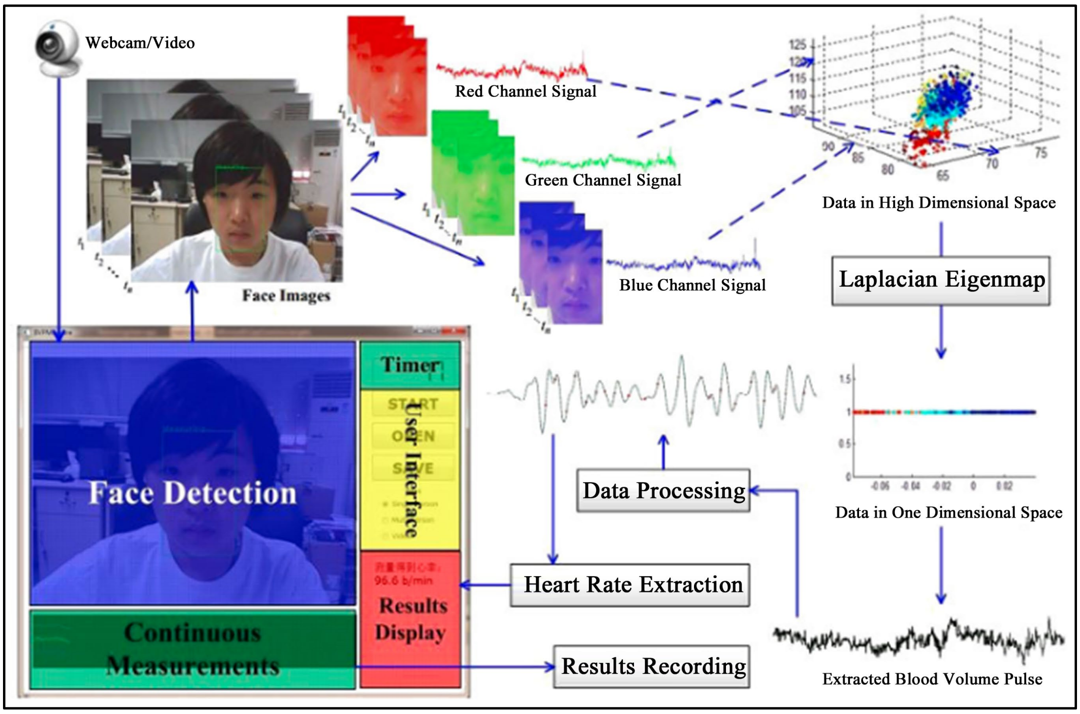

Figure 6. System architecture [18].

In 2014, Monkaresi *et al.* employed an artificial intelligence methodology to identify the pulse component from all channels (RGB components). This methodology comprised the use of power spectrum analysis, k-nearest neighbours (KNN), and linear regression analysis on each component derived from ICA to extract signals that helped classification. KNN surpassed linear regression methods in taking pulse signal components to determine HR. Nevertheless, applying the model across new people may produce various results or display poor performance when additional people not included in the training dataset are introduced to the system, potentially resulting in failures in practical applications. Additionally, the research was performed in a regulated setting with defined illumination parameters [19].

Eulerian video magnification (EVM) was originally employed to determine variations in the facial region of subjects. The core idea of EVM is to amplify small, subtle changes in a video over time while keeping the overall structure of the video intact. It focuses on temporal changes in pixel values, which can indicate physiological signals like blood flow. After recording the video, it is converted into sequential frames. The RGB signals are extracted for each frame. Then, the filter is applied to remove unwanted frequencies. After that, the EVM is used to magnify the slight change in the RGB signal for all frames. Then, the heartbeats are calculated from the final signal after applying FFT. This strategy was used for data in which subjects were stationary. This method is impractical for heart rate monitoring in real-world scenarios when people may be in motion. Furthermore, its performance may be degraded in the presence of significant noise within the signal [20].

