

Validating linear mechanical simulation of human respiratory motion using optical flow for camera-based vital signs monitoring

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Abstract— Problem: Camera-based vital sign monitoring offers an additional safety layer to general wards, but developing and validating such systems requires representative datasets of human respiration patterns. Current approaches rely on costly and time-consuming recruitment of human participants, limiting algorithmic development and benchmarking. A linear mechanical respiration simulator could reduce this burden, but only if it produces respiration patterns that the optical flow algorithm detects the same way it detects real human breathing. **Methods:** A respiration simulator was constructed and validated to faithfully reproduce human respiration patterns derived from a respiratory belt. A dataset of eight subjects was used across three scenarios where the subjects were lying still. Optical flow was extracted from videos of both the human subject and the respiration simulator performing the same respiration pattern using the Farneback optical flow algorithm. Correlations between human and simulator optical flow were evaluated separately for each scenario using Fisher’s z-transformation and one-sample t-tests. **Results:** Equivalence between detected movement by the optical flow for the human subject and respiration simulator was confirmed across all three scenarios, with mean r-values of 0.938 (95% CI: [0.895, 0.963]), 0.916 (95% CI: [0.845, 0.955]), and 0.935 (95% CI: [0.885, 0.964]), all significantly different from zero ($p < 0.001$). The respiration simulator reproduced respiration belt input signals with high fidelity (range: 0.895-0.995), and optical flow tracking of simulator movement was robust across physiological amplitudes and frequencies ($r > 0.952$). **Conclusions:** A simple linear mechanical simulator can replicate human respiratory motion in a manner equivalently detectable by optical flow algorithms. This validates the use of such a simulator as a controllable, repeatable alternative to human participants for developing, training, and benchmarking camera-based respiratory monitoring systems.

Keywords: *mechanical respiration simulator, respiratory movement, optical flow, camera-based vital signs, contactless monitoring, signal equivalence*

Contents

1	Introduction	4
1.1	Project context and motivation	4
1.2	Literature context and research question	4
2	Experimental Setup	5
2.1	Physiological basis and input signal justification	5
2.2	Design requirements	6
2.3	Setup	6
2.3.1	Hardware	6
2.3.2	Software	7
3	Methodology	7
3.1	Extracting respiration patterns with optical flow	8
3.2	Technical validation	8
3.3	Human simulation validation	8
3.3.1	Creating input signals for respiration simulator	9
3.3.2	Data analysis	9
3.3.3	Metrics	9
4	Results and Analysis	10
4.1	Technical validation	10
4.2	Human-simulator validation	10
4.2.1	Movement tracking validation	11
4.2.2	Movement input equivalence	11
4.2.3	Optical flow equivalence	11
5	Discussion	12
5.1	Technical validation	12
5.2	Movement tracking validation	12
5.2.1	Tracking of the movement of the respiration simulator	12
5.2.2	Tracking of the movement of the human subject	12
5.2.3	Comparison of tracking quality across the respiration simulator and human subjects	12
5.3	Movement input equivalence	12
5.4	Optical flow equivalence	13
5.5	Limitations and future directions	13
5.5.1	Study conditions	13
5.5.2	Dataset	14
5.5.3	Respiration belt attachment	14
5.5.4	Baseline drift removal	14
5.6	Implications	14
5.6.1	Optical flow algorithm validation and training	14
5.6.2	Testing detection of abnormal respiration patterns	14
5.6.3	Design for respiratory sensor benchmarking	14
6	Conclusion	15
7	Acknowledgements	15
8	AI statement	15
	References	15
A	Region of Interest	17
B	Ratios of the Input Signals	18
C	All metrics	19
D	Extra Figures of the Lab Study	20
E	Literature study	24

1 Introduction

Continuous monitoring in the Intensive Care Unit (ICU) has been essential in improving outcomes for critically ill patients [1], [2]. However, replicating this level of alertness in general wards remains challenging: appropriate monitoring systems are scarce, and there is a shortage of personnel for continuous monitoring [3], [4]. In routine clinical care, nursing staff generally check and document vital signs several times a day. When assessing respiratory rate (RR), nurses typically observe torso movements over a brief period [5], [6]. This method can lead to counting errors; as the observation period decreases, the potential for errors increases. The long intervals between assessments also make it difficult to detect early signs of deterioration, particularly during night shifts or in busy wards [7].

However, continuous monitoring of vital signs, including RR, heart rate (HR), body temperature and blood pressure, can help predict life-threatening conditions such as sepsis¹ and brain injury, and reduce mortality through increased awareness and timely clinical intervention [9]. Numerous studies even demonstrate that an abnormal RR is a predictor of potentially serious clinical events, underscoring the need for nurses and doctors to be aware of respiratory abnormalities [10].

This gap necessitates an additional safety layer for monitoring on the general ward, leading to the development of contactless and scalable monitoring solutions [3]. One approach is radar-based systems that utilise the Doppler effect. These systems work by transmitting a radio frequency signal and analysing the time-varying phase shifts in the reflected waves. Torso movements during respiration and heartbeats cause these shifts. The radar-based systems offer insensitivity to ambient light, the ability to operate through bedding, and inherent privacy preservation [11]. However, they require careful positioning and calibration, limiting their adaptability in different ward settings [11], [12].

Camera-based vital-sign monitoring offers a promising alternative. It tracks the respiratory motion of the torso by utilising algorithms to monitor the vertical and horizontal trajectories of pixels as lung volume changes, and it enables additional use cases such as fall detection and occupancy monitoring [13], [14].

1.1 Project context and motivation

Building on these capabilities, Philips is currently developing a camera-based respiration-monitoring system for use on hospital general wards. In the future, this system may resemble the scenario depicted in Figure 1, where a camera is placed in the hospital room to monitor the vital signs of a patient.

The system estimates respiration motion using pixel-wise motion vectors between consecutive frames, which are computed using the Farneback dense optical flow algorithm [15]. Which estimates motion by fitting local polynomial expansions to intensity variations across

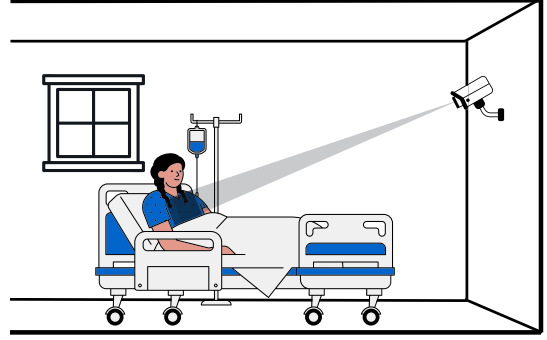


Figure 1: A patient in a hospital whose respiration rate is monitored in a region of interest by a camera-based vital-sign system.

consecutive frames to track the ventral (back-to-front) displacement (dy) of pixels within a defined region of interest (ROI). The decision to operate exclusively on a single axis is validated by Wang and Den Brinker [16], who state that respiratory energy is predominantly in one direction.

Developing and validating such a monitoring system requires a broad, representative dataset of respiration patterns, covering both normal and abnormal patterns. Currently, this data is collected from human participants in laboratory and clinical settings, which is both time-consuming and costly. Moreover, experience shows that finding individuals who want to participate and who collectively represent a sufficiently broad range of breathing behaviours is challenging. Therefore, a respiration simulator, a mechanical system capable of reproducing controlled, repeatable breathing patterns, offers a promising alternative. A simulator reduces the burden of participant recruitment and allows systematic testing of conditions difficult to achieve clinically (such as extreme respiratory amplitudes, precise phase delays, or irregular patterns). Lastly, it provides a stable benchmark for comparing algorithms, cameras, angles, and lighting conditions, since the underlying respiration pattern remains identical across tests.

1.2 Literature context and research question

To determine the most suitable simulator design, a literature review was conducted, see Appendix E. The review identified two categories of existing respiration simulators: anthropomorphic phantoms and mechanical motion platforms. Researchers primarily developed these technologies for quality assurance in medical imaging. Additionally, clinical educators utilise them for skills training in resuscitation and mechanical ventilation. This includes both custom phantoms and commercially available manikins. A smaller subset was designed to validate non-contact vital sign sensors, but those targeted radar-based rather than camera-based systems. Only Ulrich et al. [17] developed a torso motion simulator for evaluating surface-based respiratory gating systems with a camera. The thorax performs a rotational movement, whereas the abdomen has a linear up-and-down motion. The review also identified other design principles most relevant to this study. Existing respiration simulators rely on one of two actuation strategies, each with a distinct limitation.

¹Sepsis is a life-threatening condition that arises when the body's response to an infection injures its own tissues and organs [8].

Volumetric expansion systems inflate artificial lungs or airbags to produce surface movement, generating realistic, multi-directional deformation. However, they lack the fine control needed to reproduce precise, programmable and complex respiration patterns. Electromechanical systems, driven by linear actuators or stepper motors, provide precisely that control, but their motion is typically confined to a single axis. For applications requiring full three-dimensional torso deformation, that single-axis constraint is a limitation. For this study, it is not; the optical flow algorithm tracks only the ventral (back-to-front) displacement (dy) of pixels, so a linear actuator executing programmable, single-axis motion therefore reproduces exactly what the algorithm measures.

This leads to the central research question of this graduation project: *Can a linear actuator replicate human breathing movement in a way that is equivalently detectable by a camera-based optical flow algorithm?*

This central research question is divided into five sub-questions:

1. *What physiological features of human breathing are relevant for designing a respiration simulator?*
2. *What components are required to design a setup that simulates human breathing movement with a linear actuator?*
3. *How can a human respiration belt signal be scaled and converted into a valid displacement input for the respiration simulator?*
4. *Does the respiration simulator accurately reproduce the commanded displacement across the physiologically relevant range of frequencies and amplitudes?*
5. *Is the optical flow signal extracted from the respiration simulator statistically equivalent to the optical flow signal extracted from a human subject performing the same respiration pattern?*

These questions are answered by first exploring the physiological features of human breathing in the literature. And then, based on those features, create a setup which is validated based on certain design requirements. To generate realistic input signals for the respiration simulator within this setup, the signal from a respiration belt was transformed. Respiration patterns were recorded during a laboratory study conducted by Philips across various scenarios. All these different scenarios were then simulated with the respiration simulator and recorded. Next, three aspects were assessed: First, the tracking of both the human subject and the respiration simulator against their respective optical flow signals. Second, whether the respiration simulator accurately replicated the input signal from the respiration belt, by comparing the data from the belt to the laser measurements. Finally, the analysis determined whether the optical flow extracted from the videos of the human subject and the simulator was statistically equivalent. All four signals and their comparisons are shown in Figure 2.

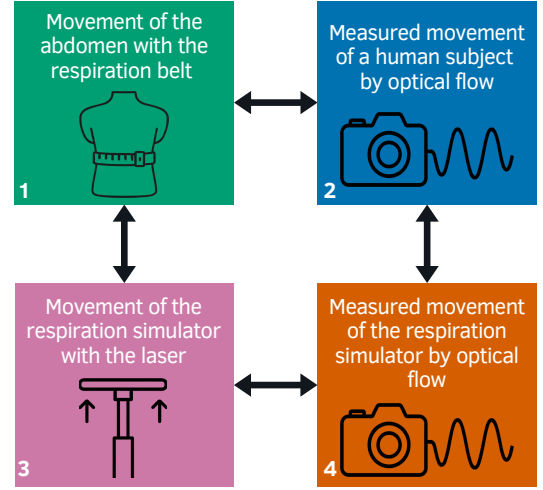


Figure 2: The four signals: (1) Respiration belt, (2) Optical flow signal of the human subject, (3) Laser tracking the respiration simulator, (4) Optical flow signal of the respiration simulator. And the double arrows represent the comparisons made between them.

