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# BENCHMARKING OF CAMERA-BASED RESPIRATION MONITORING ALGORITHMS

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*This work presents the selection of technical and software tools for the organization of input and output data and the comparative analysis of algorithms in the suggested research scenarios. It reveals the existing advantages/disadvantages and areas of application.*

***Keywords:*** *respiration monitoring, signal processing, computer vision, object online tracking, subpixel image registration, filtering.*

**Formulation of the problem.** In recent years, a camera-based respiratory monitoring is gaining in popularity. However, the robust remote measurement of respiratory rate is still a dissatisfied need in clinical and home conditions and though the predicted value of respiratory rate for a patient's health is well known, this sign of life is often measured inaccurately or not at all. So, we decide to research the monitoring systems based on the camcorder developed by Philips for reliable measurements of respiration without any contact with the body.

**Analysis of recent research and publications.** The given publication has wide scientific and practical potential, since such methods and algorithms have no analogues, but they are widely gaining popularity abroad. But for the first time such a wide range of algorithms was studied simultaneously under various measuring conditions.

**The purpose of the paper –** to explore two methods - AutoROI and rPPG, for detecting human respiration signals using the camera-based systems.

**1. Introduction**. In physiology, respiration is defined as the mechanism of transporting oxygen from outside air to the cells within tissues and carbon dioxide in the opposite direction. A typical respiration system consists of tubes that filter incoming air and transport it into the microscopic alveoli where gases are exchanged. It has been well recognized that the adequate respiratory activity is essential in supporting the life of human beings. Thus monitoring human's respiratory status to aid diagnosis becomes a widely studied topic in healthcare research. Due to the fact that respiration behaviour is accompanied by many physical phenomena, so it is possible to quantitatively analyse the respiratory signal by measuring the variations in physical status, such as respiratory sounds, airflow, skin impedance change, chest movement, etc. As the most important diagnostic signal in respiration measurement - respiratory rate, defined as the number of breaths taken in certain amount of time, is widely used to predict the potential serious clinic events in patient surveillance. Therefore, numerous methods have been proposed to measure the respiratory rate from different aspects [1]. Example of breathing patterns in respiratory signal is shown in Figure 1.

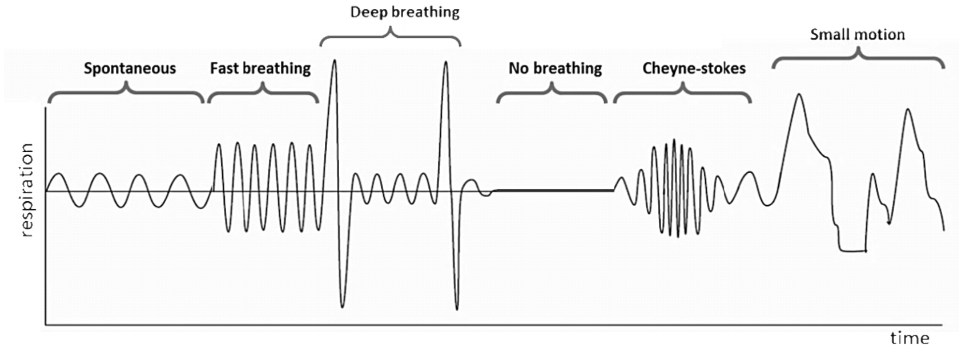


Figure 1: Example of typical breathing patterns in respiration: It can predict the potential clinic events by detecting the abnormal breathing patterns in patients' respiration.

Current technology for respiration monitoring can be divided in two categories: contact and non-contact-based methods.

On the one hand contact-based methods include analysis of respiratory sounds (microphone), respiratory airflow measurement (thermistor-based, pressure transducer), oximetry probe $SpO_2$, chest/abdominal motion measurement (inductance plethysmography (IPG)) and electrocardiogram derivation (EDR). Contact-based methods may interfere with normal breathing. On the other hand, non-contact methods include radar, optical, or thermal based solutions.