In 2020, Laurie *et al.* proposed an exposure management strategy that improves the SNR by modifying the camera shot period to maximize it with the absence of distortion. Nonetheless, the method is weak in terms of subject flexibility, and shows a prolonged time of execution compared to normal controls. Subjects must remain somewhat motionless to ensure accuracy, as movement may result in color channel overloading. The extended execution time may restrict its applicability in real-time contexts [21].

In 2013, the authors designed a new rPPG signal filtering technique, which depends on chrominance and is termed CHROM. They researched the movement problem, leading to the development of far more advanced chrominance-based approaches. The primary issue with rPPG is its resilience to subject movement. The authors examined how motion affects the pulse signal and derived more robust rPPG algorithms from this analysis, achieving superiority surpassing all previous techniques in SNR and movement resilience. The main idea behind chrominance algorithms is to isolate and analyze the color components (like red, green, and blue) of the video to detect subtle changes caused by blood flow. When blood rushes to the skin's surface, it alters the skin's color, which can be quantified and used to extract the heartbeat signal. The study was conducted on 117 healthy volunteers with different skin colors. Face detection, as established by Viola and Jones [17], was utilized to mark an ROI. Subsequently, RGB color data served as the basis for analysis. A Bandpass filter is applied to the initial signal to remove unwanted frequencies. After that, the CHROM method is used to analyze the signal and get a signal close to the heartbeat signal, and finally, FFT is applied to obtain the HR result, as shown in **Figure 7**. The SNR was also affected by the color of the skin type; it suffered from a decrease in people with dark skin compared to people with white skin, and this decrease is logical; the elevated melanin level Soaks up a portion of the reflected, diffuse light that conveys signal information PPG. CHROM showed more sensitivity to motion-induced distortions compared to approaches based on PCA and ICA [22].

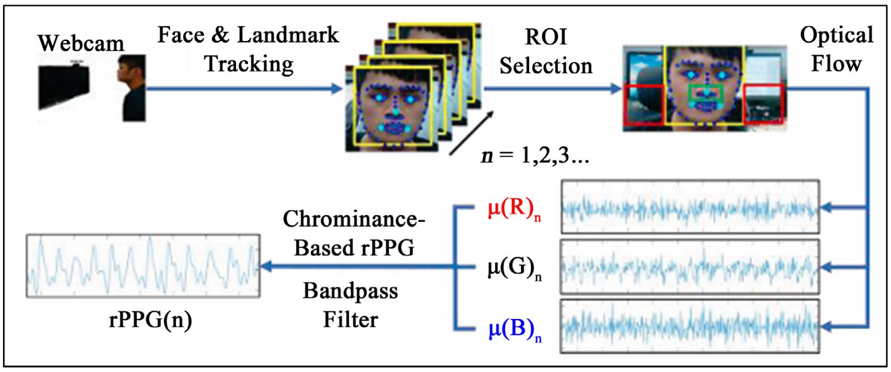

Figure 7. The common operating principle of rPPG using CHROM [23].

In 2017, the authors introduced a plane orthogonal-to-skin (POS) technique that presents the PPG signal onto a plane orthogonal to the skin's color for the extraction of the heart signal. The POS technique surpassed CHROM, PCA, and ICA methodologies. This approach computes the spatial average of the RGB colors from skin cells in each frame to determine the spatial RGB mean utilizing a standard RGB camera. Following that, it dynamically concatenates values from every frame into a matrix and splits the RGB signals into various orthogonal bands of frequency for sub-band heartbeat extraction. After isolating and attenuating the various motion frequencies across distinct frequency bands, a coherent pulse signal can be synthesized by amalgamating the results of processing from the several sub-bands to derive the heart rate [24].

In 2021, the authors employed a two-stage convolutional neural network (CNN) methodology, wherein one CNN identifies the face and collects the rPPG signal, while the other CNN predicts the HR from the obtained signal. The main idea behind CNNs is to use multiple layers of filters (or convolutions) to detect patterns in the input data automatically. Each layer learns to identify increasingly complex features, from simple edges in the first layers to more complicated shapes in deeper layers. This feature extraction process allows CNNs to effectively analyze the visual information in video frames for rPPG applications. The quantity of research publications employing techniques based on deep learning (DL) for remote heartbeat monitoring has risen yearly and will probably keep going in its growth. End-to-end supervised learning methodologies are unquestionably effective due to their simple model optimization procedure, yet they demand substantial training data, which can be challenging to obtain. This method has shown promising results compared to previous approaches. However, the results were mixed when applying this technique in real-world scenarios without controlling the light source. The success of this method depends on the registered databases, their size, the diversity of samples (including different skin colors), and the variety of registered environments. All of these factors must be considered to increase the accuracy of this approach [25].

2.2. Heartbeat Measurement Based on Subtle Head Movements

Balakrishnan *et al.* improved another method for rPPG-based HR, which was calculated from video to identify smaller head motions generated by heartbeats. According to Newton's law, for every action, there is a reaction; the heartbeat produces slight movements in various parts of the human body. While this movement is complex for the eye to perceive, advancements in computer vision have made it possible to detect these movements [26]. This approach complements the calculation of the HR from the video through the study of tiny color variations in the outer layer of the skin caused by the flow of blood [15] [16]. This method does not rely on visualizing the skin to detect changes in color values resulting from the heartbeat; instead, it focuses on head movement. The video is recorded using traditional cameras, with head movement extracted through feature tracking on the face. The signal is then processed to isolate unwanted movements, such as those from the person's motion or breathing, by removing frequencies that are far from the heartbeat frequencies, as shown in **Figure 8**. Then, PCA decomposes the trajectories into a collection of independent sources of signals that define the primary components of head movement. The frequency spectra are examined to select the appropriate source for analysis and compute the duration of individual beats, and the source with the most apparent central frequency is chosen. The mean rate of the pulse is determined by this frequency, and the peaks of the obtained signal are counted over time to determine the heart rate. This approach has demonstrated high accuracy; compared with ECG as ground truth values, the average mean error for all subjects was 1.5%. The motion-based approach is particularly advantageous when the person's skin is not visible. However, the limitations of this method include extreme changes in lighting and the person's movement during speech, which require advanced filtering methods to isolate the heartbeat signal from other noise signals [26].

In 2013, the author proposed a method to extract heartbeats from the head movement caused by the heartbeat. In this method, the focus was on tracking and processing a few feature points instead of many points to track the movement. This method was to record video using a camera of smartphone and then count the frequency movement of the head from selecting and tracking a single point from the face, then apply the ICA technique for isolating independent signals from a collection of data that comprise linear combinations of the fundamental sources after that used bandpass filter to remove unwanted signal and apply FFT then count the peak of signal to extract the heart rate. The author additionally used the PCA method to analyze the obtained signal and compare the results with the ICA method. The results were more accurate when ICA was used during the signal analysis. In addition, it was found that the error rate decreased when tracking

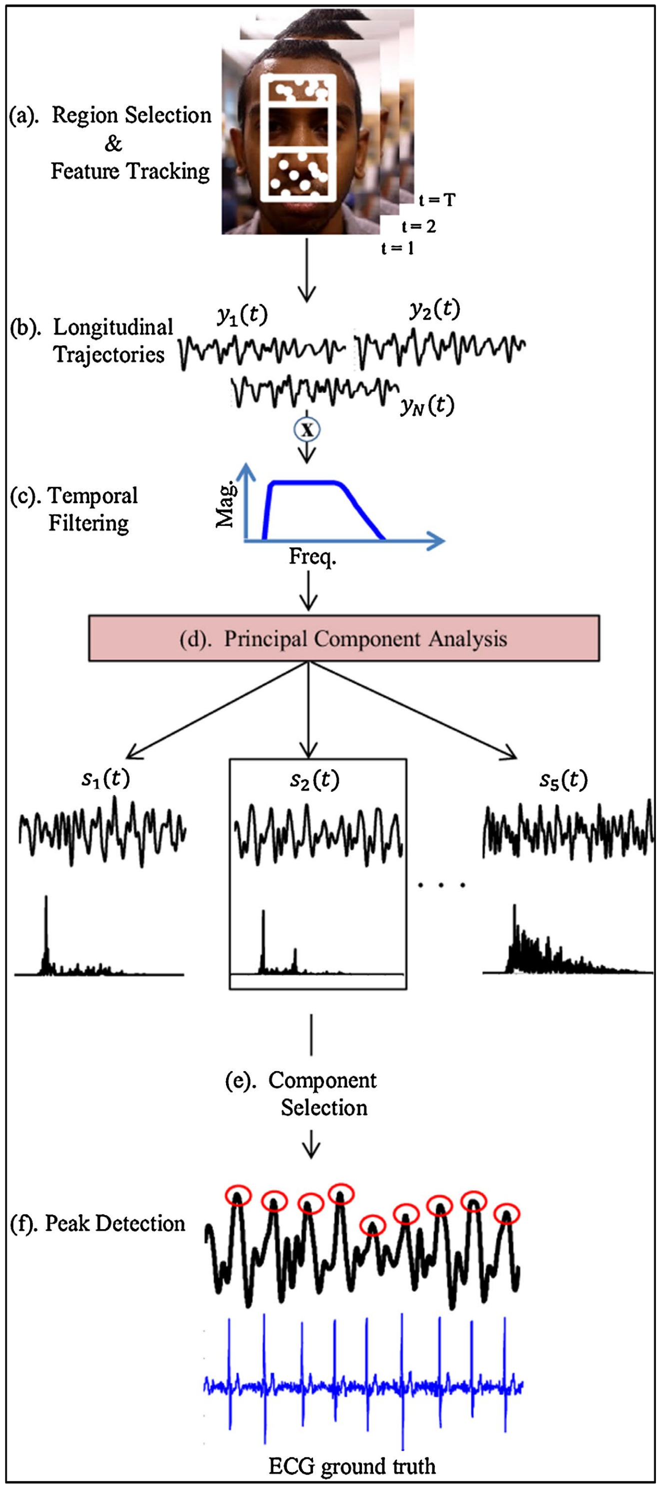

Figure 8. Summary of our heartbeat prediction methodology. (a) A specific area within the human head has been chosen, and feature locations are monitored across all video frames. (b) The vertical component is collected from every feature element direction. (c) Each track is later dynamically filtered to remove unnecessary frequencies. (d) PCA splits each trajectory into signals from the source s1, s2, s3, s4, and s5. (e) The component showing the clearest focused frequency is chosen. (f) Peak monitoring determines the beats of the signal [26].

a small number of features [26].

Haque *et al.* (2016) proposed a new approach to enhance system limitations by selecting facial landmarks to identify the features and track their movement to obtain the initial signal. A bandpass filter is applied to remove unwanted frequencies. Finally, discrete cosine transform (DCT) instead of FFT was applied to get the final frequency through which the heartbeats were calculated. However, the obtained signal was influenced by people's range of motion, hence significantly hindering the advancement of this technology [27].

Table 2 includes various system metrics for performance, including root mean square error (RMSE), correlation (r), and standard deviation error (σ), from prior research.

Table 2. Performance of lab-based HR systems: σ, RMSE, and r [28].

Year	Author	S.D. (σ)	RMSE	r
2010	Poh *et al.* [15] (sitting still)	2.29	2.29	0.98
2010	Poh *et al.* [15] (with slight movement)	4.59	4.36	0.95
2014	Monkaresi *et al.* [19] (ICA)	25.54	35.31	0.53
2014	Monkaresi *et al.* [19] (ICA + KNN)	4.33	4.33	0.97
2014	Monkaresi *et al.* [19] (CA + KNN + Regression)	13.7	13.69	0.58
2013	de Haan *et al.* [22]	2.6	1.1	0.97
2014	Hsu *et al.* [29]	-	5.48	0.88
2014	Li *et al.* [30] Video HR database	0.72	1.27	0.99
2014	Li *et al.* [30] MAHNOB-HCI database	-3.3	7.62	0.81
2015	Lam *et al.* [31]	8.54	10.34	0.66
2016	Haque *et al.* [27]		3.85	
2017	Qi *et al.* [32]	3.65	5	0.74
2019	Qi *et al.* [33] (still)	-	7.21	0.76
2019	Qi *et al.* [33] (head movement)	-	8.7	0.69
2019	Qi *et al.* [33] (active HR)	-	17.88	0.47
2021	Huang *et al.* [25] (MAHNOB-HCI dataset)	6.31	6.42	0.84
2021	Huang *et al.* [25] (UBFC-rPPG dataset)	6.45	7.24	0.73
2022	Pirzada *et al.* [34] (various movements)	0.018	7.8	0.85

