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INTRODUCTION

Respiratory Rate (RR) is one of the key signs when determining the health status of a patient. Changes in it can be indicative of life-threatening conditions, so detecting them in real-time is crucial, especially when monitoring infants.

In clinical environments, RR is measured with: capnographs, pulse oximeters and ECG-based monitoring systems. These require close contact with the skin, which can become uncomfortable. Therefore, remotely monitoring RR with various methods has garnered a lot of attention.

Multiple ways of measuring RR remotely:

- acoustic measurements
- thermal images of exhaled air
- laser vibrometry
- depth camera
- **RGB camera**

The main advantage of using RGB cameras over other methods is the low price point. With a proper algorithm, even a laptop webcam should suffice.

Methods of measuring RR from RGB camera feed:

- Photoplethysmography - the colour of the skin changes depending on the level of oxygenation
- **Motion-based methods - the body rhythmically moves during inhaling and exhaling**

The aim of this project is to compare motion-based algorithms of extracting RR out of RGB camera feed, in the practical context of monitoring infants. The discoveries should aid in further developing algorithms meant for use on embedded platforms. Three algorithms have been chosen for the comparison: Pixel Intensity Changes (PIC), Optical Flow (OF), and Eulerian Video Magnification (EVM). They are also mentioned in Massaroni et al. [1].

RESEARCH QUESTION

How well do different motion-based algorithms of extracting respiratory rate from video camera feed perform in the real-time monitoring of infants?

Subquestions:

- What level of precision in respiratory rate can the different methods achieve relative to traditional medical devices?
- How computationally intensive is each of the methods? Is this feasible for real-time deployment?
- Under which conditions (lighting or position) does each of the methods perform best or worst?

REFERENCES

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2. T. Guo, Q. Lin, and J. Allebach, "Remote estimation of respiration rate by optical flow using convolutional neural networks," Electronic Imaging, vol. 33, no. 8, pp. 267–1–267–1, 2021. [Online]. Available: <https://library-imaging-org.tudelft.idm.oclc.org/ei/articles/33/8/art00004>
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METHODOLOGY

Steps for estimating RR:

- The chest Region of Interest (ROI) is selected
- The motion intensity is determined using one of the algorithms
- The outputted motion signal is analysed

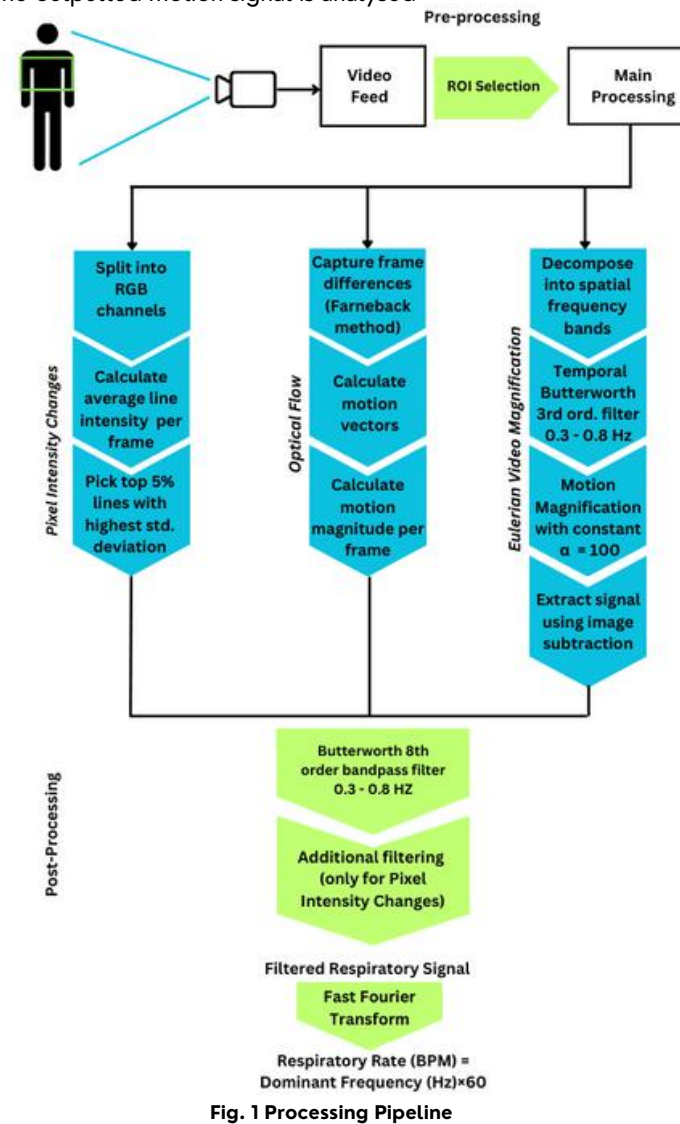


Fig. 1 Processing Pipeline

Algorithms are compared based on:

- Accuracy compared to ground truth: Root Mean Squared Error (RMSE), Pearson's Correlation coefficient (ρ), Mean Phase Coherence (R)
- Computational Complexity (CPU load, processing time per frame)

RESULTS

Accuracy

Method	RMSE	ρ	R
PIC	7.78	0.13	0.40
OF	7.90	0.01	0.37
EVM	7.59	0.02	0.39
Guo et al. [2]	6.74	0.32	-
AirFlowNet [3]	5.40	0.72	-

Table 1: Overall results of the three algorithms, as well as two other methods tested on the same dataset

Position	Algorithm	RMSE	ρ	R
Back	PIC	7.02	0.12	0.42
	OF	5.32	0.08	0.43
	EVM	5.73	0.03	0.43
Stomach	PIC	7.32	0.13	0.40
	OF	6.58	-0.03	0.36
	EVM	6.86	0.05	0.36
Side	PIC	8.35	0.13	0.39
	OF	9.68	0.01	0.35
	EVM	8.76	0.00	0.38

Table 2: Results of the algorithms on different positions of the subjects

Computational Complexity

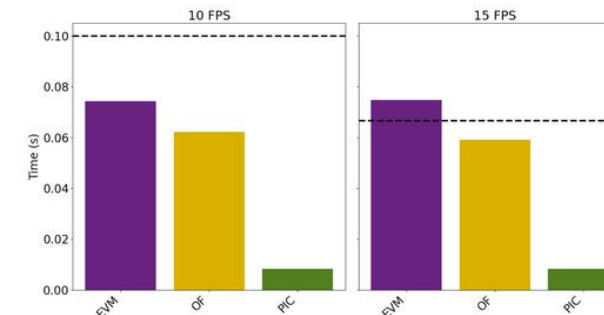


Fig. 2 Average Processing Time Per Frame, Split by number of FPS. Black line = delay threshold = 1 / fps second

LIMITATIONS

- Ground truth RR was not provided, only respiratory signal
- Challenging dataset (many positions, ROI obstructed by clothes and blankets, even Neural Network methods didn't perform that well)
- ROI selection was done manually
- ML techniques were not considered due to the high computational cost

R was introduced as a mean of comparing the extracted signal to the ground truth respiratory signal.

$$R = \left| \frac{1}{T} \sum_{t=1}^T e^{j\Delta\phi(t)} \right|$$

Position	Algorithm	RMSE	ρ	R
Coloured	PIC	7.64	0.18	0.45
	OF	7.58	-0.03	0.43
	EVM	7.54	-0.04	0.44
Greyscale	PIC	7.83	0.11	0.38
	OF	8.00	0.03	0.35
	EVM	7.62	0.03	0.36

Table 3: Results of the algorithms depending on video colour

- PIC performed the best out of the three, but still had a poor performance
- Having the subject on the back yielded the best results
- PIC performs better on coloured videos than on grayscale
- Higher R but very low ρ - the algorithms can extract a motion signal similar to ground truth, but it is not close enough to estimate the RR

	PIC	OF	EVM
Average CPU Load	6.42 %	2.79 %	2.37 %

Table 4: Average CPU Load throughout processing per algorithm

- PIC is the fastest by far
- Only PIC and OF can be considered real-time (on the machine that they have been run on)
- PIC requires more CPU power, but it is still very low, and also for a shorter time

CONCLUSION

- The poor performance of all of the algorithms suggests that such methods are not ready for real-life deployment yet.
- The PIC algorithm does show more promise, given the better accuracy and much faster performance.
- There remains much work to do for optimisation: e.g., improving the filter chain, determining the right window size for calculation, improving the ROI selection.