Nowadays, thorax IPG or EDR are some methods of choice, but are still penalized by some disadvantages, such as cabling and signal artifact. It is clear that non-contact methods are preferable for these reasons: such solutions avoid damaging fragile skin of neonates, and increase the comfort of babies 1. Thus, this project focuses on camera-based monitoring of respiration, which is challenging given the advantages that such a method could bring in practical situations.

**2. AutoRoi.** This algorithm builds up upon the preclassification algorithm hereon called ProCor.

In the first step, the input monochrome frame is divided into equal sized rectangular blocks. Each of these blocks is now independently processed for the next few steps. A motion detection algorithm is used to detect large motions. This results in a value per block which indicates the ratio of block area where motion is detected to the total block area. Concurrently, ProCor is applied on each block to extract a raw signal. This signal from every block is buffered and used to select candidate blocks using spectral analysis (Spectrum) [2].

In the next step of persistence computation, weights for each block are computed based on how often it was selected as a candidate block. For each block a counter is incremented when it is selected as a candidate block and decremented when it is not (until a lower bound of 0). The weight is then computed as the ratio of this counter to the total number of frames passed since the initialization of the algorithm. Persistence takes the advantage of respiration being a spatio-temporal consistent phenomenon, with the same spatial region having respiration like movements consistently over time.

Thresholding the persistence value appropriately allows for the visualization of the ROI (region of interest). However, when the subject moves substantially, the periodic temporal consistent nature of respiration is broken. Under such a situation the motion detection, sensitive only for larger motions, triggers the reset of the entire algorithm. On reset, the algorithm enters the initialization state, where all buffers and variables are cleared.

In the final step, the respiration signal is computed using all blocks within the ROI, as the weighted sum of respiration from individual blocks from which the respiration rate is extracted. A visualization of the entire procedure is shown in Figure 2.

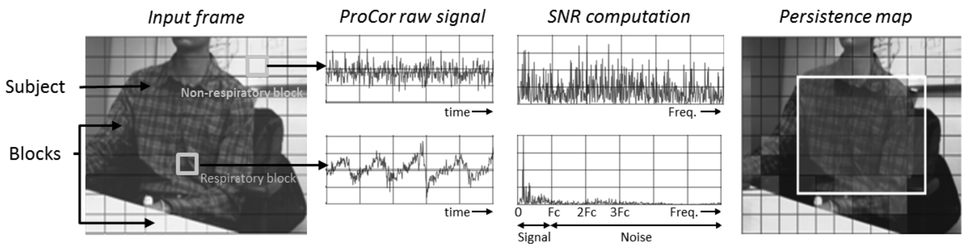


Figure 2: Visualization of the AutoROI steps.

**3. rPPG.** An overview of our proposed processing framework is visualized in Figure 3.

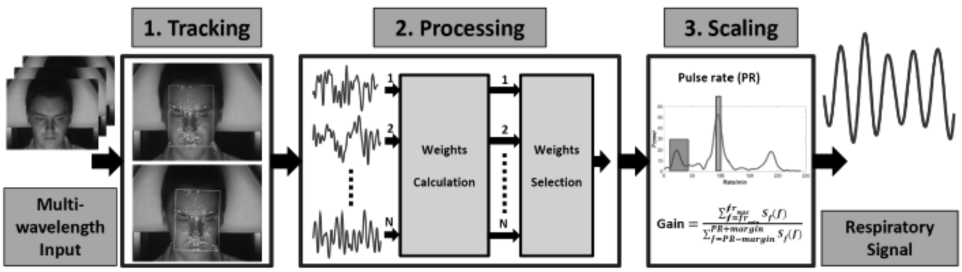


Figure 3: Overview of the proposed framework for robust respiration detection from remote PPG. 1) The manually initialized bounding-box indicating the face is tracked over time and divided into equally-sized subregions. 2) The weights for each (sub)region are calculated. From this collection of weights, the best are selected based on the SNR values of the pulse signals. 3) The extracted respiratory signal is scaled based on the ratio of respiratory and pulse energies.