2 Experimental Setup

This section describes how the respiration simulator was designed and built. It first establishes the physiological basis for the simulator's operating range, then specifies the design requirements that follow from it, and finally describes the hardware and software components of the experimental setup.

2.1 Physiological basis and input signal justification

To answer this question, the simulator must first be grounded in the physiological characteristics of human respiration. The average resting RR for adults is 12-20 breaths per minute (bpm) [18].

In the study of Kaneko and Horie [19], the mean RR in the supine position is 14.6 ± 3.7 bpm. Regarding displacement amplitude, they measured the three-dimensional displacement of different places on the thorax of 100 healthy participants. For this use case, the displacement of the third rib is most representative of the expected movement region of the simulator. In the supine position, the displacement of the third rib was $3.23\text{mm} \pm 1.85\text{mm}$ (right side) and $3.02\text{mm} \pm 1.78\text{mm}$ (left side) during regular breathing, rising to $30.86\text{mm} \pm 8.72\text{mm}$ (right side) and 30.00 ± 8.70 (left side) during deep breathing. These values, however, represent the total three-dimensional displacement and must be projected onto the ventral axis alone before being used as design targets.

Zhao et al. [20] demonstrates that torso motion during supine respiration occurs primarily in two directions: ventral (back-to-front) and cranial (feet-to-head). Assuming these two components contribute approximately equally to the resultant displacement (where the motion vector lies at roughly 45 deg between the two axes), the ventral component of any measured three-dimensional displacement is approximately $\frac{1}{\sqrt{2}}$ of the total magnitude. This assumption results in a required range of motion of 2.1 mm to 21.8 mm for the simulator, when using the

smallest and largest displacement value of Kaneko and Horie [19]. While this equal-contribution assumption is a simplification, it provides a conservative and reasonable bound given the available data.

To select an appropriate input signal for driving the linear respiration simulator, the study of Shafiq and Veluvolu [21] was used. In their research, they evaluated 11 participants using three different modalities for measuring cardiorespiratory function across four breathing conditions: free breathing, apnoea, irregular breathing, and post-exercise recovery. They recorded three-dimensional motion of the torso surface using 16 optical markers, applied a respiratory belt to assess respiratory effort, and utilised a nasal thermal sensor to monitor airflow through the nose. All measurements were taken while the participants lay in a supine position.

Using wavelet phase coherence, Shafiq and Veluvolu [21] found that the respiratory belt signal showed the highest correlation with ventral marker displacement across all conditions, with Maximum Phase Coherence in a selected Band exceeding 0.9 in 43 of 44 free-breathing trials and above 0.7 in the majority of irregular and post-exercise trials. This shows that a respiration belt signal is a reliable and practical input for driving a linear respiration simulator.

2.2 Design requirements

Based on the physiological analysis above, the selected input signal, and the constraints of the hospital deployment context, the following design requirements are established for the respiration simulator:

- Respiration frequency range: 12 to 20 bpm;
- Range of motion: 2.1 mm to 21.8 mm;
- Easy to control;
- Capable of reproducing multiple patterns derived from respiration belt signals;
- Must operate realistically on a hospital bed and underneath a bed sheet;
- Cost-efficient, given the early development stage and limited available resources.

2.3 Setup

An overview of the total setup is shown in Figure 3. The setup consists of the respiration simulator lying in a hospital bed and a camera, at a height of 1.85 meters, on a tripod 1.90 meters away from the footboard of the bed. It was constructed in an existing lab at Philips at the High Tech Campus in Eindhoven.

2.3.1 Hardware

For constructing the setup the following hardware was used:

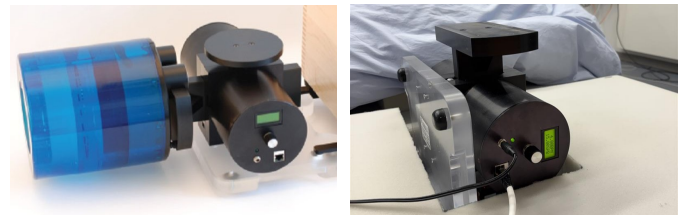
1. The Quasar Catphan Shaker (Modus Medical Devices Inc., Canada);
2. The laser sensor optoNCDT ILD1420 50 mm (Micro-Epsilon, Germany);
3. National Instruments USB-6008 (National Instruments, United States);



Figure 3: The setup in the Philips lab with a camera on a tripod (in the white square) and the respiration simulator underneath a sheet.

4. Resusci First Aid Anne (Laerdal Medical, United States);
5. Camera IDS U3-3290SE-C-GL (IDS Imaging Development Systems GmbH, Germany);
6. Basler Lens C11-1220-12M f12mm (Basler AG, Germany);
7. BP550 Near-IR/UV-Block Visible Bandpass Filter (Midwest Optical Systems, United States).

The *Quasar Catphan Shaker*, short *Quasar*, was used for simulating the human respiration pattern. This device helps ensure the quality of 4D CT (computed tomography) images by moving a Catphan phantom in the horizontal direction with programmable respiratory motion profiles, as shown in Figure 4a. In this study, the Catphan phantom was not connected, as it was not utilised for quality assurance. Also, the Quasar was mounted onto two Bosch profiles to rotate the moving platform 90 degrees since it was originally designed to move in the horizontal plane, see Figure 4b.



(a) The Catphan phantom attached to the left side of the Quasar [22]. (b) The Quasar turned 90 degrees, so the rectangle platform is up.

Figure 4: **Left:** The position of the Quasar for the original use case. **Right:** The position of the Quasar for this study.

The *laser sensor* was used to validate the movement of the Quasar, as it does not have an internal log system. This laser sensor is attached underneath the Quasar and tracks the moving platform, see Figure 5. The laser and a simple resistance were connected to a National Instruments USB, see Figure 6. The raw voltage is converted into a current value using a measurement resistance of $0.4692k\Omega$. Finally, this signal is scaled to measure the actual laser distance, ranging from 0 to 50 mm with an accuracy of $0.5\mu m$. The frequency was approximately $10Hz$.

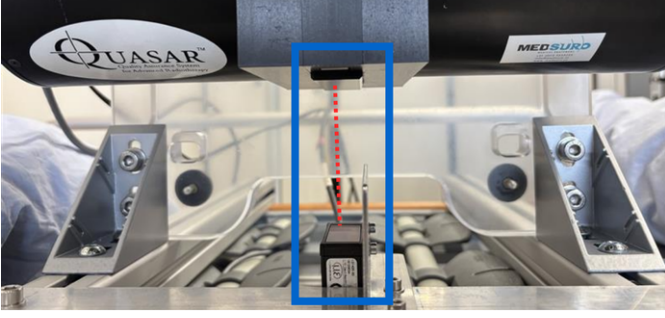


Figure 5: The laser and its path underneath the Quasar are shown in the blue rectangle. The red dotted line shows the path of the laser tracking the motion of the Quasar platform.

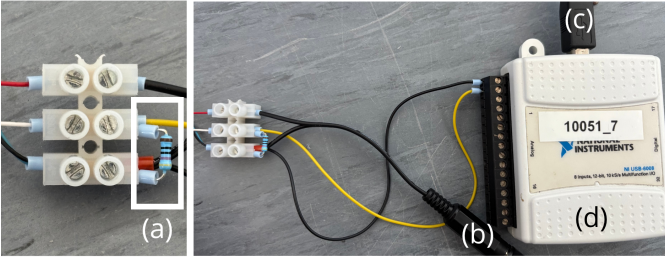


Figure 6: The laser is connected to a wire harness connector with the three wires on the left, and on the right side, the resistance of $0.4692k\Omega$ (a) and the power (b) are connected. The National Instruments USB (d) is connected through the analogue input and connected to the laptop via a USB (c).

The *Resusci First Aid Anne* is a manikin designed for training in resuscitation techniques. The front flap of the torso is unattached from the manikin and is attached to the Quasar, as shown in the Figure 7, to replicate the human shape of the torso. The head of Anne was also unattached and was placed on a pillow to create a more realistic scenario.

All components were assembled, resulting in the final respiration simulator. It was placed on the hospital bed, and a foam mattress was cut to fit on top of the Quasar and torso. The cut-out material served as legs, which were covered with a light blue, plain sheet.

A camera with an IDS system, equipped with a Basler lens and BP550 filter, was used to record the videos. The filter was implemented to block all light outside the visible spectrum since all tests were conducted in daylight. The camera was connected to a computer using an HDMI cable and recorded at a frame rate of 15 frames per second.

2.3.2 Software

The software programs which were used for controlling the setup are:

1. QUASAR programmable respiratory motion (Modus Medical Devices Inc., Canada);
2. NI LabVIEW 2018 (32-bit) (National Instruments, United States).

The Quasar is equipped with a software program called "*QUASAR Programmable Respiratory Motion*". This program allows users to load various existing or custom-made



(a) The Quasar mounted on the Bosch profiles.



(b) The Quasar covered by the foam mattress.



(c) The front flap of the torso of the Resusci First Aid Anne.



(d) The components of Anne on top of the Quasar.

Figure 7: Overview of all the components of the respiration simulator.

respiration patterns into the Quasar. The respiration pattern files are called "QRM files" and consist of a single column of values. The first value represents the title, the second specifies the number of values, and the third indicates the amplitude. The remaining values are position values scaled from -1 to 1, with a frequency of 100 Hz.

The laser sensor utilises a measurement program provided and developed by TU Delft. This is programmed in *LabVIEW 2018*, where data is collected via a National Instruments USB module (Analogue Input). The measured laser distances were then exported as a CSV file.

3 Methodology

This section describes the procedures used to compare all the signals from the human subjects and the respiration simulator. It covers the extraction of optical flow signals from video recordings, the technical validation of the simulator, the data processing, and the statistical approach used to compare the respiration simulator and the human signals.

3.1 Extracting respiration patterns with optical flow

The recordings of the camera were exported as a ZBIN file. However, to see it and make it compatible, it needed to be converted to an MP4 file. To process and analyse all the gathered data, *Python 3.14.2 (Python Software Foundation, United States)* was used in *Visual Studio Code (Microsoft Corp., United States)*. To extract the respiration movement from the recorded video data, a custom Python script utilising the OpenCV (*cv2*) library is developed. The prompt *cv2.calcOpticalFlowFarneback* was used to estimate the motion of all pixels within a predefined ROI by analysing the intensity changes between consecutive frames. Within the selected ROI, the vertical displacement (dy) of pixels is averaged for each frame to capture the ventral (back-to-front) movement of the respiration motion. When using the optical flow, it is essential to note that movement upward, defined as a positive y-direction, is equivalent to a negative pixel movement in the optical flow. The detected movement by optical flow is expressed in pixels per frame, representing the mean vertical pixel displacement within the ROI between consecutive frames.

The ROI was fixed for the setup, see Figure 8, but was manually set for the subject data. The size of the ROI was equal in all these, with a width of 125 pixels and a height of 90 pixels. And all the different ROI's used for extracting the optical flow signal out of the videos can be seen in Table 3 in Appendix A.

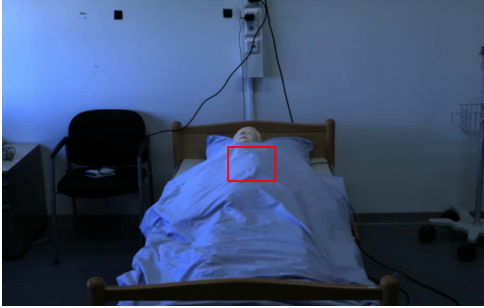


Figure 8: A frame of a video with the fixed region of interest for the respiration simulator (zoomed in).

