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An evaluation study of vital parameter determination with RGB cameras in the field of ambient assisted living

Abstract: The remote determination of vital parameters can contribute to the field of ambient assisted living (AAL) to face the challenges of a steadily ageing society. In this study, we examined the possibility to remotely measure the four vital parameters heart rate, respiration rate, oxygen saturation and blood pressure in AAL environments. For this, we evaluated the state of the art, implementations and concepts. While, the determination of heart and respiration rate is ready for usage, further attention has to be paid to the determination of oxygen saturation and blood pressure.

Keywords: Vital Parameters, Contact-less Measurement, Image Processing, Ambient Assisted Living

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1 Introduction

A major challenge Germany will be facing in future is a steadily ageing society. According to the national German statistical agency, 29 % of the population will be older than 65 years in 2030 [1]. This goes hand in hand with a lack of medical personnel to care for the elderly. Nowadays, in the field of ambient assisted living (AAL), research focussed on emergency detection, such as falls [2], and behavioural analysis [3]. To date, however, these systems are not able to monitor a person's current health status in order to act pre-emptively in case of indications for emergencies.

This issue could be solved by monitoring vital parameters by means of RGB cameras. The aim of our project is to outline the possibilities to monitor vital parameters, such as heart rate, respiration rate, oxygen saturation and blood pressure, in videos. To this end, several methods from image and signal processing were applied.

A crucial advantage of these methods is their contact-less working mode, so that the patients do not have to wear any additional devices. In this way, effects such as skin irritations and discomfort can be avoided. In case of variations of the vital parameters from standard values, medical personnel or relatives could be informed. Apart from the field of AAL, such a method would be most beneficial for the prevention of sudden infant death syndrome at neonates, in e-rehabilitation, for sleep monitoring and for monitoring a driver's well-being.

In this work, we will present the state-of-the-art methods for determining the four vital parameters heart rate, respiration rate, oxygen saturation and blood pressure by means of an RGB camera. Moreover, we evaluate their potential for AAL applications.

2 Heart rate

In the recent century, human heart rate measurement using different ways was a well-studied research topic in medicine. One method is the photoplethysmography (PPG), which was proposed by Hertzman and Spealman in 1937 [4]. Besides the commonly used transmissive approach, which determines the PPG on earlobes or fingers, there is the remote photoplethysmography (rPPG) [5]. Based on this, Verkruysse et al. introduced the first heart rate determination based on RGB cameras in 2008 [6]. This was followed by the first automated approach by Poh et al. [7], which comprises an independent component analysis (ICA) for a more robust determination of the heart rate. In a first step of this method, a face was detected within an RGB colour stream. Based on the detected face, a region of interest (ROI) was determined. This ROI is usually chosen to be a region with a small amount of movements, shadows and reflections and a sufficient number of superficial vessels. A spatial averaging of the pixels in the ROI resulted in a time varying signal for the three colour channels R, G and B. Subsequently, the dominant frequency within the signal could be identified with

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a spectral analysis. There exist several extensions of this basic approach. Lewandowska et al. suggested to use principal component analysis (PCA) to improve the computational speed [8]. Further works proposed to improve the processing chain by applying temporal filters [9], autoregressive models [10] or adaptive filtering [11]. In general, these methods are referred to as intensity-based heart rate determination methods.

An alternative approach, the so-called motion-based method, was proposed by Balakrishnan et al. in 2013 [12]. Their method made use of small head motions caused by the heart bump triggered blood flow. By using several striking feature points a person's face, these small head motions could be tracked over time. After that, a PCA determined the principal components, which represent the motions caused by the heart bump. Finally, the heart rate was determined by using a frequency analysis.

As shown in [13], intensity- and motion-based approaches have advantages and disadvantages. Intensity-based methods are capable of overcoming motion artefact in the video, whereas motion-based methods are unable to deal with large motions. This can be explained with the overlap of the heart bump motion signal and the motion artefact in the spectrum, because they share the same frequency bands. On the other hand, motion-based methods are less sensitive to illumination artefacts, such as shadows and reflections. By making use of this knowledge, intensity-based methods can be applied when less intensity artefacts occur and, analogue to this, the motion-based methods when less motion artefacts occur. This was implemented in a ratio-based method proposed in [13].

In order to evaluate the intensity-, motion- and ratio-based method, an evaluation process with 20 videos of different scenarios was carried out. The probands sat 0.5 to 2 metres away from the camera and were allowed to perform small motions. No additional light sources were used in these scenarios. The probands were instructed to perform squads before the recording of some of the scenarios to attain a higher variability for the heart rate. A Polar FT1 heart rate monitor was used as a reference system. The results are shown in Table 1.

In general, the intensity-based method performed better with an RMSE of 6.01 BPM than the motion-based-method with 7.58 BPM. Hence, it can be concluded that motion artefacts were the most crucial error sources in the scenarios. The ratio-based method, which represents a combined approach, showed the best result with 4.83 BPM.

Table 1: Root mean square error (RMSE) in beats per minute (BPM) for different heart rate determination methods

Method	RMSE in BPM
Intensity-based method	6.01
Motion-based method	7.58
Ratio-based method	4.83

The presented results show that the heart rate can be determined robustly. In order to make the approach more feasible for AAL applications further studies have to be conducted.