3. Potential Applications

Heart Rate Monitoring: rPPG can be employed in fitness applications and devices to track heart rate during exercise, helping users enhance their daily activities. In hospitals, the rPPG allows continuous heart rate monitoring of patients without physical touch, therefore reducing the danger of infection [35].

Stress Detection: This method can measure the level of stress in individuals during indirect investigations by authorities [36].

Sleep Monitoring: rPPG can be utilized to assess heart rate and blood flow during sleep, offering significant insights into sleep quality and possible sleep problems [37].

Chronic Disease Management: Patients with chronic diseases, like hypertension and heart disease, can be monitored remotely. This allows healthcare providers to monitor vital signs continually [38].

Virtual Consultations: During telehealth consultations, physicians can evaluate patients' heart rates in real time, thereby improving the quality of distant assessments [38].

Non-Invasive Pediatric Care: rPPG is especially useful in pediatric environments, where non-invasive techniques are favored for the monitoring of health indicators in newborns and children [39].

Driver Monitoring: Sudden health crises contribute to an increasing number of driving accidents and fatalities each year. In many cases, drivers may be oblivious to these latent health risks. Therefore, in-cabin cardiac monitoring has attracted interest from automotive manufacturers [40].

4. Advantages and Limitations

PGP allows measurements of health indicators without physical contact or invasive methods, making patients comfortable; it supports remote health monitoring, which is especially useful for telehealth applications, allowing healthcare providers to monitor patient's conditions remotely. Employing standard video cameras, such as those found in smartphones and webcams, reduces the need for costly medical equipment, which improves the accessibility of health monitoring. Remote photoplethysmography (rPPG) can provide continuous, real-time data on heart rate and other health indicators, allowing for timely interventions when abnormalities are detected. This technology can be applied in various environments such as hospitals, homes, and fitness facilities, enabling variable application. Despite the fact that this technology has many advantages, it is not devoid of limitations, including subject movement, which can add noise, resulting in incorrect readings; these limits are used in dynamic environments. Inadequate or variable illumination might obstruct the detection of subtle variations in the color of the skin, thus affecting the accuracy of the final results. The efficacy of rPPG may change among various skin tones, potentially resulting in biased results in various populations. At the same time, the integrity of the obtained signal might be affected by variables such as camera quality, distance from the camera, and capture angle [36].

5. Conclusion

This paper offers a review of rPPG-related studies that can measure heart rate. The paper discussed the reason for the interest in this technology and the increasing amount of research related to it, in addition to discussing the methods used, samples, and the environment in which the experiments were conducted. The databases used in deep learning methods, in addition to the performance of each method and the limitations that affect performance. Several things must be taken into consideration during the design stage of the rPPG, including the physical distance from the camera that records the video and the person, controlling the number of frames during processing, the various environments and lighting conditions, the diversity of samples that the systems are tested in terms of age, gender and skin color. The natural movement of people during the test must also be taken into account, as well as the extent to which movement affects the results. The makeup on the sample's faces must also be taken into account, as well as its effect on the results. The methods that use deep learning must consider the previous matters in the database used to make the results more accurate. In summary, the topic of rPPG has achieved significant improvements in the last few years. We focused on various facets of these studies and pointed out the critical results, applications, challenges, and limitations that they have faced. Processing these challenges is essential to obtain good results; thus, these techniques can be used in real-world scenarios.

Conflicts of Interest

The authors declare no conflicts of interest.

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