3.2 Technical validation

To validate the respiration simulator, various simple signals were used as input. The amplitudes and frequencies selected for validation were determined based on those of a healthy adult. Therefore, based on the design requirements mentioned in subsection 2.2, the input signals created are a combination of different amplitudes of $1mm$, $4mm$, $7mm$, and $10mm$ and frequencies ranging from $12bpm$ to $20bpm$, leading to a total of 12 signals. As mentioned, the software "QUASAR programmable respiratory motion" comes with some standard respiration patterns. All 12 patterns were created by adjusting the frequency and amplitude of the standard respiratory signal. All the standard input signals were flipped around the x-axis to compensate for the fact that the QUASAR was rotated 90 degrees, see Figure 4b. These patterns were then filmed and further processed with the optical flow

to compare the generated movement with the detected movement.

3.3 Human simulation validation

Philips gathered human data in the setup with the camera lab study². This study consists of 12 subjects, who were measured and filmed in multiple positions and situations, named scenarios. Since the respiration simulator lies vertically on the bed, only the captured data while a subject lying in a supine position on a horizontal bed with no movement is used. Just three scenarios met these requirements, see Table 1. All these scenarios were recorded during daylight.

Scenarios	Time
3.1: Not moving in supine position	2 minutes
5.1: Not moving in supine position with a medical mask covering the nose and mouth	2 minutes
7.1: Not moving in supine position with the sheet covering the whole body, including the head	2 minutes

Table 1: Three scenarios where the subjects were lying in supine position.

Of the 12 subjects, only eight subjects included all the required data, so in total, 24 different (8 subjects in 3 scenarios) situations were used. The eight subjects, five women and three men, had an age between 35 and 69 and a BMI between 19.5 and 44.7, of which only one subject had a healthy BMI ($18.5 - 25$) [23].

In the study, the respiration belt of the Alice NightOne (Philips Respironics, United States) was used for gathering human respiration data. The subjects wore the respiration belt around their abdomen, see Figure 9.

The respiration belt operates on the principle of Respiratory Inductance Plethysmography (RIP), in which a conductive wire is woven in a sinusoidal pattern across the width of an elastic belt. As the abdomen expands and contracts during breathing, the cross-sectional area enclosed by the wire loop changes, altering its inductance [24]. This change in inductance is measured and converted into a continuous, relative signal proportional to the breathing movement. The resulting output is a dimensionless, linearly scaled waveform in which inhalation (expansion of the torso) corresponds to a peak, and exhalation corresponds to a trough.

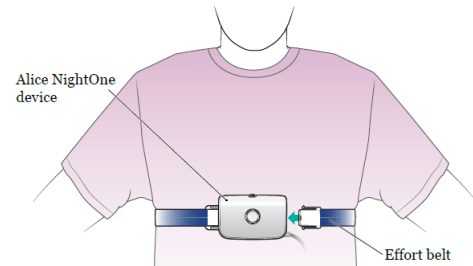


Figure 9: The respiration belt (Alice NightOne) attached to the human torso [25].

²METC Maxima MC N25.082, protocol: SEF-2025-301445.

3.3.1 Creating input signals for respiration simulator

To extract data from the respiration belt (Alice NightOne), the Sleepware G3 software (Philips-Respironics, United States) was used. The files were exported as EDF files and manually synced to the frame numbers of the MP4 video. This synchronisation was achieved per subject by identifying the moments when the respiration belt was being pulled, which produced small peaks in the data.

After the syncing, all the start times and durations of the 24 situations were used to crop the EDF files. To use the EDF files as an input for the respiration simulator, they needed to be transferred to a linear movement. Therefore, they need to be scaled to mm and converted to a QRM file. The ratio between the expansion of the respiration belt and its conversion to linear movement of the respiration simulator was determined by first calculating the number of pixels per unit. Subsequently, through validation measurements, the ratio was established between millimetres of movement and pixels, using data from the technical validation, which was found to be $5.46\text{mm}/\text{pixel}$. Together, these findings provided a conversion factor to translate the respiration belt signal into a linear motion of the respiration simulator, of which the final amplitudes can be seen in Table 4 in Appendix B.

3.3.2 Data analysis

After creating the input signals for the respiration simulator, the videos were recorded for each situation, which resulted in four types of data for all 24 situations:

1. The EDF files of the respiration belt;
2. The MP4 file of a human subject in a certain scenario;
3. The CSV file of the laser, which tracked the movement of the respiration simulator;
4. The MP4 file of the respiration simulator.

Pre-processing: First, the optical flow signal was extracted from the MP4 files. To make sure that the results are as reliable as possible, the four signals were corrected for drift and centred. A two-step pre-processing was implemented to remove low-frequency drift and centre the signal. In the first step, a rolling mean with a 6.5-second window was subtracted from the raw signal to remove slow background fluctuations. This window duration was selected to match the slowest breathing rate, so the longest breath time. Given the lowest observed breathing frequency of approximately 9.4 bpm, this equals about 6.4 seconds per breath. Then, the signal was centred around zero to make it easier to process. And lastly, since the optical flow detects the movements reversed compared to real life, the optical flow signals are reversed.

Synchronisation: The synchronisation was performed in three steps. First, since the signals differ in unit, all signals were first z-normalised to zero mean and unit variance. This standardisation made the result insensitive to differences in magnitude. The z-normalisation was chosen to limit the influence of outliers, which does happen when using standard normalisation between -

1 and 1. Second, due to differences in the sample rates in the signals, they were resampled to a common frequency using interpolation. Finally, the lag at which the cross-correlation reached its maximum value was used to identify the time offset between each pair of signals. The target signal was then adjusted to align with the reference signal.

3.3.3 Metrics

To compare the overlap between the input signal and the measured movement by the optical flow in the ROI, the Pearson correlation coefficient was calculated. Singh et al. [9] uses the Pearson correlation coefficient to determine the similarity between simulated waves and a reference signal of chest wall motion due to respiration and heartbeat.

The Pearson correlation coefficient (Equation 1), also known as Pearson's r , measures linear correlation between two sets of data. A high Pearson's r indicates that the video signal accurately captures the movement of the respiration simulator or the human subject [26].

$$r = \frac{\text{Cov}(Y_{\text{OpticalFlowCamera}}, Y_{\text{Laser/RespirationBelt}})}{\sigma_{\text{Camera}} \sigma_{\text{Laser/RespirationBelt}}} \quad (1)$$

Where the formula for covariance is:

$$\text{Cov}_{X,Y} = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{n - 1} \quad (2)$$

Pearson's r is calculated for the human and respiration simulator movement and its detected movement (the vertical arrows in Figure 2). Also, the r -values of the two movement signals and the two optical flow signals (vertical arrows in Figure 2) are calculated.

To compare the differences in pixels of the two extracted optical flow signals, the Mean Absolute Error (MAE) (Equation 3) was determined.

$$\text{MAE} = \frac{\sum_{i=1}^n |Y_{\text{OF, human}} - Y_{\text{OF, simulator}}|}{n} \quad (3)$$

The MAE is suited for this study because the signals have the same unit, and all errors must be weighted equally. Another metric for measuring errors is the Root Mean Square Error (RMSE). The RMSE is the square root of the average of all squared differences between predicted and actual values. This metric was not chosen because larger errors are disproportionately heavy because they are squared, and it does not represent the performance of the two optical flow signals. To compare the MAE of all the different situations, it is important to compensate for the difference in amplitude. A higher amplitude will result in a higher MAE; therefore, the relative MAE is also calculated. This is done by first multiplying the MAE by the ratio of mm per pixel, followed by dividing it by the mean amplitude in mm of the specific scenario measured by the laser, resulting in a dimensionless metric.

To assess whether the correlation between the two optical flow signals is statistically significant, a one-sample t -test was applied separately for each scenario, with the null hypothesis that the true population correlation equals zero

($H_0: \rho = 0$). The null hypothesis $\rho = 0$ was selected not because a specific correlation target was established, but rather to investigate the actual magnitude of the correlation. While it is highly unlikely that the true correlation equals zero, the combination with the confidence interval provides sufficient information to assess the strength of the correlation. Analysing the scenarios separately, rather than averaging across them, preserves potential differences between conditions and avoids obscuring a scenario effect behind a combined estimate. The eight r -values within a scenario are independent because each value comes from a different subject.

A direct one-sample t -test on the r -values is not valid, however. When the true population correlation ρ is not zero, the sampling distribution of r is skewed rather than normal. This skew worsens as ρ approaches 1, because r is bounded at 1 and cannot exceed it. Although the null hypothesis assumes $\rho = 0$, the test itself does not presuppose this is true. The purpose of hypothesis testing is to evaluate whether the assumption holds. Because the true value of ρ is unknown, it cannot be assumed that r will be normally distributed, and thus the standard error of r cannot be estimated without transformation. Fisher [27] showed that transforming each r using

$$r' = \frac{1}{2} \ln \left(\frac{1+r}{1-r} \right) = \tanh(r) \quad (4)$$

resolves both problems. The transformed values r' are approximately normally distributed regardless of whether $\rho = 0$ or $\rho \neq 0$, and their standard error is constant across all values of ρ [26], [27].

For each scenario, the mean and standard deviation of the eight r' -values were computed as

$$s_{r'} = \sqrt{\frac{\sum_{i=1}^n (r'_i - \bar{r}')^2}{n-1}} \quad (5)$$

from which the standard error was derived as $SE = s_{r'}/\sqrt{n}$. The test statistic was computed as

$$t = \frac{\bar{r}'}{SE} \quad (6)$$

which follows a t -distribution with $df = n - 1 = 7$ degrees of freedom. The two-tailed p -value was obtained from this distribution. The mean Pearson's r and its 95% confidence interval were computed in r' -space and back-transformed to r with:

$$95\% \text{ CI} = [\tanh(\bar{r}' - t_{0.975,7} \cdot SE), \tanh(\bar{r}' + t_{0.975,7} \cdot SE)] \quad (7)$$

Where a confidence interval positioned entirely above zero confirms that the correlation is statistically significant, and its location and width further indicate how large the correlation is in practice [26].

4 Results and Analysis

4.1 Technical validation

For 12 different input respiration signals, the displacement was tracked using optical flow. The Pearson's r values of the displacement of the respiration simulator compared with the tracking of the movement by the optical flow are shown in Figure 10.

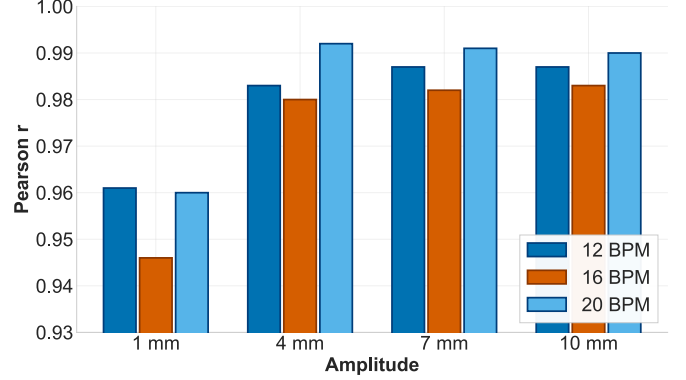


Figure 10: The Pearson's r -values between the movement of the respiration simulator measured by the laser and its tracking with optical flow for the technical validation.

In Figure 11, the laser and optical flow signals of the respiration simulator of the combination (1 mm and 16 bpm) with the lowest r -value is shown.

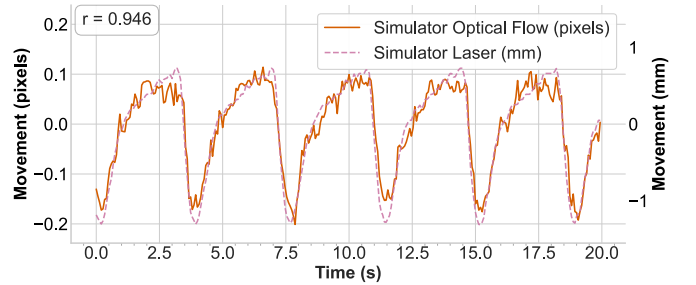


Figure 11: Frequency of 16 breaths per minute with amplitude of 1 mm: The validation of the displacement of the respiration simulator measured by the laser and the detected movement by the optical flow plotted for 20 seconds.

