AMSE
IIETA International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Modelling, Measurement and Control C
Vol. 79, No. 4, December, 2018, pp. 173-178
Journal homepage: http://iieta.org/Journals/MMC/MMC_C

Remote sensing of vital signs and biomedical parameters: A review

Frédéric Bousefsaf*, Choubeila Maaoui, Alain Pruski

Laboratory of Conception, Optimization and Systems Modeling (LCOMS), University of Lorraine, LCOMS, F-57000 Metz, France

Corresponding Author Email: frederic.bousefsaf@univ-lorraine.fr

https://doi.org/10.18280/mmc_c.790404

Received: 11 September 2018
Accepted: 31 October 2018

Keywords:
vital signs, physiology, remote technologies, cardiovascular system, telemedicine

ABSTRACT

According to the World Health Organization, cardiovascular diseases correspond to the prime cause of death globally. Several technologies are employed to measure vital signs remotely. For instance, webcams correspond to ubiquitous systems that can be used to detect cardiovascular pathologies by sensing important physiological parameters like pulse rate. A review of technologies and methods used to remotely measure vital signs and biomedical parameters is proposed in this article. Remote sensing of physiological parameters concerns every person: from healthy, ill or hospitalized persons to people with disabilities or with reduced autonomy.

1. INTRODUCTION

Cardiovascular diseases are designated by the World Health Organization as the prime cause of death worldwide [1]. Because the risk increases as we age, cardiovascular diseases impose a burden in terms of mortality and morbidity, disability and functional decline. Telemedicine solutions provide interesting health care services over a distance through the use of telecommunications technologies. Solutions are designed to remotely monitor and diagnose (telediagnosis) important vital signs like heart and breathing rate.

Remote sensing of physiological signals and biomedical parameters is very relevant in the context of teleconsultation: the physician and the medical staff can improve their diagnostic as they chat with the patient through ICT (smartphone, laptop). Ideally, the remote measurements must be effected in a non-invasive and non-intrusive way; without any specific hardware or additional medical instrumentation; without any contact, preferably through cameras that are already embedded in mobile devices; in real-time. Remote sensing of medical parameters concerns every person: from healthy, ill or even hospitalized persons to people with disabilities or with reduced autonomy.

A large set of technologies has been developed or utilized over the last years to remotely measure important biomedical parameters [2]. These non-contact systems are increasingly preferred over contact devices, the latter being prone to irritation and discomfort if worn over a long period. In addition, infants in neonatal intensive care units and patients that present skin ulcers or burns may not be able to wear contact probes. Technologies that have been employed by the researchers in this particular scientific field can be categorized into three groups [2-4]: sensors based on the Doppler effect; thermal imaging; video camera imaging.

A review of technologies and methods used to remotely measure biomedical parameters is proposed in this article. A particular focus over video camera imaging is proposed in the last subsections of the article.

2. REVIEW OF METHODS: REMOTE MEASUREMENT OF PHYSIOLOGICAL AND VITAL SIGNS

A review of recent techniques that were developed to sense physiological signals is proposed in this section. Vital signs and biomedical parameters like pulse rate, pulse rate variability, breathing rate and oxygen saturation are continuously measured and monitored during abnormal episodes or when the person suffers from typical pathologies like brady- and tachycardia (pulse rate is respectively too low or too high), brady- and tachypnea (breathing rate is respectively too low or too high) or hypoxemia (when blood oxygen level is too low) [2].

The human cardiovascular and respiratory systems allow the proper functioning of all the different body organs [5]. The cardiovascular system, which is composed by the heart and the blood vessels, ensures transportation of blood, nutrients and oxygen throughout the body by the pulmonary and systemic circuits (Fig.1 A). The respiratory system supplies the body with oxygen and dispose of carbon dioxide through respiration processes (Fig.1 B).

Cardiovascular and respiratory activities lead to several physical and physiological body modifications. These effects cannot always be seen by the naked eye. However, they contain information of interest that can be sensed and measured with probes and sensors. For instance, skin color changes that are synchronized with heart contractions can be observed by standard camera [6]. This particular phenomenon, which is called photoplethysmography [7], consists in observing modifications between incident light and matter to sense blood volume variations and compute pulse rate and other relevant physiological signals.