3 Respiration rate

Another vital parameter is the respiration rate. There exist multiple ways to determine the respiration rate in a clinical environment. They are respiratory effort belts, nasal thermistors or pressure transducer, for example. However, neither of these methods works contact-less. But there are already a number of publications in the field of remote respiration rate determination. Although a lot of work was carried out using thermal cameras or the Microsoft Kinect, we will focus on RGB cameras. A simple approach was suggested by Tan et al., who used frame differencing and edge detection [14]. Other approaches used 1D-profiles of persons in adjacent frames [15], determined intensity changes of the skin [16] or applied the Eulerian Video Magnification [17]. However, the most frequently utilised methods were tracking and optical flow based methods. Lukac et al. [19] proposed to use a KLT tracker [18] for the opical flow. This idea was extended with a PCA by Koolen et al. [20] and applied on the chest of a person by Li et al. [21].

For our approach, we first selected an ROI, which is placed on the chest or the back of a person's upper body [22]. Moreover, we split the ROI in four subregions. In the next step, minimum Eigen features were detected and tracked continuously with a KLT tracker during the videos. The y-trajectories of the tracked features were averaged in each of the four subregions, which resulted in four time signals. Subsequently, a bandpass filtering, a PCA, a channel selection and a frequency determination were performed.

In order to assess this approach, we recorded 35 different videos in total, which cover various scenarios [22]. In these scenarios, the distance from the camera, the illumination, the influence of clothing and the orientation of the probands were taken into consideration. For evaluation, the probands performed pre-defined guided breathing patterns with 30, 25, 20, 15 and 7.5 breaths per minute.

As a result, it could be shown that this method is suitable to accurately detect a person’s breathing pattern even when there was a large distance between camera and proband or when the proband wore texture-less clothing or a thick jacket. Furthermore, the algorithm does not depend on the proband’s orientation towards the camera. A source of noise are motion artefacts that can lead to incorrect respiration rates, because they exist in the same frequency band as the usual breathing pattern. Nevertheless, this method shows high potential to be used in the field of AAL. At this point, only measurements when the person is not moving should be taken into consideration.

4 Oxygen saturation

The remote determination of the oxygen saturation is a more challenging task than the remote heart rate and respiration rate determination. For the usual clinical usage, a pulsoximeter is taken for the measurement. For that, two LEDs with different wavelengths irradiate thin body parts, such as fingers, toes or earlobes. On the other side of the body part, a photodiode measures the intensity of the transmitted light. By using a calculation method called “ratio-of-ratios”, the concentration of the two relevant substances oxyhemoglobin (HbO_2) and hemoglobin (Hb) can be determined. The typical wavelengths for the LEDs are 660 nm and 940 nm.

There exist two general concepts to remotely determine the oxygen saturation with imaging devices. One method evaluates the pixel intensities of the red and blue channel of one RGB-camera, because they have different wavelengths. A disadvantage of this method is that the bandwidth for the red and blue channel is quite broad. A narrow band is to be preferred. The second setup consist of two cameras, which are equipped with narrow optical bandpass filters [24]. This approach is accurate in combination with the ratio-of-ratio approach. The major challenge at this point is an accurate pixel-to-pixel matching of the two cameras to determine the oxygen saturation of the same regions.

However, to date, these approaches work only in laboratory settings. A major challenge are motion artefacts, which effect the accuracy of the results. With this issue solved, these methods will contribute to the field of vital parameter determination. Another contribution would be the measurement of an oxygen saturation distribution map on the skin by the means of image sensors, as shown in [23]. Based on such a map, anatomic abnormalities could be localised. The application of these approaches in the field of AAL is generally possible.

5 Blood pressure

In contrast to the oxygen saturation, only little is known about remote blood pressure determination. We could not identify a single publication that is concerned with this issue. However, we propose an idea to solve this problem. Usually, the blood pressure is measured with the help of a blood pressure cuff. A direct determination of the pressure is impossible, but there is a linear relationship between the blood pressure and the pulse wave velocity. If we detect the peak on two positions on the body for the same pulse wave using the aforementioned rPPG, we can compute the time difference between these two measurements. Afterwards, we divide the distance of the positions by the determined time and obtain the pulse wave velocity. By introducing calibration parameters, the blood pressure can then be estimated. Since this method is a beat-to-beat determination of the pressure, the limiting factor will be the frame rate. Assuming a distance of 30 cm between two positions cm and a pulse wave velocity of 8-9 m/s in the A. femoralis [25], a frame rate of at least 100 fps is required for a proper peak detection. In addition to this, this idea has to be validated in the field.

A key strength of the presented idea is the increasing comfort for patients who have to measure the blood pressure regularly. For future medical applications, a peripheral arterial disease might be diagnosed by a measurement on the single limbs.

6 Conclusion

Our literature review and our measurements showed that a robust determination of heart and respiration rate is possible. At this point, we identified that further works have to concentrate on the determination of oxygen saturation and blood pressure measurements, see Table 2.

Table 2: Feasibility of the different vital parameters for AAL

Vital Parameter	Feasibility
Heart rate	Ready for usage in the field
Respiration rate	Ready for usage in the field
Oxygen saturation	Further improvement necessary
Blood pressure	Proof of concept necessary

In further, we want to robustly detect the oxygen saturation in real world scenarios and prove our concept for the blood pressure determination. Furthermore, we want to create an experimental setup to measure these vital parameters simultaneously.

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