The first stage of the framework is the tracking stage, where the movements of the selected ROI, indicated with the bounding box, are being tracked. For this task, the feature-based Kanade-Lucas-Tomasi (KLT) tracker is employed because of its accuracy, simplicity and limited assumptions made about the underlying image. Feature points (indicated with white crosses) are calculated using the minimum eigenvalue algorithm [3]. The geometric transformation of the feature points between two consecutive frames is calculated and applied to the bounding box. This bounding box is subsequently down-sampled into equally-sized subregions. For each frame, the spatial average of both the pixels within the ROI and each subregion are calculated, which enables to discard distorted, unreliable subregions.

After obtaining the motion-compensated, normalized pixel differences, we aim to find the optimal linear combination to construct the cardiac pulse signal, and hereafter, the respiratory signal. The processing stage consists of two operations: 1) weights calculation, and 2) weights selection. From the collection of weights from each (sub)region, the 'best' weights need to be selected, which are subsequently applied to the normalized differences of the entire ROI, which include only respiratory frequencies. This is achieved by selecting the weights which provide the pulse signal with the highest SNR. These weights suppress distortions best and are consequently best capable for the extraction of the respiratory signal to suppress distortions in this frequency band.

In eliminate the influence of the momentary strength of the PPG-signal on the amplitude of the respiratory signal, a gain factor, $k$, is computed by the ratio between the energies in the respiratory frequency band, e.g. 10-40 breaths/min, and the energy of the pulse signal. It is fair to assume that when the pulse amplitude doubles, also the respiratory amplitude doubles. Hence, by using the relative amplitude of respiratory energy versus pulse energy, one gets rid of the variations in pulsatility over time [4]. After scaling, the partially overlapping time-intervals are glued together with an overlap-add procedure by using Hanning windowing on individual intervals.

**4. Experimental setup and dataset.** In setup, participants in the experiments are asked to follow a particular breathing pattern visualized on a screen in front of the participant.

The video sequences are recorded with a global shutter RGB CCD camera (type USB UI-2230SE-C of IDS) and stored in an uncompressed data format, at a frame rate of 20 frames-per-second (fps), with a resolution of 768×576 pixels and with 8 bits depth. Recordings are made in a room with stable light conditions. Participants wear a finger sensor (pulse-oximeter), which data is synchronized with the video frames. To include both the face and chest-region, the camera is placed at a distance of 1 meter. An illustration of the experimental setup is visualized in Figure 4.

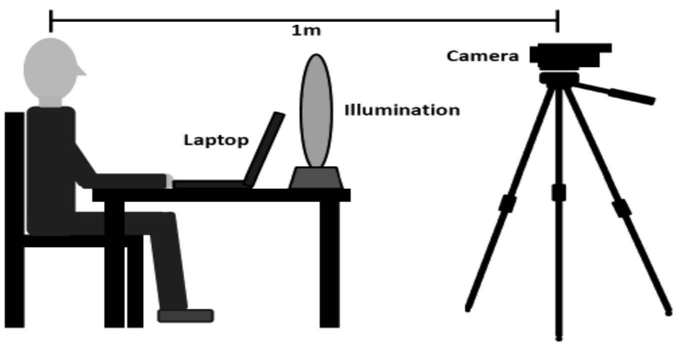


Figure 4: Overview of the experimental setup used for the creation of the dataset.

The performance of proposed method is evaluated on guided breathing of healthy adults in a laboratory setting. Recordings are made of healthy, Caucasian adult males, which are in sitting position. The duration of each recording is 120 or 150 seconds, depending on the scenario. The participants are asked to follow the breathing patterns displayed on a screen in front of them and to keep their head steady for all non-motion scenarios.

The proposed algorithm is implemented in Matlab (The Mathworks, Inc.) and executed on a laptop with a Intel Core i5 2.60 GHz processor and 8-GB RAM. A rectangular ROI indicating the face region is initialized manually in the first frame of the sequence.

**5. Objective measurements.** In order to quantitatively compare the overall performance of our methods, three objective measurement metrics are applied to evaluate the signals from different aspects: (1) *Peak to peak accuracy measurement*. In this method, the accuracy of extracted signals is measured by peak detection, such as how many peaks can be correctly or falsely detected, visualized in Figure 5. (2) *Respiratory rate measurement*. This method compares the signal changing rate between reference signal and extracted signal. Since the respiratory rate is a frequently used clinical variable, this method can provide a straightforward view for the quality of extracted signal [5].

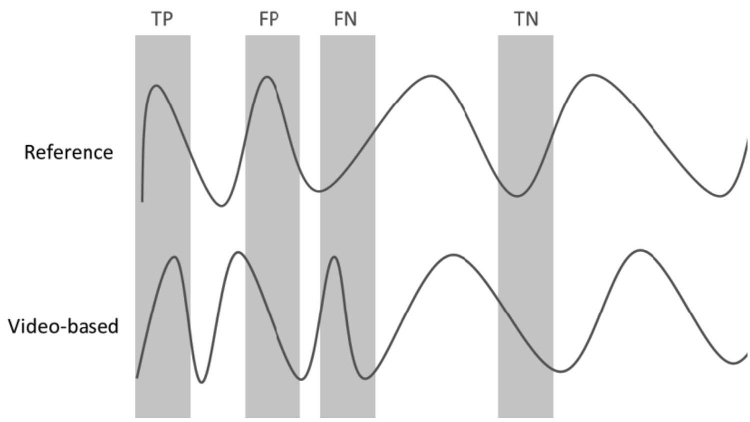


Figure 5: Peak to peak accuracy measure. TP: true positive, FP: false positive, FN: false negative, TN: true negative.

*Table 1*

**The mix matrix of peak to peak accuracy measure**

| Reference / Video-based | Peak | No peak |
|---|---|---|
| Peak | True positive (TP) | False positive (FP) |
| No peak | False negative (FN) | True negative (TN) |

**6. Results.** Example of the frame and results for two methods are visualized in Figure 6, Figure 7 and Figure 8 in accordance. In peak to peak accuracy measurement, AutoROI outperforms the rPPG in precision (0.9472 versus 0.4968), sensitivity (0.9543 versus 0.6669) and accuracy (0.9136 versus 0.4053). In respiratory rate measurement, AutoROI has lower Mean Squared Error compared with rPPG (0.6251 versus 5.5033) (Figure 9).


Figure 6: Example of the frame for object 1, video 1.

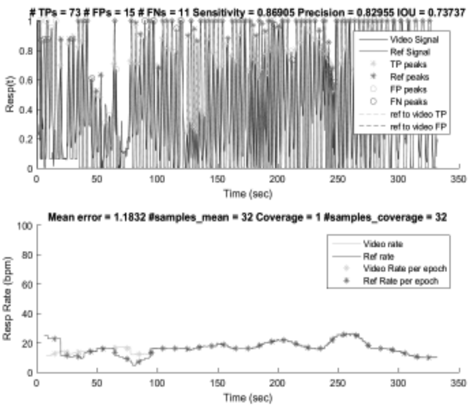


Figure 7: AutoROI results for object 1, video 1.

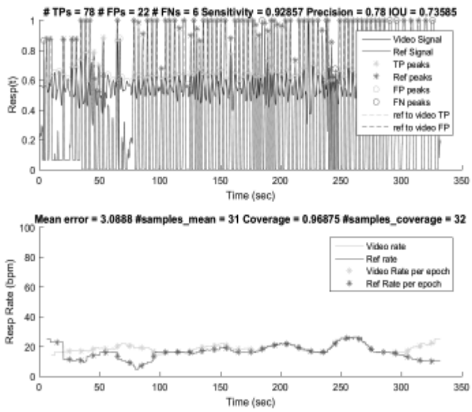


Figure 8: rPPG results for object 1, video 1.

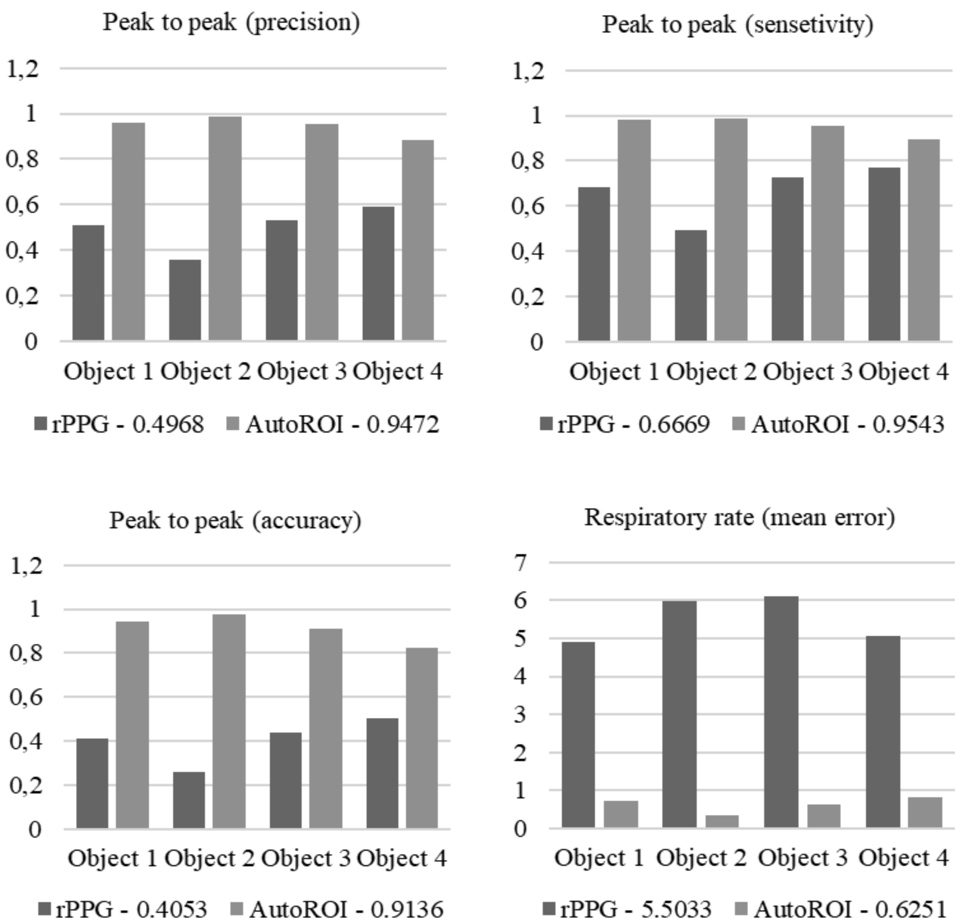


Figure 9: The overview of the comparison between rPPG and AutoROI in video set.

**Conclusions.** Video monitoring of breathing is an attractive new alternative to contrast with sensory techniques, which offers comfortable convenient and comfortable measurements. Implementing video surveillance for breathing is a great benefit for doctors, drivers and parents. However, the available methods for extracting respiratory signals are sensitive to many artefacts, especially in the case of involuntary body movement in the case of AutoROI and ProCor. The reasons for the failure of the above methods when working with the movement of the body are related to the initial models on which they are based. They suggest that the change in the low intensity in frames is caused by the breath and simulates the respiratory signal as the similarity (or differences) between sequential frames of the image. Changes in intensity that must be caused by motion or other noise are also considered as breathing on the basis of this assumption. Therefore, it is not surprising that the given respiratory signal will be damaged by body movement and other noise. In order to deal with non-breathable movements, we must first involve them in the model that we build.

In the case of rPPG, the metrics were much lower in any measurement scenario, but the algorithm is rather "raw" and works with only three methods for modulating the respiratory signal with a cardiogram, possibly with further research, based on Peter H. Charlton [6], the performance of the algorithm can be improved.

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## БЕНЧМАРКІНГ АЛГОРИТМІВ МОНІТОРИНГУ ДИХАННЯ НА БАЗІ ВІДЕОКАМЕРИ

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*Стаття представляє вибір технічних і програмних інструментів для організації вхідних та вихідних даних та порівняльного аналізу алгоритмів у ході запропонованого дослідження. Вона розкриває наявні переваги/недоліки та сфери застосування.*

***Ключові слова:*** *моніторинг дихання, обробка сигналів, комп'ютерне бачення, відстеження об'єкта, реєстрація субпіксельного зображення, фільтрація.*

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