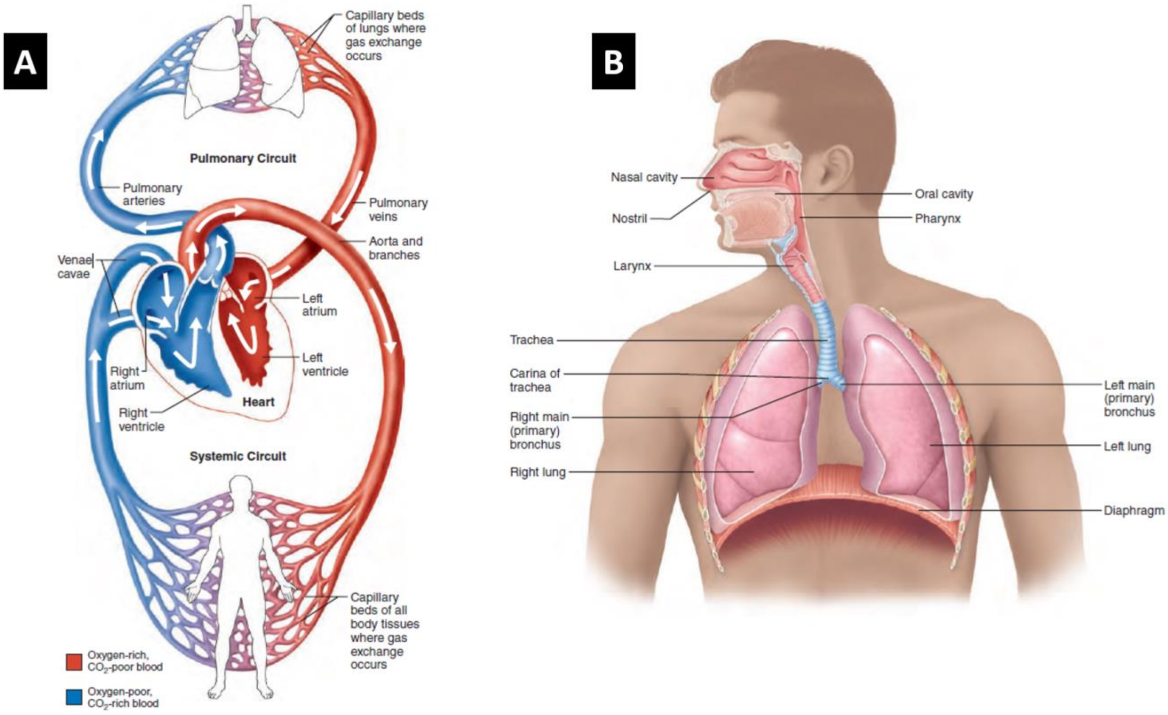

Figure 1. (A) The cardiovascular system and (B) the respiratory system. Modified from [5]

Myocardium (cardiac muscle) contractions cause periodic blood volume and blood pressure rises [5]. These modifications impact the body by causing unintentional head [8] and chest [3] movements that can be measured by remote sensors.

Physiological changes caused by the cardiorespiratory system can be sensed to compute biomedical parameters like pulse rate, pulse rate variability, breathing rate and oxygen saturation [2]. Recent researches include methods that relate to the Doppler Effect (section 2.1), thermal imaging (section 2.2) and video camera imaging (section 2.3).

2.1 Doppler effect

Volumetric changes orchestrated by the heart muscle are partially transmitted to the chest, producing slight unintentional chest displacements (Fig.2). Radars based on Doppler effect were employed for remotely sensing heart rate [3] and respiration [9]. These two physiological functions are concurrently present when observing human chest displacements. Thus, the challenge consists in efficiently separating raw signals before computing biomedical parameters. Because they produce significant noise and artifacts in signals, natural movements correspond to the main limitation of this technology.

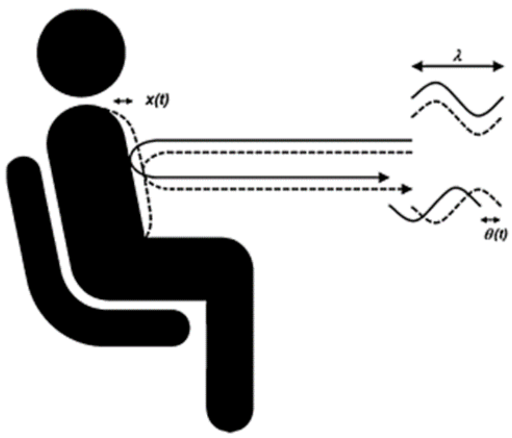

Figure 2. Pulse rate and breathing rate engender unintentional movements of the chest. These displacements can be sensed by the Doppler effect. The frequency and the phase of the reflected signal are slightly different from those of the source signal. From [3]

2.2 Thermal imaging

Thermal cameras are employed to remotely and passively (the camera does not emit any electromagnetic energy) detect radiations transmitted by bodies, herein by the human body. Sensors embedded in thermal cameras are manufactured to operate in the infrared spectral range (between near and far infrared). Pulse rate [10] and breathing rate [11] have been measured from thermal images (Fig.3).