Since all the values are above 0.946, the results confirm that the simulator operates as intended, satisfying the precondition for the human-simulator validation in the following section.

4.2 Human-simulator validation

All the Pearson's r -values and relevant information about the different subjects and scenarios are structured in Table 5 in Appendix C.

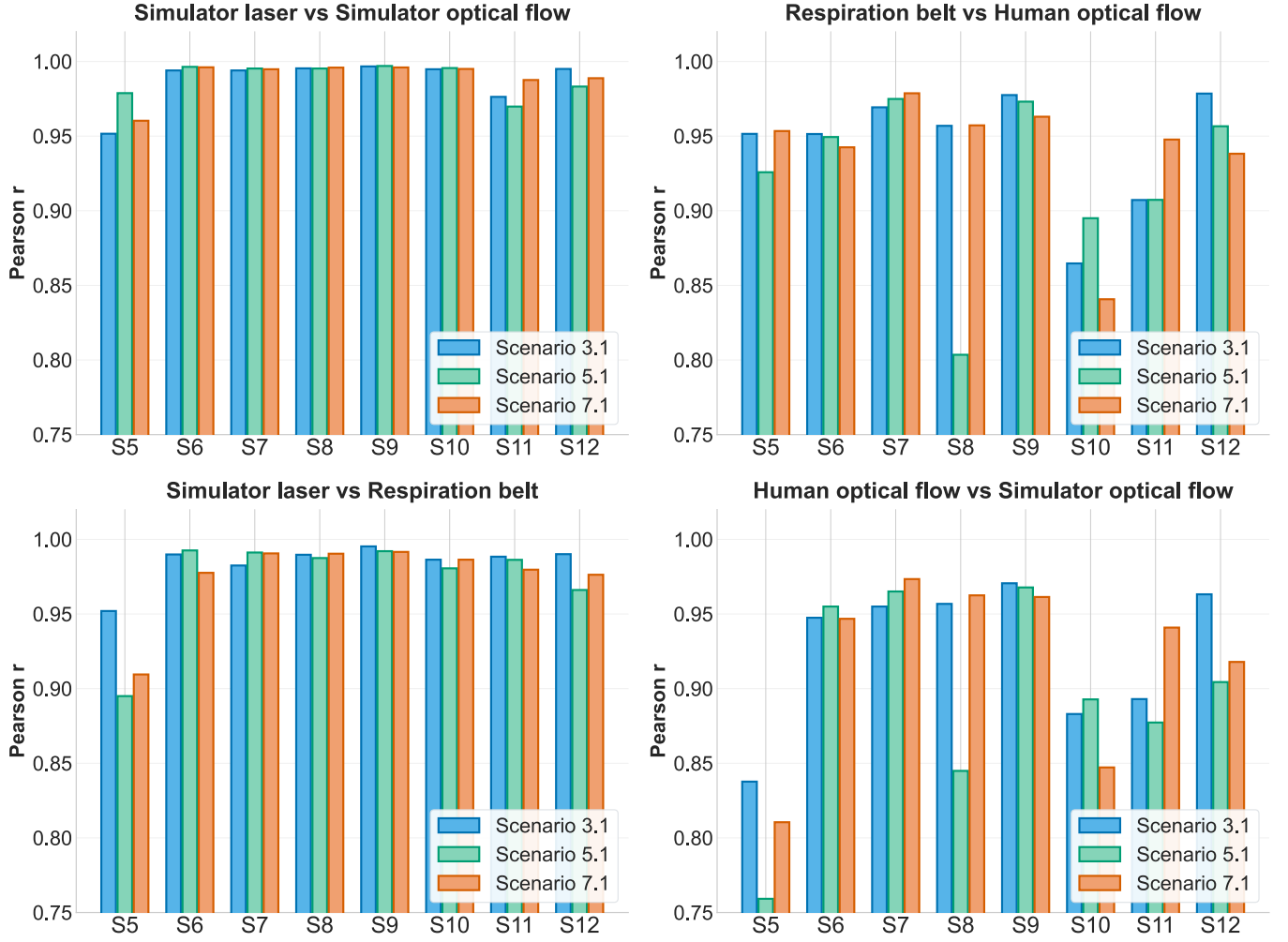


Figure 12: **Top left:** The Pearson's r-values between the respiration movement of the respiration simulator measured by the laser and its tracking with optical flow. **Top right:** The Pearson's r-values between the respiration movement of the human subject measured by the respiration belt and its tracking with optical flow. **Bottom left:** The Pearson's r-values between the respiration movement of the respiration simulator measured by the laser and the respiration movement of the human subject measured by the respiration belt. **Bottom right:** The Pearson's r-values between the detected movement of the respiration simulator and the detected movement of the human subject, both tracked with optical flow.

4.2.1 Movement tracking validation

Tracking of the movement of the respiration simulator: The Pearson's r-values between the real movement and the detected movement of the respiration simulator (between 3 and 4 in Figure 2) are calculated and can be seen on the top left in Figure 12. And all r-values are above 0.952. To see if the quality of the tracking by optical flow signal of the respiration simulator was related to the amplitude and/or frequency, it is plotted against the mean amplitude of the movement and the frequency (bpm) of the movement, this is showed in respectively Figure 14a and Figure 14b in Appendix D.

Tracking of the movement of the human subject: Pearson's r-values between the real movement and the detected movement of the human subjects (between 1 and 2 in Figure 2) are calculated and presented in the top right in Figure 12. All the r-values lie between 0.804 and 0.979. The respiration belt and the optical flow signal of scenario 5.1 of subject 8 are presented in Figure 15 in Appendix D, since this scenario is an outlier.

4.2.2 Movement input equivalence

To control whether the respiration simulator has accurately reproduced the breathing signals from the respiration belt, these signals are compared (between 1 and 3 in Figure 2). For each subject and scenario, the results can be seen in the bottom left in Figure 12, where all the r-values lie within the range of 0.895 – 0.995. The r-values of subject 5 are the lowest, with values of 0.952, 0.895, 0.910 and can be seen in Figure 16 in Appendix D.

4.2.3 Optical flow equivalence

The two optical flow signals are compared to see if the detected movement is equal for the human subject and the respiration simulator (between 2 and 4 in Figure 2). The r-values between the detected movement of the human subject and the respiration simulator, simulating the same respiration, are shown in the bottom right in Figure 12. Of all the situations, the MAE and the relative MAE are also calculated and presented in Table 5 in Appendix C. Figure 13 shows the relative MAE against the Pearson r of all the situations.

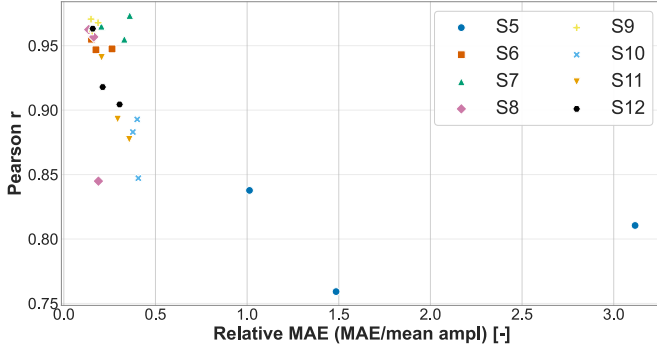


Figure 13: The Pearson r and the Mean Absolute Error between the two optical flow signals extracted from the human movement and the respiration simulator performing the same movement.

In Appendix D, Figure 17a shows the raw optical flow signals of the situation with the highest MAE (Subject 10 scenario 5.1), and Figure 17b shows the raw optical flow signals with the highest relative MAE (Subject 5 scenario 7.1).

Lastly, to tell something about the statistical significance of these correlations, the results of the one-sample t -tests are shown in Table 2.

Scenario	$\bar{r}$	95% CI	$t(7)$	p
3.1	0.938	[0.895, 0.963]	14.95	< 0.001
5.1	0.916	[0.845, 0.955]	11.43	< 0.001
7.1	0.935	[0.885, 0.964]	13.35	< 0.001

Table 2: Results of one-sample t -tests on Fisher-transformed r -values between human and simulator optical flow, tested against $H_0: \rho = 0$, per scenario ($n = 8$ subjects).

5 Discussion

5.1 Technical validation

The respiration simulator was easy to control with the existing software of Quasar and, therefore, capable of producing a wide range of patterns. Furthermore, the respiration simulator was inexpensive, as all components were already available and with a few creative adaptations, it was able to lie inside the hospital bed. Across the 12 validation signals, it moved within the required range of motion and frequency range, and the optical flow tracked this movement with a Pearson r above 0.946. Pearson’s r -values showed that 1 mm amplitudes had a lower correlation than larger movements (4, 7, and 10 mm). This reflects a general limitation of the optical flow for detecting sub-pixel motions. A displacement of 1 mm corresponds to approximately 0.2 pixels, and at sub-pixel displacements, the motion approaches the resolution limit of the optical flow, and noise becomes a significant fraction of the total signal power [16]. The respiration simulator itself contributed to this degradation: it exhibited slight, shaky movements with small amplitudes, which also could lead to increased noise in the data. However, this finding does not compromise the simulator’s validity for

its intended purpose, as the r -values remain above 0.946 for all subjects.

5.2 Movement tracking validation

With the technical capability established, it should now be checked whether the optical flow successfully tracks the respiration simulator’s movement and the human subject’s respiration.

5.2.1 Tracking of the movement of the respiration simulator

Pearson’s r between the actual movement and the detected movement of the respiration simulator is approximately equal for all amplitudes above 1.5 mm, but decreases for amplitudes lower than this. This corresponds to the findings during the technical validation. Regarding respiratory frequencies, the quality of detection showed no systematic relationship to breathing rate since the r -values were distributed across all tested frequencies. Overall, the respiration simulator’s movement was tracked with high accuracy across all amplitudes, with r -values consistently above 0.952.

5.2.2 Tracking of the movement of the human subject

Overall, most of the subjects are tracked very accurately since most of the r -values are around or above 0.907. There are some exceptions, for example, subject 10, whose respiration was tracked less consistently across all scenarios, whether by optical flow or the respiration belt. This issue can arise from two factors: first, slight movements that create noise in the respiration belt signal; and second, movements of other body parts within the region of interest (ROI) that the respiration belt on the abdomen does not capture, but which the optical flow signal does detect. Another outlier appeared in scenario 5.1 with subject 8: between 15 and 20 seconds into the recording, the optical flow did not detect any movement or expansion, despite clear signals in the respiration belt. In the rest of the recording, the tracking of respiration was highly accurate. Overall, the movement of the human subjects was tracked very accurately by the optical flow.

5.2.3 Comparison of tracking quality across the respiration simulator and human subjects

The optical flow algorithm demonstrated consistently higher correlations when tracking the respiration simulator compared to human subjects. This difference is understandable, as the simulator remained stationary during recording, producing consistent and regular movements without sudden displacements. In contrast, human subjects displayed postural variations, incidental movements, and occasional shifts in body position, which introduced variability unrelated to respiration. In summary, the optical flow signal from the simulator has less baseline variation and allows for cleaner tracking, whereas the signals from human subjects are more dynamic.

5.3 Movement input equivalence

Movement tracking depends critically on the fidelity of the input signal. The respiration simulator (a linear actuator

driven by a respiration belt signal) has demonstrated equivalence between the respiration belt signal and the movement of the respiration simulator. Based on Shafiq and Veluvolu [21], the respiration belt was used as an input signal for the linear respiration simulator. The laser measurements confirm that the commanded and reproduced patterns were nearly identical across all situations, with Pearson's r between 0.895 and 0.995 and 20 of the 24 values above 0.970. The respiration simulator, therefore, reproduces the human respiration pattern convincingly, supporting the respiration belt as a practical input source.

5.4 Optical flow equivalence

Having verified that the respiration simulator reproduces the input signal, the optical flow signals derived from human and simulator video are assessed. The results show that the correlation between human and simulator optical flow was statistically significant in all three scenarios ($p < 0.001$). However, this significance was largely anticipated: because the null hypothesis $H_0: \rho = 0$ was selected to investigate the actual magnitude of correlation rather than to test a pre-determined threshold, rejecting it is unsurprising. The more informative finding lies in the magnitude and precision of the correlation itself. The mean Pearson's r -values coefficients ranged from $\bar{r} = 0.916$ to $\bar{r} = 0.938$, with 95% confidence intervals ranging from $[0.845, 0.955]$ to $[0.895, 0.963]$. These confidence intervals provide compelling evidence that human and simulator optical flow are equivalent in their detection by the optical flow. The narrow width of the intervals further indicates high precision in the estimates, suggesting the simulator reliably replicates human respiratory motion across the different scenarios and subjects.

The lower r -values between the optical flow signals can be related to their cause:

- Subject 8 in scenario 5.1 exhibited notably lower optical flow correlation. Upon investigation, it was found that these signal dropouts came from the transformation of the input signal. The respiration belt signal differed from the movement observed in the video, leading to a false input signal for the respiration simulator and ultimately affecting the optical flow extraction. This is a systematic error rather than random noise.
- With subject 5, all the r -value between the two optical flow signals is lower than that of the other subjects. This aligns with the observation that the movement signal produced by the respiration simulator was less correlated with the respiration belt for this subject compared to others. Consequently, this resulted in two different measured movements being recorded by the optical flow analysis.
- Lastly, it can be observed that in the remaining scenarios with lower r -values in the bottom right of Figure 12, also the r -values of the respiration belt with the human optical flow signal were lower (Figure 12 top right). This logically affected the input signal for the respiration simulator and, therefore, the simulator's optical flow signal, resulting in a lower correlation between the two optical flow signals.

Also, the detected amplitude of the human subject and respiration simulator were not equal; for subjects 6 to 12,

the relative mean absolute error (MAE) ranged from 0.136 to 0.407. Meaning that the MAE was 13.6% to 40.7% of the mean amplitude of the respiration simulator. For subject 5, the MAE reached up to three times the mean amplitude. This subject had the lowest respiratory rate and the smallest amplitudes across all scenarios. While other subjects with small amplitudes tracked accurately, subject 5's combination of slow respiration and small displacement may exceed the respiration simulator's response limits. However, since there is no similar respiration pattern in this dataset, it can not be definitively said what caused this.

Several possible explanations for the difference in amplitude of all subjects exist: (1) An error may have occurred during the calculation of transforming the amplitude for the human subject, leading to a fault in the respiration simulator's amplitude. (2) The space between the respiration movement and the sheet may have varied with the human subject. This possibly introduced air between the sheet and the thoracic movement, which would complicate the accurate detection of thoracic displacement. (3) The area where the respiration belt was attached may not have been within the selected ROI, as the belt was attached to the abdomen. (4) The subject's distance from the camera may have varied in comparison to the respiration simulator, resulting in differing pixel movements despite the same camera angle.

The consistently high and precise correlations observed across various scenarios and subjects support the conclusion that the respiration simulator accurately replicates the timing and pattern of human breathing. Lower correlation values found for certain subjects and scenarios do not undermine this conclusion, as they can be attributed to identifiable systematic sources rather than random errors. The discrepancies in amplitude mentioned relate to magnitude rather than the respiration pattern itself. Since the breathing pattern is crucial for determining the respiratory rate, it is the most important feature for its intended use as a validation tool in vital signs monitoring. Therefore, the differences in amplitude are less significant than the high correlation between the detected respiratory patterns.

5.5 Limitations and future directions

5.5.1 Study conditions

All comparisons were drawn from eight subjects lying supine and motionless on a horizontal bed in daylight, with the simulator reproducing a single dominant axis of motion. The findings, therefore, establish equivalence for this controlled case, not for the full range of conditions on a general ward. Within that scope, however, the results support the simulator as a valid stand-in for human breathing movement in optical flow detection, which is the precondition for using it as a development and benchmarking tool. In the future, the setup could then be tested against more realistic conditions, such as different camera angles, the simulator positioned on a bed put at an angle, and with different lighting. Consequently, the equivalence findings apply to supine, motionless subjects in standard lighting, which establishes a proof-of-concept but does not generalise to typical ward conditions.

5.5.2 Dataset

The study demonstrated a statistically significant correlation between the two optical flow signals. However, it's important to differentiate between statistical significance and clinical relevance. The research included only 8 healthy subjects, with a total of approximately 48 minutes of video, predominantly consisting of individuals with a high body mass index (BMI) and an age range of 35 to 69 years. This homogeneous sample, while effective for initial proof-of-concept validation, does not confirm that the findings can be generalised to more diverse patient populations. Additionally, validation against abnormal respiration patterns (such as Cheyne-Stokes and Kussmaul respirations) is necessary before the simulator can be utilised for training algorithms aimed at disease detection. The current findings regarding equivalence only apply to normal breathing in healthy individuals.

5.5.3 Respiration belt attachment

The respiration belt was attached to the abdomen, while the simulator replicated motion at chest height. As a result, the input signals do not accurately represent the movement of the human chest. For future studies, the respiration belt should be placed on the chest region instead. Alternatively, a time-of-flight camera could be used, just as Ulrich et al. [17], because it can directly capture displacement. This eliminates the need to convert measurements from the abdomen to the ventral area and ensures that the input signal is independent of the camera's position. As a result, future iterations should place the respiration belt on the chest or use a time-of-flight camera to directly measure displacement, eliminating the conversion step.

5.5.4 Baseline drift removal

Baseline drift was removed using a rolling mean with a 6.5-second window, selected to match the slowest observed breathing period (approximately 64 seconds, corresponding to 9.4 breaths per minute). This design choice was intentional: by matching the window duration to the longest breathing cycle, the filter avoids unintended suppression of valid respiratory signal in subjects with longer breaths. However, this fixed-window method leads to asymmetric filtering across subjects with different respiratory rates. The choice of window width has a statistical impact; alternative window durations would yield different correlation outcomes. So, a single window cannot be optimal for all subjects simultaneously. Future work should prioritise adaptive detrending functions that adjust the window duration to each subject's measured respiratory frequency before signal filtering. Such an approach would ensure symmetric baseline removal and frequency-matched filtering across heterogeneous respiration patterns, improving both comparability and fidelity in respiratory signal analysis.

5.6 Implications

5.6.1 Optical flow algorithm validation and training

The design of the respiration simulator demonstrates that a relatively simple linear mechanical respiration simulator

can simulate a diverse range of respiration patterns. This validates the foundational concept established by Ulrich et al. [17], who successfully generated abdominal motion as linear up-and-down displacement. However, the present work achieves something previous studies did not: it transfers human respiration signals directly into a mechanical simulator and validates the optical flow result against the original human video. No prior study had demonstrated this human-to-simulator equivalence or provided a design suitable for validating optical flow algorithms with human-equivalent patterns. Commercial manikins simulate realistic breathing but cannot import custom patient signals; they therefore serve only for standardised, nominal patterns. By leveraging Quasar's existing hardware and software, this simulator opens a practical alternative: researchers can now generate unlimited training data with human-equivalent fidelity without continuous participant recruitment.

5.6.2 Testing detection of abnormal respiration patterns

Beyond training algorithms on normal respiration, the simulator enables validation of clinically significant irregular respiration patterns. To advance this goal, future researchers would identify respiratory signatures of abnormal respiration patterns, incorporate real patient data into the simulator, and assess whether optical flow algorithms reliably detect these patterns. Such capability is essential for deploying camera-based vital sign monitoring in hospital wards, where abnormal respiration often signals clinical deterioration.

5.6.3 Design for respiratory sensor benchmarking

The respiration simulator was designed and validated specifically for optical flow, but its fundamental principle is not limited to any single modality. This opens up the potential to use it as a universal reference platform for validating various non-contact respiratory monitoring technologies. Recent studies have also employed simulators to evaluate radar-based monitoring systems [28], [29], [30]. However, these simulators are not suitable for benchmarking against optical flow because they consist only of a small moving plate. In contrast, the current setup generates raw physical displacements in a realistic environment, allowing different modalities to theoretically measure the same known motion and thus be compared. To ensure compatibility with radar and other modalities, dedicated validation would be necessary, using a method similar to the one employed in this study.

This design is also relevant for comparing different algorithms. Wang and Den Brinker [16] compared six algorithmic approaches for respiratory signal extraction but noted that their validation was limited by reliance on a simple physical phantom that did not capture human variability. The present respiration simulator, uniquely validated against actual human breathing patterns across eight subjects, provides a more realistic foundation for such comparative studies. It thus strengthens benchmarking of algorithmic approaches while maintaining reproducibility and control.

6 Conclusion

A linear actuator can replicate human breathing movement and is equivalently detected by a camera-based optical flow algorithm. The respiration simulator was capable of moving a wide range of respiratory patterns and operated reliably within the hardware constraints of a hospital bed. The displacement signals produced by the respiration simulator showed strong correlation to the respiration belt input across 24 situations (8 subjects in 3 scenarios), with Pearson's r -values between 0.895 and 0.995. The optical flow extracted from human video and simulator video showed statistical significance in equality, with mean r -values of 0.916, 0.935, and 0.938 across the three breathing scenarios with $p < 0.001$, and 95% confidence intervals consistently exceeding 0.845. These results establish equivalence within a controlled scope: supine, stationary subjects in daylight. Residual differences between the two optical flow signals were attributable to subject-specific factors, such as slow respiration or belt-to-video misalignment, rather than to respiration simulator limitations. The validated respiration simulator offers a practical and controllable alternative for generating training data and for benchmarking optical flow algorithms on human-equivalent motion. By decoupling algorithm development from continuous participant recruitment, this design reduces the logistical burden of validation while preserving the physiological realism required for deployed respiratory monitoring on a general ward. Future work should extend validation to diverse body types and postures, explore abnormal respiration patterns for clinical relevance, and test whether the same physical reference can serve other non-contact monitoring modalities, such as radar, for which comparable motion simulators have already proven valuable.

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8 AI statement

Google's Gemini was used to help write the Python scripts. Anthropic's Claude was used to make the Python scripts neat and make the plots. Grammarly was used to correct the grammar and enhance the structure of sentences.

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A Region of Interest

Subject	Scenario	Human ROI				Simulator ROI			
		x	y	w	h	x	y	w	h
5	3.1	955	584	125	90	940	625	125	90
5	5.1	977	598	125	90	940	625	125	90
5	7.1	958	589	125	90	940	625	125	90
6	3.1	985	578	125	90	940	625	125	90
6	5.1	984	576	125	90	940	625	125	90
6	7.1	964	573	125	90	940	625	125	90
7	3.1	957	587	125	90	940	625	125	90
7	5.1	954	587	125	90	940	625	125	90
7	7.1	949	593	125	90	940	625	125	90
8	3.1	972	580	125	90	940	625	125	90
8	5.1	964	597	125	90	940	625	125	90
8	7.1	967	586	125	90	940	625	125	90
9	3.1	956	579	125	90	940	625	125	90
9	5.1	965	582	125	90	940	625	125	90
9	7.1	956	576	125	90	940	625	125	90
10	3.1	1019	577	125	90	940	625	125	90
10	5.1	1009	608	125	90	940	625	125	90
10	7.1	996	580	125	90	940	625	125	90
11	3.1	957	603	125	90	940	625	125	90
11	5.1	967	596	125	90	940	625	125	90
11	7.1	969	577	125	90	940	625	125	90
12	3.1	940	568	125	90	940	625	125	90
12	5.1	950	584	125	90	940	625	125	90
12	7.1	954	580	125	90	940	625	125	90

Table 3: The Region of Interest (ROI) coordinates in the videos of the human subject and respiration simulator for doing the optical flow analysis.

Note: x, y = top-left corner coordinates (pixels); w, h = width and height (pixels). The coordinates of the human subject videos do not correspond exactly to the ones of the respiration simulator video.

B Ratios of the Input Signals

Subject	Scenario	Ratio OF/Belt (pixels/unit)	Ratio OF/Belt (pixels/mm)	Max value (mm)
5	3.1	0.0479	0.2615	1.1
5	5.1	0.2146	1.1717	2.5
5	7.1	0.0947	0.5171	1.4
6	3.1	0.2619	1.4300	10.9
6	5.1	0.1784	0.9741	8.4
6	7.1	0.3151	1.7204	12.2
7	3.1	0.1349	0.7366	3.2
7	5.1	0.1169	0.6383	3.5
7	7.1	0.1340	0.7316	3.2
8	3.1	0.2707	1.4780	4.7
8	5.1	0.1778	0.9708	8.4
8	7.1	0.1228	0.6705	3.7
9	3.1	0.1442	0.7873	6.9
9	5.1	0.1288	0.7032	6.2
9	7.1	0.1217	0.6645	5.0
10	3.1	0.5685	3.1040	10.2
10	5.1	0.6625	3.6173	15.1
10	7.1	0.5082	2.7748	8.8
11	3.1	0.0472	0.2577	1.5
11	5.1	0.0368	0.2009	1.5
11	7.1	0.0476	0.2599	2.0
12	3.1	0.0499	0.2725	2.9
12	5.1	0.0204	0.1114	1.5
12	7.1	0.0288	0.1572	2.0

Table 4: Ratio between the amount of movement in pixels detected by the optical flow per unit and mm of the respiration belt. And the maximum value for creating the signal in the QUASAR programmable respiratory motion program as input for the respiration simulator with the signal of the respiration belt.

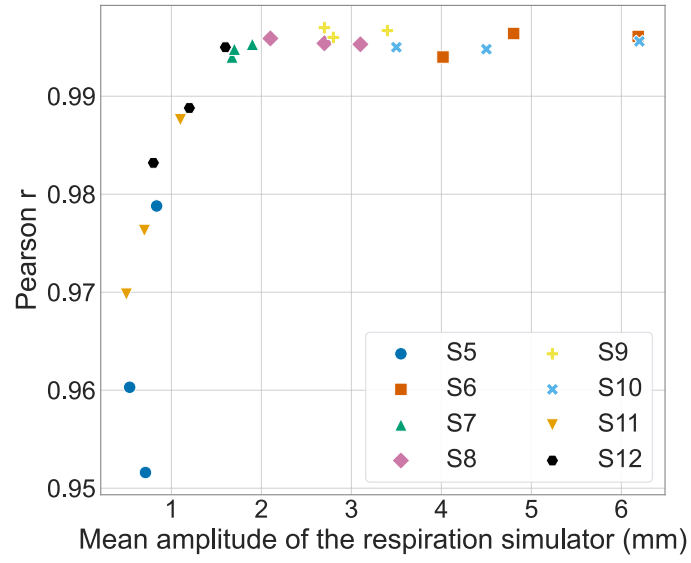
C All metrics

S	Sc	Time (s)	Pearson Correlation (r)				Error & Amplitude			BPM	BMI
			Belt Human OF	Laser Simulator OF	Belt Laser	Simulator OF Human OF	MAE (pixels)	Relative MAE	Mean ampl. (mm)		
5	3.1	121.2	0.952	0.952	0.952	0.838	0.132	1.013	0.7	9.4	31.2
5	5.1	121.9	0.926	0.979	0.895	0.759	0.227	1.485	0.8	12.8	31.2
5	7.1	119.1	0.953	0.960	0.910	0.811	0.306	3.117	0.5	12.6	31.2
6	3.1	121.5	0.951	0.994	0.990	0.948	0.193	0.263	4.0	20.2	44.7
6	5.1	121.8	0.949	0.996	0.993	0.955	0.133	0.151	4.8	20.2	44.7
6	7.1	116.8	0.943	0.996	0.978	0.947	0.199	0.175	6.2	21.6	44.7
7	3.1	94.1	0.969	0.994	0.983	0.955	0.101	0.330	1.7	17.2	19.5
7	5.1	120.2	0.975	0.995	0.991	0.965	0.071	0.205	1.9	16.0	19.5
7	7.1	113.5	0.979	0.995	0.991	0.973	0.112	0.360	1.7	14.8	19.5
8	3.1	120.3	0.957	0.995	0.990	0.957	0.081	0.164	2.7	18.0	26.7
8	5.1	120.6	0.804	0.995	0.988	0.845	0.107	0.189	3.1	17.4	26.7
8	7.1	121.9	0.957	0.996	0.990	0.963	0.052	0.136	2.1	17.7	26.7
9	3.1	106.9	0.978	0.997	0.995	0.971	0.092	0.148	3.4	18.5	28.0
9	5.1	114.4	0.973	0.997	0.992	0.968	0.092	0.187	2.7	19.4	28.0
9	7.1	127.1	0.963	0.996	0.992	0.961	0.079	0.155	2.8	19.4	28.0
10	3.1	97.6	0.865	0.995	0.986	0.883	0.310	0.377	4.5	21.5	40.1
10	5.1	122.5	0.895	0.996	0.981	0.893	0.455	0.400	6.2	18.6	40.1
10	7.1	124.3	0.841	0.995	0.986	0.847	0.261	0.407	3.5	20.3	40.1
11	3.1	118.8	0.907	0.976	0.988	0.893	0.038	0.294	0.7	21.7	30.5
11	5.1	121.2	0.907	0.970	0.986	0.877	0.033	0.357	0.5	23.8	30.5
11	7.1	120.6	0.948	0.988	0.980	0.941	0.041	0.206	1.1	18.4	30.5
12	3.1	121.7	0.979	0.995	0.990	0.963	0.046	0.158	1.6	14.8	29.8
12	5.1	113.6	0.957	0.983	0.966	0.904	0.045	0.304	0.8	11.1	29.8
12	7.1	115.6	0.938	0.989	0.976	0.918	0.047	0.212	1.2	14.5	29.8

Table 5: Summary of key metrics: respiratory parameters, correlation coefficients, and signal fidelity.

Note: S = Subject; Sc = Scenario; Belt = Respiration Belt; OF = Optical Flow; Laser = Laser of the Respiration Simulator; MAE = Mean Absolute Error; ampl = amplitude; BPM = Breaths per minute; BMI = Body Mass Index.

D Extra Figures of the Lab Study



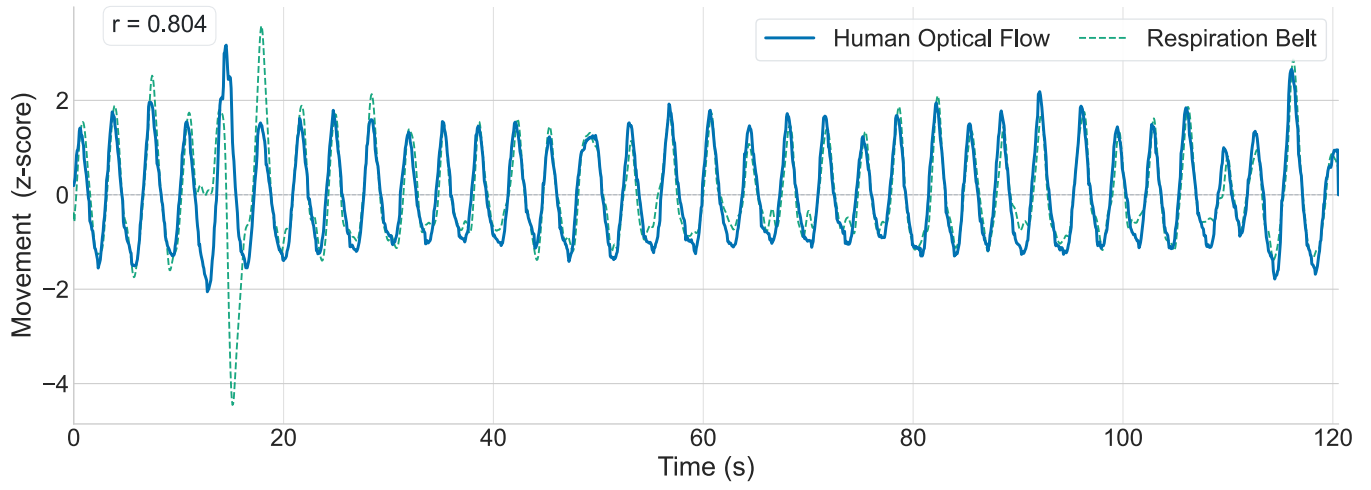
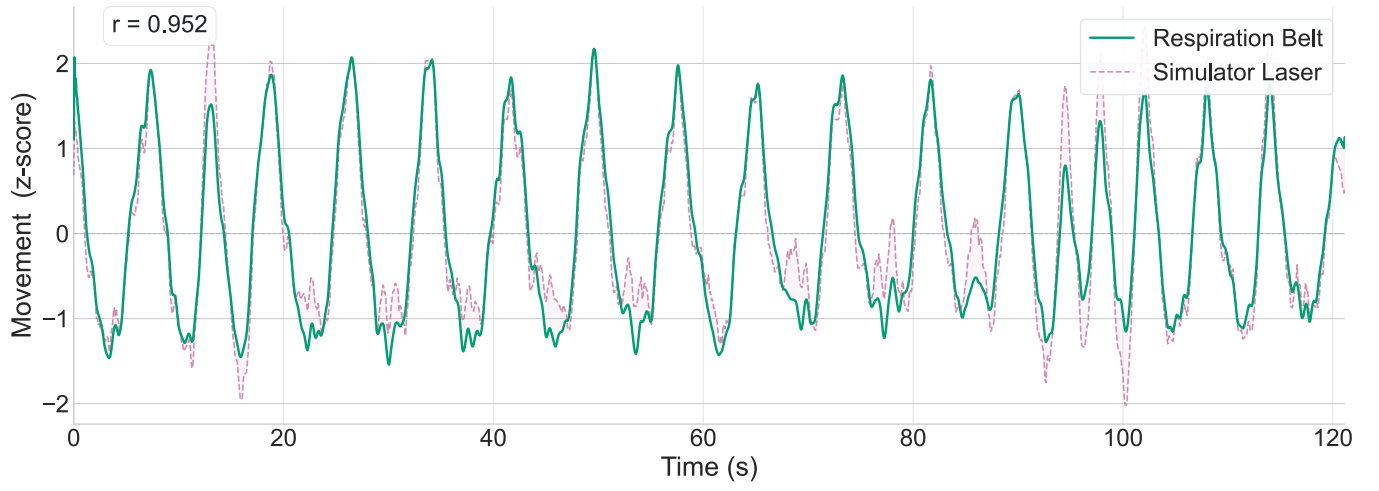
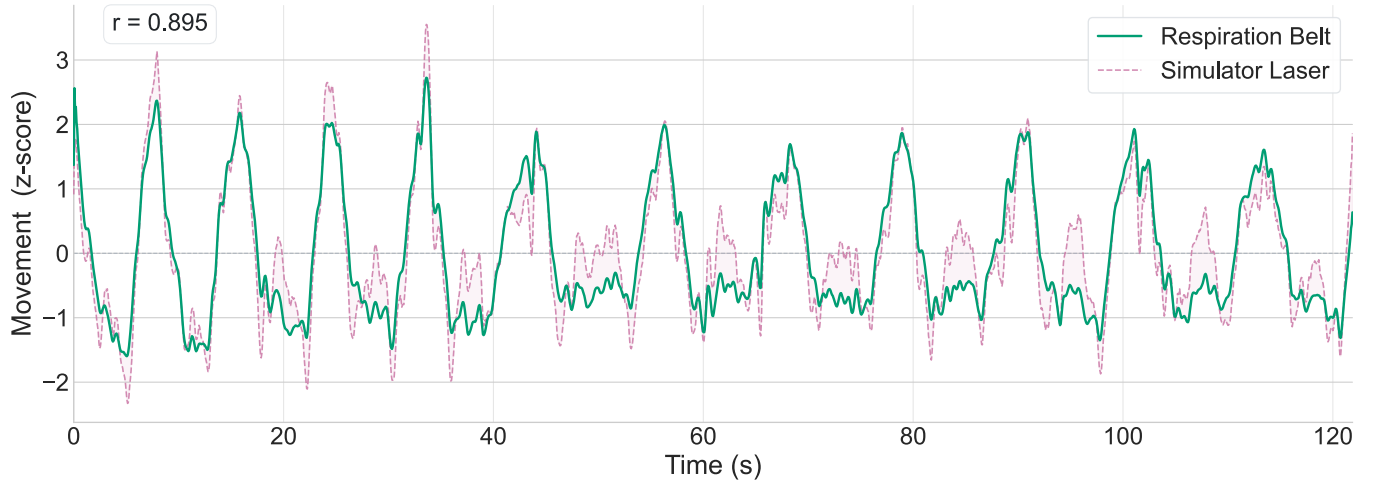


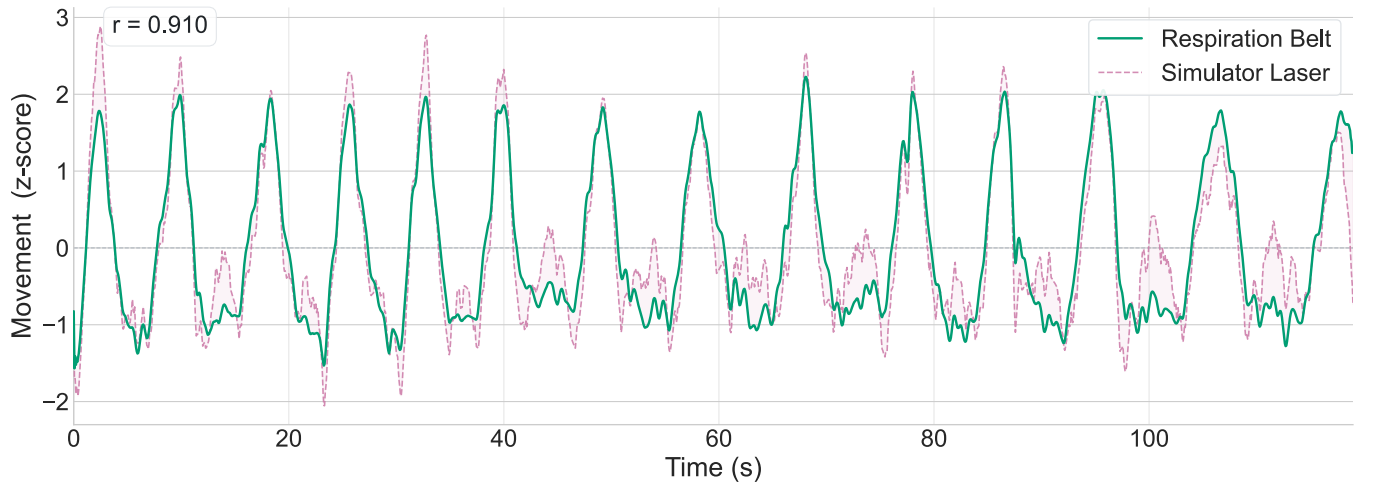
Figure 15: The two measured z-normalised signals of subject 8 in scenario 5.1, where (1) the human optical flow is the signal extracted by the optical flow of the video of the human subject and (2) the respiration belt is the expansion of the abdomen of the human subject.



(a) Scenario 3.1

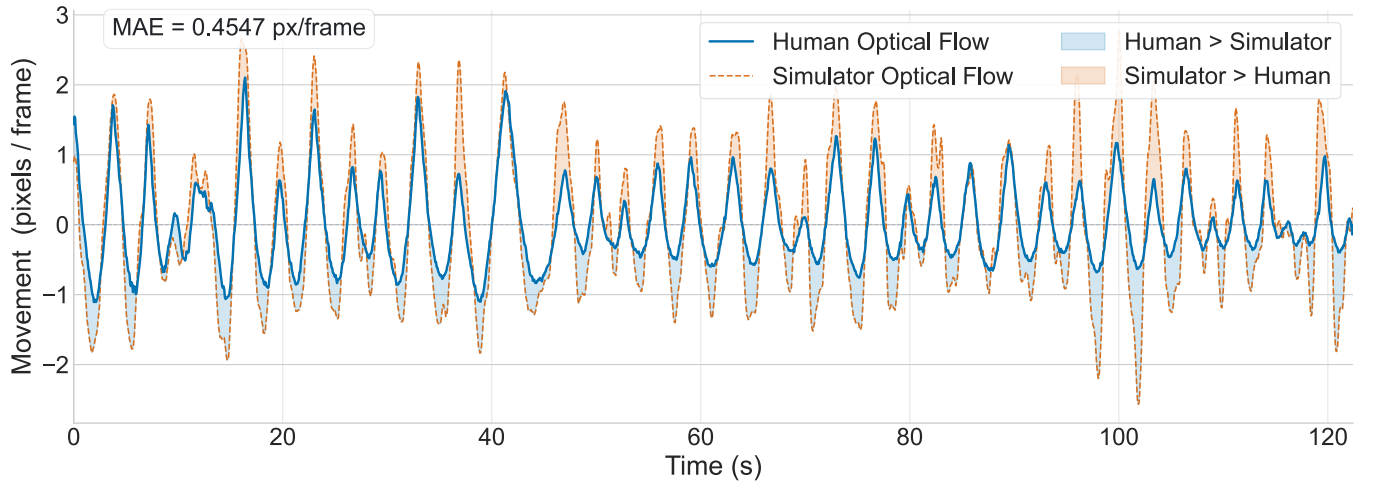


(b) Scenario 5.1

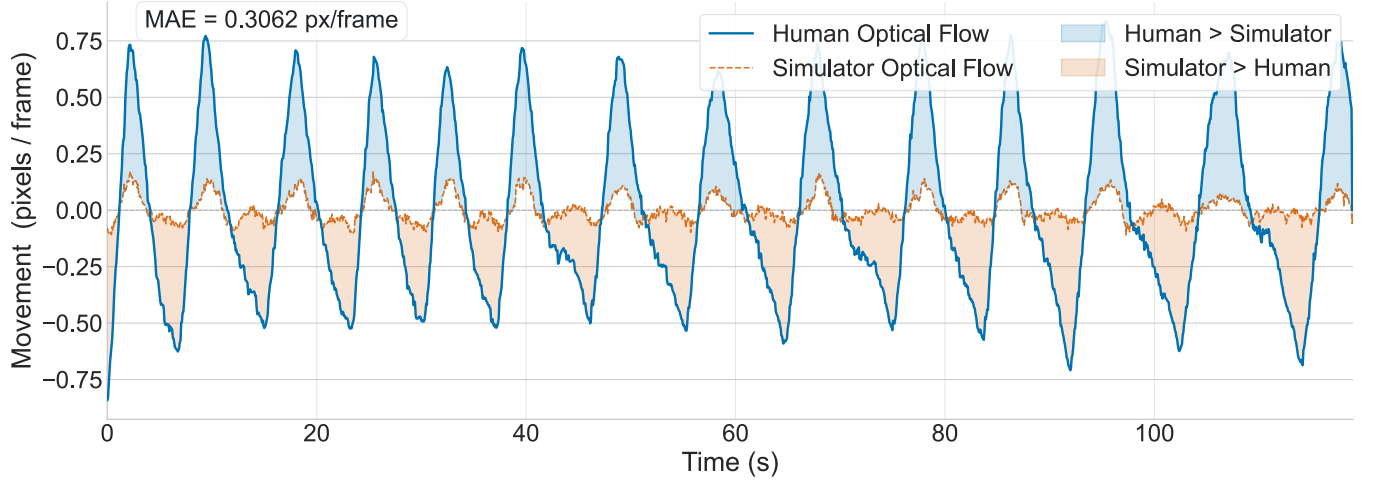


(c) Scenario 7.1

Figure 16: The two measured z-normalised signals of subject 5 in three scenarios, where (1) the respiration belt is the expansion of the abdomen of the human subject and (2) the simulator laser is the movement of the respiration simulator measured by the laser.



(a) The situation with the highest MAE (Subject 10 scenario 5.1)



(b) The situation with the highest relative MAE (Subject 5 scenario 7.1)

Figure 17: Plots of the detected movement by the optical flow for the human subject and the respiration simulator.

E Literature study

Requirements for a respiration simulator for training and validating a camera respiration-rate detection system

Lidewij te Hennepe

Abstract—This literature review investigates which existing respiratory simulators are capable of reproducing visually observable breathing patterns for adults in a supine position and identifies the components most critical for training a camera-based visual respiration-rate detection system. A structured search was conducted in PubMed and Scopus following PRISMA guidelines, complemented by snowballing and targeted searches for commercial simulators. These were categorised into anthropomorphic phantoms, mechanical motion platforms and validation studies. Across the literature, three elements emerged as essential for realistic simulation: (1) input signal models, where physiologically grounded, non-sinusoidal and variable respiratory waveforms outperform simple periodic signals; (2) mechanisms for motion generation, with volumetric expansion systems providing the most realistic breathing movement; and (3) surface dynamics, where accurate reproduction of thoracic and abdominal motion, sex- and posture-dependent differences and cardiac micro-motions is crucial for training robust visual algorithms. No single simulator met all criteria, but the synthesis highlights that hybrid systems combining anatomically realistic shells with programmable, physiologically driven lung mechanics are best suited for developing and validating camera-based respiration-rate detection.

Index Terms—Respiratory simulators, Camera-based monitoring, Breathing motion modelling.

I. RESULTS

A. Study selection

Conducting a manual search in PubMed and Scopus using the search queries listed in Appendix A resulted in 519 studies from PubMed and 375 studies from Scopus. These studies were assessed following the PRISMA method, mentioned in ??, which is displayed in Figure 1. After duplicate removal and title-abstract screening, 59 studies were reviewed by reading the full text. Of which 12 were included in the final review. Many studies focus on the suitability of respiratory simulators for training medical personnel. Some of the studies focus on intubating, so they only include the head and neck, instead of the whole thorax. Or they were focused on resuscitation and therefore concentrated on compression instead of expansion of the thorax. The snowball method resulted in thirteen relevant studies.

The combination of the search methods resulted in 25 relevant studies. To organise the findings and compare different simulator types systematically, the included studies were grouped into three categories:

- Anthropomorphic phantoms
- Mechanical motion platforms

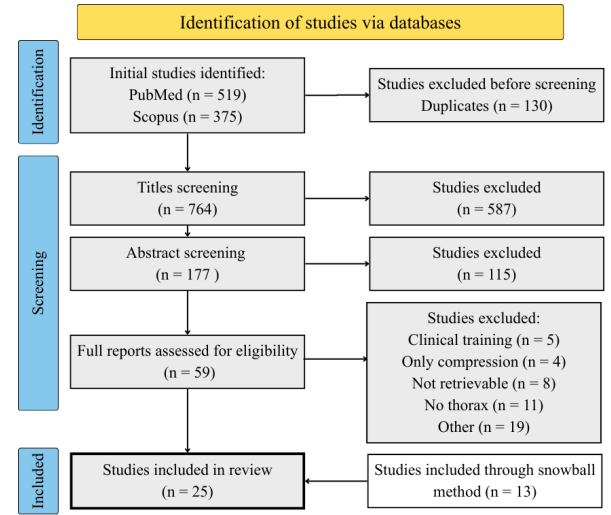


Fig. 1. Flowchart showing literature retrieval and selection process using the PRISMA-method

• Validation studies

Based on the features of the respiratory simulator, it was put in the specific category. The anthropomorphic phantoms include all the respiratory simulators designed to mimic the physical geometry and/or physiological motion of the human body. The mechanical motion platforms category includes all the respiratory simulators which have a flat surface and only move in the horizontal or vertical direction. The last category, validation studies, was included to validate the data of the other literature and gain more insight. In Table I, the categorisation of the gathered literature can be seen.

TABLE I
INCLUDED STUDIES DIVIDED IN THREE CATEGORIES

Anthropomorphic phantoms	Mechanical motion platforms	Validation studies
Lin et al. [1], Chrysanthou-Baustert et al. [2], Valencia et al. [3], Abdollahi et al. [4], Ulrich et al. [5], Brosch et al. [6] and Bolwin et al. [7]	Fitzpatrick et al. [8], Kissick et al. [9], Litzenberg et al. [10], Dunn et al. [11], Jiang and Dahnoun [12], Malinowski et al. [13], Song et al. [14], Tay et al. [15], Tay et al. [16] and Pentari et al. [17]	Singh et al. [18], Sameera et al. [19], Calabrese et al. [20], Johansson et al. [21], Zhao et al. [22], Lujan et al. [23], De Groote et al. [24] and Kaneko and Horie [25]

B. Extracted data

Three data categories were defined: input signals, mechanisms and surface dynamics. Together, these data categories describe the process of creating a breathing pattern with a respiratory simulator. First, the simulator needs a specific input signal to actuate the used mechanism, which translates it into a visible surface movement. See Table II for an overview of the included studies and the corresponding data they reported on.

TABLE II
OVERVIEW OF REPORTED DATA IN INCLUDED STUDIES.

Study	Input signals	Mechanisms	Surface dynamics
Lin et al. [1]	•	•	•
Chrysanthou-Baustert et al. [2]		•	
Valencia et al. [3]		•	
Abdollahi et al. [4]		•	
Ulrich et al. [5]		•	
Brosch et al. [6]		•	
Bolwin et al. [7]		•	
Fitzpatrick et al. [8]		•	
Kissick et al. [9]	•		•
Litzenberg et al. [10]	•	•	
Dunn et al. [11]	•	•	
Jiang and Dahnoun [12]	•		•
Malinowski et al. [13]		•	
Song et al. [14]	•		
Tay et al. [15]		•	
Tay et al. [16]		•	
Pentari et al. [17]	•	•	•
Singh et al. [18]	•		•
Sameera et al. [19]			•
Calabrese et al. [20]			•
Johansson et al. [21]			•
Zhao et al. [22]			•
Lujan et al. [23]	•		
De Groote et al. [24]			•
Kaneko and Horie [25]			•

In the following subsections, first, all the simulators will be explained based on the three categories of Table I. Where the anthropomorphic phantoms will be discussed in subsection I-C, the mechanical motion platforms in subsection I-D and the validation studies subsection I-E. Following this, the components of the named studies are highlighted, where the input signals used in the included studies will be presented in subsection I-F. And finally, the used mechanisms will be explained in subsection I-G and the surface dynamics in subsection I-H.

C. Anthropomorphic phantoms

Based on the reviewed literature, these phantoms can be categorised by their primary design objectives, ranging from imaging quality assurance to clinical skills training. The existing anthropomorphic phantoms are suited for different purposes that influence their features and motion characteristics.

1) *Quality assurance of medical imaging*: A significant number of phantoms are designed for the quality assurance of medical imaging. Medical imaging creates pictures of the inside of the body, which help diagnose health problems, monitor and guide medical procedures. These devices prioritise the accurate replication of internal organ motion to validate imaging modalities. For instance, Abdollahi et al. [4] developed the Dynamic Anthropomorphic Thorax Phantom (DATPHA) (Figure 2a) specifically for quality assurance and to replicate a patient's size, anatomy, and tissue density for conducting "stereotactic body radiotherapy" (SBRT) and validating "four-dimensional computed tomography" (4DCT) motion management. Similarly, Brosch et al. [6] constructed a mechanical phantom of human respiration (Figure 2b) to characterise respiration noise in "functional magnetic resonance imaging" (fMRI), focusing on fluctuations caused by changes in abdominal volume. While Chrysanthou-Baustert et al. [2] utilised a phantom (Figure 2c) filled with water to simulate soft tissue, to investigate respiratory motion of the heart in single-photon emission computed tomography (SPECT) and computer tomography (CT). Similarly, Bolwin et al. [7] presented the "Wilhelm" phantom (Figure 2d) designed to simulate cardio-respiratory motion for not only SPECT and CT, but also positron emission tomography (PET) and magnetic resonance imaging (MRI). Ulrich et al. [5] developed a torso motion simulator with thorax and abdomen (Figure 2e) for evaluating surface-based respiratory gating systems with a camera, making it directly relevant for training a camera-based visual respiration-rate detection system.

2) *Clinical skill training phantoms*: Other phantoms are designed for clinical skills training, which prioritise haptic feedback and anatomical interaction over properties relevant for radiological purposes. The "Lapman simulator" (Figure 3a), described by Mazilu et al. [26], replicates the human torso for urologic laparoscopy training. Lin et al. [1] later adapted the Lapman torso for image-guided intervention validation, specifically utilising it to track thorax movement. And the SimVep (Figure 3b) by Valencia et al. [3], is a simulator designed to emulate the physiological behaviour of obstructive and restrictive pulmonary conditions.

3) *Off-the-shelf anthropomorphic phantoms*: The traditional, off-the-shelf, CPR training phantoms or phantoms for other medical training purposes are not included in relevant studies about respiratory movement. However, to ensure completeness, it is important to include the existing phantoms which can simulate visual breathing patterns and their specifications in this literature study. The following information about the manikins has been provided by the manufacturers through brochures.

Simulators, such as the AmbuMan Advanced (Figure 4a) [27], Laerdal Resusci Anne QCPR (Figure 4b) [28] and the Brayden CPR training manikin (Figure 4c) [29], are primarily

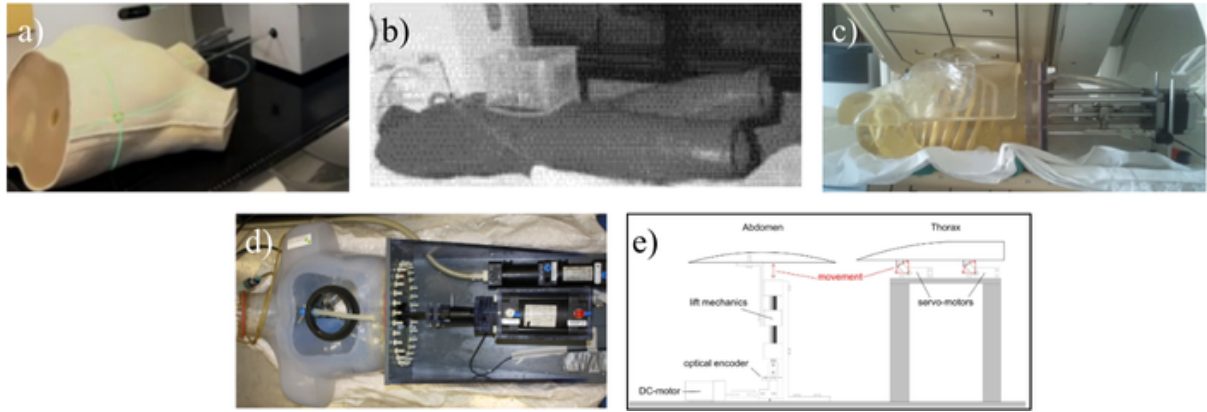


Fig. 2. The anthropomorphic phantoms for diverse purposes: a) The DATPHA phantom [4] b) Brosch mechanical model [6] c) Dynamic ALDERSON phantom with overlay breasts to simulate the female body [2] d) Wilhelm phantom [7] e) Ulrich torso motion simulator [5].

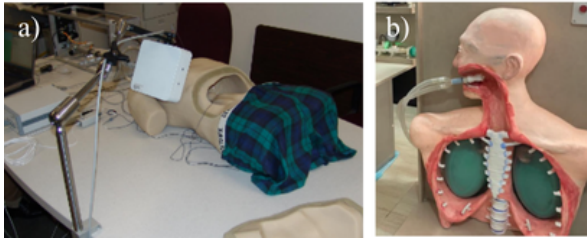


Fig. 3. The anthropomorphic phantoms for clinical skills training from literature: a) The Lapman torso [1] b) SimVep [3].

engineered for the training of cardiopulmonary resuscitation (CPR). They focus on mechanical feedback, such as compression rate, compression depth and hand position. The Brayden CPR Training Manikin also utilises a visual feedback system with LED lights beneath the skin to represent blood flow and thorax compression quality [29]. All three phantoms include a plastic bag that simulates the lungs. These lungs can produce a rise and fall of the thorax when using an external ventilator, such as mouth-to-mouth or a bag-valve mask. However, they do not allow for the creation of autonomous or spontaneous breathing patterns. As a result, these phantoms provide useful insights into the characteristics of a realistic body, but they do not provide information on creating a realistic breathing pattern.

The Gaumard HAL Series (S3201 and S1000) (Figure 4d) are patient simulators that are designed for training with advanced clinical interventions and emergency care. Both the HAL S3201 and HAL S1000 feature programmable spontaneous thoracic rise. It is possible to control the rate and depth of respiration to generate observable thoracic movements. Furthermore, these models support independent left and right lung control, allowing for the simulation of asymmetric thoracic breathing¹ [34] [30].

The CAE training simulators Apollo and Ares (Figure 4e & f) are designed for prehospital, like medical emergencies on the street, and nursing simulation. Both models are equipped

¹With asymmetric thoracic breathing, one side of the thorax rises while the other doesn't or moves symmetrically.

with spontaneous breathing capabilities [31] [32]. The IngMar RespiSim System (Figure 5) includes different parts and is focused on a high level of accuracy and realism in mechanical ventilation training. This system utilises the ASL 5000 respiratory simulator, which employs a piston-in-cylinder mechanism to create precise, realistic breath profiles. The system includes the RespiPro Manikin, which is equipped with symmetric and asymmetric thoracic breathing. This allows for the physical visualisation of complex respiratory conditions [33].

D. Mechanical motion platforms

The literature search identified several mechanical motion platforms designed to simulate respiratory mechanics. While these platforms share the common goal of reproducing physiological motion, they differ significantly in their primary applications. The reviewed mechanical platforms generally fall into three application categories: quality assurance for medical imaging, simulation of lung mechanics and validation of non-contact vital sign monitoring sensors.

1) *Quality assurance of medical imaging:* A significant portion of the identified platforms was developed for radiation therapy, specifically to address motion artefacts in 4D Computed Tomography (4D CT) and to validate tumour tracking or gating systems. Malinowski et al. [13] developed the "4D Phantom" (Figure 6a) to serve as an end-to-end quality assurance device for radiation therapy. Kissick et al. [9] utilised the "Washington University 4D Motion Phantom" (Figure 6b), derived from the design of Malinowski et al. [13] to move a spherical "tumour" inside an anthropomorphic chest phantom (LUNGMAN), enabling the evaluation of dose-painting delivery without active motion management. Similarly, Dunn et al. [11] modified a commercial QUASAR phantom (Figure 6c) for quality assurance of motion management in radiotherapy. Fitzpatrick et al. [8] (Figure 6d) and Litzenberg et al. [10] (Figure 6e) focus on creating platforms capable of irregular, patient-specific motion to assess 4D CT image reconstruction algorithms and dose delivery accuracy. