Review and Evaluation of Heart Rate Monitoring Based Vital Signs, A case Study: Covid-19 Pandemic

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***Abstract*— The monitoring of vital signs is essential in the clinical setting, including temperature, respiratory, and heart rates. Remote monitoring devices, systems, and services are emerging as vital signs monitoring must be performed daily. Different types of sensors can be used to monitor breathing patterns and frequency. However, the respiratory rate remains the least measured vital sign in many scenarios due to the intrusiveness of most of the sensors adopted. This is not the case with Covid-19, which directly infects the respiratory system. In this paper, we present a state of the art on the different applications that monitor temperature, heart rate, and restorative rate, as well as the evaluation of an algorithm that extracts the heart rate from an RGB camera.**

Keywords—Vital signs; Heart rates; Covid-19; RGB camera

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I. INTRODUCTION

The epidemic diseases that are growing represent a serious threat to global health. Over the last two decades, travel-related infectious diseases, such as severe acute respiratory syndrome and the novel corona virus (Covid-19), have emerged worldwide in 2003 and 2019 [1-2]. Different technologies have been proposed to diagnose people contaminated with Covid-19, but the most important is to monitor people who are in critical cases. In this context, we find that the monitoring of temperature, the respiratory and heart rate are very important. The traditional diagnosis used in most hospitals is based on sensors and other tools, which requires contact between patients and doctors. The use of technology-based on artificial intelligence and image processing will help us to have remote monitoring systems [3-5].

Breathing rate is the number of breathing cycles that occur in an individual in one minute. A breathing cycle consists of one inhalation (incoming air) and one exhalation (outgoing air). The normal breathing rate is: 40 to 60 cycles per minute in new-borns (< 1 week), 30 to 40 cycles per minute in infants (< 1 year), 20 to 30 cycles per minute in children (< age of puberty) 12 to 20 cycles per minute in adults (and adolescents).The heart rate in humans is normally around 70 beats per minute, this value varies depending on age e.g. a newborn baby to 140 ± 50 and the elderly 65 ± 5. Both parameters are very important for monitoring people infected by the Covid-19 pandemic [6]. For this reason, we find several works that try to solve the problem of surveillance the respiratory and cardiac frequency. The work of T. Negishi et al 2020, proposed a system that measures blood volume based on an RGB camera, the extraction of the volume is thanks to the variation of light on the facial areas. On the other hand, they used a thermal camera to detect the variation of temperature near the nostrils or mouth in order to extract the respiratory frequency, and then they used a technique of multiple signal classification to extract the pseudo-spectrum of cardiac signals. The evaluation of the algorithm used was tested on 28 patients based on the machine classification techniques using the MATLAB software tool, the results showed that the technique used is similar to the measurement collected by traditional sensors (thermometer, ECG and breathing belt) [7]. Another work has been proposed to measure the heart rate remotely, this approach is based on the use of a video-collector based on photoplethysmography, the proposed approach is based on conventional neural networks [8].

In this work, we propose an overview of the different techniques used to monitor people in critical cases. In this case, the most monitored signs are heart rate, temperature, and respiratory rate, in this paper we will focus on the remote measurements and see its impact on the new Covid-19 pandemic. We also propose the evaluation of an algorithm dedicated to heart rate monitoring based on an RGB camera and a desktop. The results obtained after the evaluation showed that our algorithm gives almost sensor frequency values with an error of +/- 2 beats/minute.

The proposed work is divided into 4 sections, the first section for the introduction, followed by an overview of the system for monitoring physiological signs. The third section is dedicated to the evaluation of the algorithm and the results obtained, and finally the conclusion.

II. VITAL SIGNS MONITORING: AN OVERVIEW

Heart rate monitoring is becoming widely used not only for patients, but also for people who exercise sports, to surveil their beatings. From years ago, the Heart Rate Monitoring (HRM) have been useful and helped in saving lives, and all over these years, tools changed.

200 years ago, Rene Laennec has invented the stethoscope which made it possible to listen more accurately to of heart rate variability (HRV) that may have varied heartbeat [9]. Yet, it was impossible to illustrate or represent the variances of heartbeats, which made a big challenge that time. After a while of time and precisely at the start of the 20th century, the first electrocardiograph (ECG) was invented by the

physiologist Willem Einthoven [10] which we considered that time as a jumping change in scientific field, because with this invention we could have a graphic recording of the heart electric activity. After this recording, we can find compression techniques in order to reduce the size of the recorded files and send them afterward, which is called E-health [11].

The traditional techniques used to measure heart rate are based on contact sensors. These techniques are valid in cases where the contact between the doctor and the patient has no risk, which is not the case in today's conditions for people contaminated by Covid-19. Therefore, the most reliable and risk-free diagnostic tools are based on image processing and other techniques such as deep learning and machine learning. In this context we find several works elaborated in order to classify the cardiac data of the patients [12]. We find another work based on the monitoring of the heart rate variability using a video camera [13]. The monitoring of the cardiac condition is not only limited to the medical field, but we can also find other applications such as the conduction of cars [14].

Respiratory rate monitoring is regarded as a core nursing skill, it is a very critical vital sign that should have been monitored for every patient, it is considered as a very import part of diagnostic for patients especially those who have a distress in their respiratory process. The work of C. Uysal, et al 2020 presented a technique for estimating the respiratory frequency based on the probabilistic Kalman filter. The system used in this work offers real-time processing, the proposed algorithm was evaluated on a Desktop ASUS ROG CG8580 Intel Core i7-3770K @ 4.6Ghz [15].

III. STATE OF THE ART:THE LATEST DEVELOPMENTS

The monitoring of vital signs has been used from a while, as it has been considered as a very major important and critical part of auditing and supervising patients which may help doctors in a timely intervention that may save lives. However, the best way of this vital sign's exploration is not that easy yet, in like manner, a lot of works were elaborated, as many as existing tools. As it's known now days, Cameras are taking the lead well on the way to improve and reform health care, in this context. Using camera techniques can evaluate heart rate (HR) and heart rate variability (HRV) remotely using remote photoplethysmography (RPPG), an evaluation mechanism of HR control and exploration without using any kind of sensors. It only requires video recording with a good quality and high-resolution camera. It may be constructive and helpful in various kinds of physical and health surveillance [16]. The measurement actually is done as the same technique using sensors, yet, without any contact, it measures the variance of green, blue and red lights reflection variance from the surface of skin, as the contrast between specular reflection and diffused reflection. Mingliang Chen et al, 2019 [17] have also proposed in the same line a paper where they are exploring respiratory rate (RR), standing on remote photoplethysmography purchased from face videos. Authors are based on using motion compensation, two-phase temporal filtering, and signal pruning in order to catch signals with a good quality. The figure 1 is a schema describing the framework proposed in the paper for RR measurement from face videos [17].

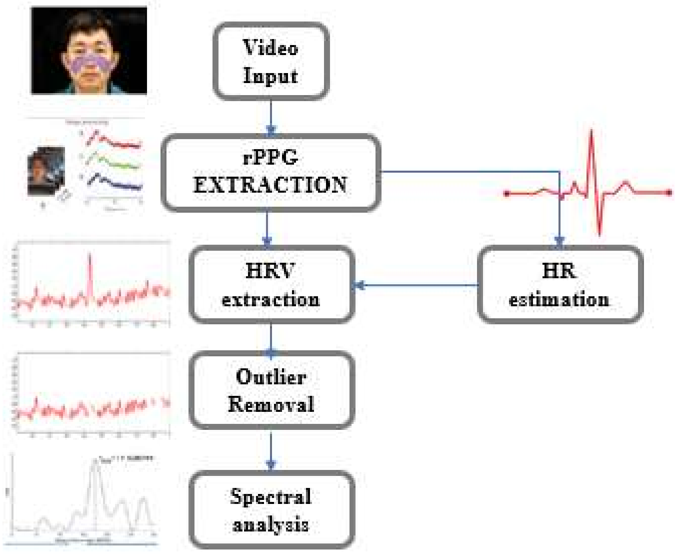


Fig. 1. Proposed framework in the paper [17] for RR measurement from face videos.

In heart rate measurement approach also, there is an algorithm elaborated by B.A Sujathakumari et al. 2018, in this article, authors proposed a method based on face tracking for HR estimation using Photoplethysmography (), with a noise reduction part using wavelet transforms [18]. The figure 2 is a schema describing the framework proposed in the paper for HR measurement from face videos [18].

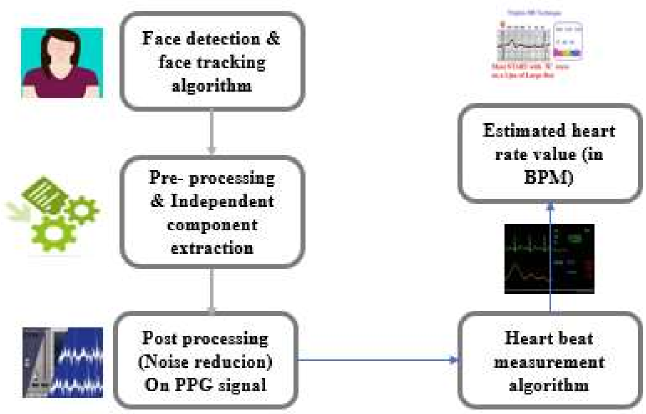


Fig. 2. Proposed framework in the paper [18] Block diagram of the framework for HR monitoring.

In addition, a noise estimation and suppression block are also used to correct data, besides, they created a real time system which extracts Independent components using

MaxKurt algorithm, and they achieved heart rate in beats per minute from a remote PPG (rPPG) from face processing.

Over and above, other algorithms and approach were based on visible light sensing (VLS), such as in [19] where authors are proposing a non-contact system of monitoring vital signs standing on VLS. The figure 3 shows the VLS-based non-contact vital signs monitoring system [19].

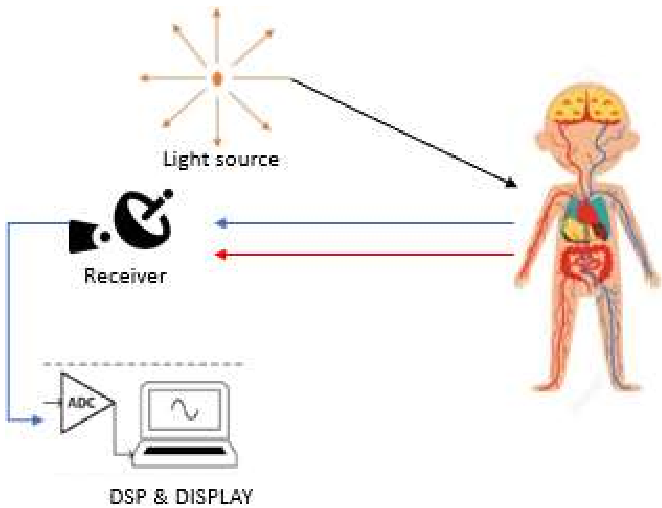


Fig. 3. Illustration of the VLS-based non-contact vital signs monitoring system.

In the same substance, [20] is a 2018 article where authors came with a new method standing, at the same time, on both RGB and NIR recorded face videos, where the approach plays on the variance between the spatial and spectral domains of suitable face patches, this method was also evaluated in different variance of light.

IV. RESULT AND EVALUATION

The algorithm proposed in this paper is devised in 6 steps, the first step is to link the USB camera with the desktop used. The RGB camera used is Microsoft LifeCam with 720p HD video chat and High precision glass element lens for sharp image quality. The camera used gives images with a resolution of 1035*691 and 30 fps. for the processing tools used we evaluated the algorithm on a desktop Intel Core i5-5200U CPU @ 2.20 GHz with 4GB RAM and GeForce 920M with 4046 MB RAM. After launching the video, the second step based on the extraction of the images captured by the RGB camera, and then the algorithm applies face detection techniques in order to focus on the color change on the face skin. This face detection will allow us to limit the calculation on the region of interest ROI to reduce the calculation on the image. Figure 4 shows the extraction of the images and the face selection.

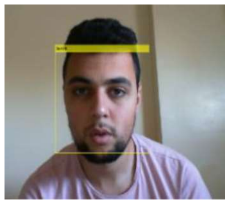
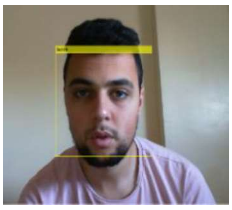


Fig. 4. Image extraction and face detection.

The third step is based on the conversion of the image to a matrix that contains the pixels of the image. Figure 5 shows this conversion in order to have a matrix for further processing.



$$\rightarrow \begin{pmatrix} RGB11\ RGB12\ RGB13 \cdots RGBn \\ RGB21\ RGB22\ RGB23 \cdots RGBn \\ RGB31\ RGB32\ RGB33 \cdots RGBn \end{pmatrix}$$

Fig. 5. Image to matrix conversion.

The 4th step is based on the separation of the bands to have one image containing red and the other containing green and blue. We can use this operation in several image processing applications which are based on band separation, e.g. monitoring in agriculture [21]. This step is very important to have an average of each band in order to be able to estimate the colour picks for each band. Our algorithm is based on the colour change in the patient's skin, after the evaluation of this block we have concluded that it consumes the execution time, to solve this problem we can use for example multispectral cameras that will help us to have images with separate bands that will reduce the execution time. The spike estimation equation for each band to estimate the heart rate is:

$$i_R(t), i_G(t), i_B(t) = \frac{\sum_{x \in ROI} I(x, y, t)}{|ROI|} \quad (1)$$

with:

- $i_R(t)$,$i_G(t)$,$i_B(t)$: are the signals of the red, green and blue components.
- I(x,y,t): the intensity of the pixel in the (x,y) position of the image over time
- |ROI|: the size of the selected region

The 5th step dedicated to filtering the images of each band in order to remove the applied noise either of movement or the blur of the images. In this step, we tested several filtering algorithms but the most effective is based on the wavelet transform.

The obtained signal will be noisy due to: subject movements, lighting changes, camera noise. To remove undesired noise from the signal, several signal processing techniques can be applied, such as low-pass filtering, bandpass filtering, adaptive bandpass filtering, discrete wavelet transform (DWT). The filtering method used in this work is based on the discrete wavelet transform, which allows precise analysis of different signal changes and elimination of noise affecting the signals. It is given by the following equation:

$$DWT(\tau_0, s_0) = \frac{1}{\sqrt{s_0^j}} \int_{-\infty}^{+\infty} x(t)\Psi\left(\frac{t - k\, s_0^j \tau_0}{s_0^j}\right) \quad (\mathbf{2})$$

With:

- $\mathbf{s_0^j}$: Scale factor
- $\boldsymbol{\tau_0}$: Translation factor
- $\boldsymbol{k\ and\ j}$: Integers

The last step is based on the estimation of the number of beats per minute after the filtering operation. This step consists of taking each image with different bands and calculating the average in order to estimate the curve of the red, blue, and worm bands, through this curve we can extract the number of beats per minute. The figure 6 shows the results obtained after the evaluation of the algorithm.

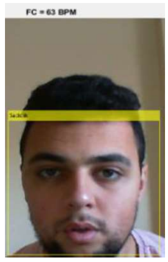


Fig. 6. Heart rate detection results.

Figure 7 shows the algorithm used in the evaluation of our algorithm with the different results obtained.

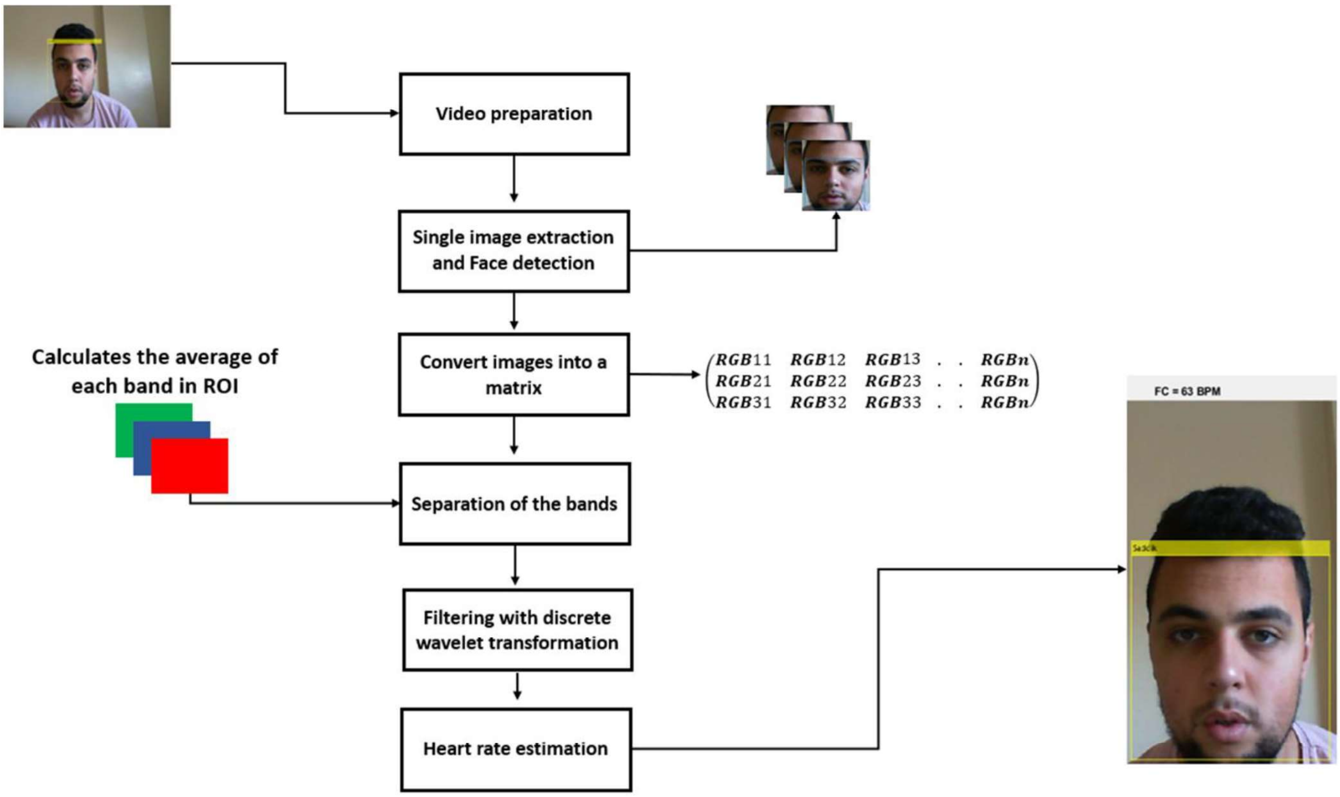


Fig. 7. Proposed algorithm.

V. CONCLUSION

The evaluation of vital sign monitoring algorithms, either respiratory or cardiac systems on conventional machines such as desktops or workstations does not imply implementation in real-time embedded systems. The use of embedded systems in this context will increase the reliability and flexibility of the system, taking into account the size and energy consumption. In this work, we have presented a state of the art on systems dedicated to non-contact monitoring of physiological signs such as respiratory and cardiac frequency. The use of these systems in hospitals will reduce the contact between the doctor and the patients, especially in this period of Covid-19 virus. As future work, we aim to develop a monitoring system that includes heart rate, respiratory rate, and temperature of patients contaminated by Covid-19, this system also contains a decision part that will help patients to get the necessary help before the doctor.

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