The propagation of the cardiac pulse produces, by convection and conduction, modulations in the temperature of tissues. The evolution of skin temperature over time reflects the cardiac pulse waveform [12]. This effect is even more perceptible in superficial blood vessels, like the carotid for example (Fig.3 A). Digital processing techniques allow pulse recovering from composite signals [10].

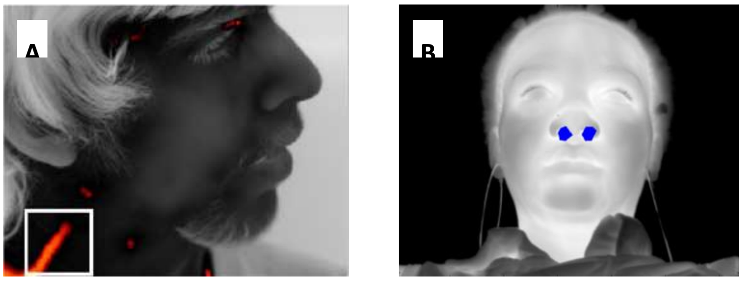

Figure 3. Temperature fluctuations of (A) carotid and (B) nostrils are continuously monitored to respectively measure pulse rate and breathing rate in thermal images. Modified from [10]

Expiration and inspiration are the two phases that characterize breathing in humans. During inspiration, heat exchanges with the external atmosphere cause a temperature decrease near the nostrils. In contrast, the expired air has higher temperature because of its interaction with the lungs and respiratory passageways. Thermal images have been employed to measure breathing by tracking nasal regions (Fig.3 B). A signal by nostril can be formed to detect a nasal congestion in left, right or even both nostrils [11]. Robust tracking of vessels in thermal images corresponds to one of the main challenges, and thus one of the main limitations, of this technology.

2.3 Video camera and webcam

2.3.1 Cardiovascular activity

Photoplethysmography [7] and ballistocardiography [8] are the two main principles for measuring pulse rate in video streams recorded by standard video camera.

Ballistocardiography (BCG) relates to the observation of small body displacements [13] that appear during systole (cardiac contraction), when the oxygenated blood is ejected into the systemic circuit and the deoxygenated blood into the pulmonary circuit (Fig.1). BCG is frequently measured on sitting subjects to minimize unintentional movements. When the heart beats, the flow of blood passes through carotid arteries at a high pressure. This generates a force on the head that is not noticeable by the naked eye but can be recorded by standard cameras using video amplification and magnification [8].

Photoplethysmography (PPG) consists in an indirect observation of blood volume variations by measuring absorption and reflection of light on skin tissues [7] (Fig.4 A). These fluctuations in volume are periodic and produced at each heartbeat: the volume of blood increases during systole (cardiac contraction) and decreases during diastole (cardiac relaxation). It must be emphasized that the definition of the principle is still discussed today: light variations that are remotely measured by the camera could in fact be produced by elastic deformations of the capillary bed (rise of the capillary density that compress tissues during systole) instead of a direct observation of the changes in section of the pulsatile arteries [14].

First measurements of PPG signals from facial videos recorded by a standard camera were proposed by Takano et al. [15] and Verkruysse et al. [16] in 2007 and 2008 respectively. The authors proposed a method that detects color fluctuations on the face from a set of predefined regions of interest. This technique has been employed on monochromatic (Takano et al.) and color image sequences (Verkruysse et al.). PPG signals are simply formed by averaging the intensity of pixels included in the region of interest.

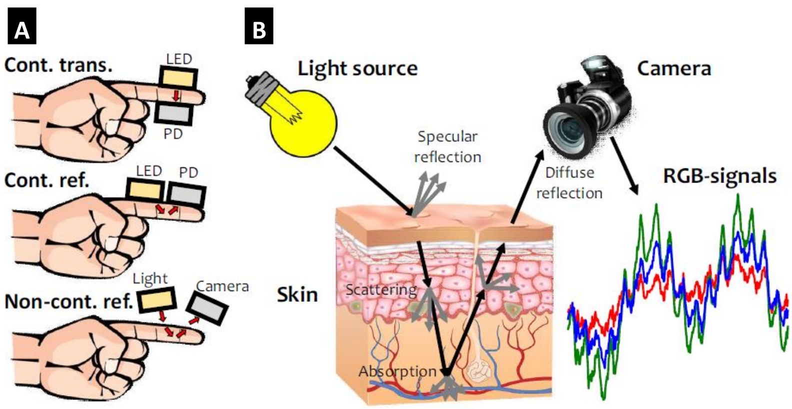

Figure 4. (A) Photoplethysmography consists in measuring variations in light absorption on skin tissues. (B) The RGB signals (one per chromatic component of the camera sensor) contain typical pulse waves whose shape depends on diastolic and systolic phases. From [17]

In practice, each color frame is converted into three RGB scalars and a full video into three RGB vectors (Fig.4 B). These signals contain several biomedical parameters of interest [18-21]: pulse rate, oxygen saturation, blood pressure and breathing rate.

Several digital processing methods [22] were proposed to process and filter PPG signals: Fourier transform [23] and continuous wavelet transform [24] have been used to create custom spectral bandpass filter in order to reduce and/or remove noise and artifacts in signals. Poh et al. [23] have employed a detrending method and independent component analysis, a blind source separation technique, to suppress artifacts induced by motion and light fluctuations in order to recover the cardiovascular pulse wave. The authors have used this filtering technique on red, green and blue signals that were computed from frames delivered by a low-cost webcam. De Haan et al. [25] proposed to transform RGB signals into two orthogonal chrominance components with parameters empirically defined from experiments.

The region of interest selected to compute PPG signals corresponds to an essential parameter of the methods [13, 16, 23]. Prior selection of pixels of interest by analysis of sub-regions [26] or using skin detection [24] has been introduced. Herein, PPG signals are computed using only the intensity of these pixels of interest.

Motion corresponds to the main limitation of PPG or BCG methods. BCG methods present two advantages over PPG methods: (1) they work even when the skin is not visible and (2) are not affected by variations of lighting conditions. They are, however, more affected by natural motion than PPG methods and are more prone to noise and artifacts when measuring over larger distances [2]. PPG has been far more exploited over the last years than BCG. Applications cover mixed reality [27], newborn health monitoring [28], physiological measurements of drivers [29], automatic skin detection and segmentation [30] and face anti-spoofing [31].

2.3.2 Blood oxygen saturation

The blood oxygen level, also known as peripheral oxygen saturation (SpO_2), is continuously monitored to detect respiratory insufficiency and respiratory diseases [7]. In healthy subjects, the rate is generally comprised between 95 and 100 percent. Hypoxemia is considered when this rate falls below 90 percent. Pulse oximeters are used to measure SpO_2 in a noninvasive fashion. These sensors, which are usually clipped to the finger, exploit PPG (see section 2.3.1 and Fig.4 A) to compute SpO_2 from PPG signals measured at different wavelengths [32]. It has been shown that SpO_2 can be remotely computed using PPG signals measured from video streams recorded by standard cameras [33, 34].

2.3.3 Respiration

Recent developments demonstrate that standard camera are relevant for sensing both the respiratory function and the breathing rate [4]. The researches can be categorized into three groups: body motion and displacements; PPG; thermal imaging (which will not be presented here, see section 2.2 for more details).

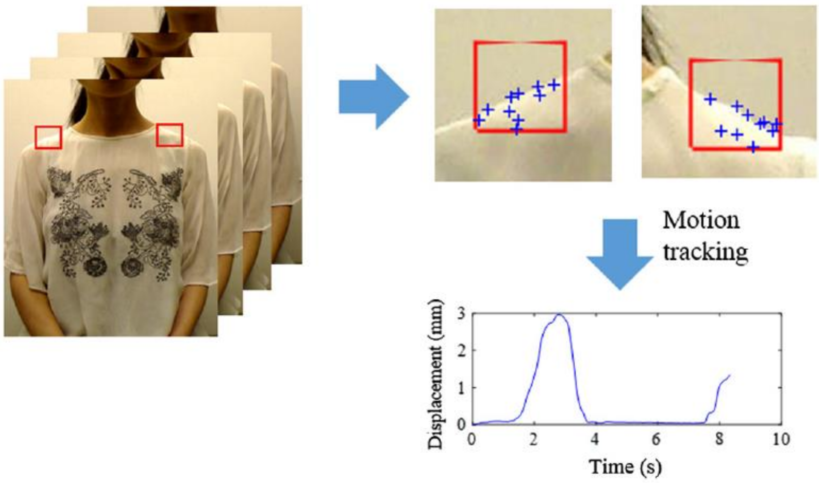

Figure 5. Breathing process produces a slight movement of the shoulders that can be tracked from video streams recorded by a camera. Computer vision techniques can be deployed to detect and track relevant features on the shoulders. A time signal that reflects the displacements, and thus inspiration and expiration phases, is computed from the tracked points. Modified from [35]

The first category regroups methods based on tracking chest motion during breathing by computer vision techniques. Shoulders are detected and continuously tracked using relevant features [35], forming a time signal that reflects shoulders displacements and thus inspiration and expiration phases (Fig.5). Other techniques employing dedicated hardware, like light projectors, multi-camera frameworks or 3D scanner have also been employed [4].

The second category of methods is based on PPG signals analysis to compute breathing rate [36]. Chest motion modifies blood pressure during breathing, which induces particular amplitude and frequency modulation of the PPG signal [37]. Digital processing methods like independent component analysis [23] and continuous [24] or discrete wavelet transform [38] were employed to extract breathing rate from raw PPG signals.

2.3.4 Blood pressure

Blood pressure is an important medical parameter. The measure enables detection and diagnostic of several cardiovascular diseases and pathologies like hypertension (high blood pressure). Different studies have shown that the Pulse Transit Time (PTT) is a promising way of measuring blood pressure in a noninvasive fashion [7]. Arterial stiffness rises when blood pressure increases, which also affects pulse wave velocity. Thus, the time the pulse wave takes to travel from one point of the arterial tree to another is reduced as blood pressure rises. Blood pressure in then estimated from pulse wave velocity using blood vessels elasticity models [7].

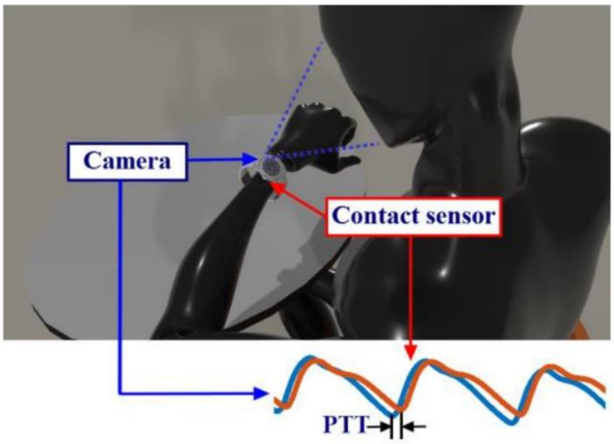

Figure 6. Pulse Transit Time (PTT) corresponds to the time the pulse wave takes to travel from one point of the arterial tree to another. In this example, PTT is computed using PPG waveform analysis of face and wrist. The physiological signals are recorded with a contact sensor (for measuring wrist signal) and a camera (for measuring face signal), both sensors being embedded in a smartwatch. From [39]

Recent studies have demonstrated that PTT can be measured unobtrusively from PPG signals taken at different body sites (Fig.6), like wrist and face using a smartwatch [39] or hand and face using a single video camera [40]. Junior et al. [41] have used smartphone camera and microphone to measure PTT: the moment the blood leaves the heart is detected by recording the heart sound with the microphone while the camera is employed to detect the time the blood reaches the finger by analyzing the PPG pulse wave.

3. CONCLUSION

The domain of physiological signals measurement using contactless devices has gained vast attention. Researches exhibit significant advancements over the last few years and demonstrate that standard video cameras correspond to reliable devices that can be employed to measure a large set of biomedical parameters without any contact with the subject. Nevertheless, and despite important advancements, the most recent methods are still not ready to satisfy real-world applications. The main challenge consists in improving robustness toward natural motion that produces undesirable noise and artifacts in the measurements. This issue is common to most of systems that record and analyze images to sense vital signs and biomedical parameters.

Clinical studies must now be conducted to confirm the relevance of methods tested in laboratory conditions and to, afterwards, constitute commercial systems. At the era of ubiquitous computing where mobile devices (smartphones, laptops, tablets) are omnipresent, cameras and webcams correspond to sensors that are already available and, thus, that are particularly interesting for unobtrusively measuring vital signs.

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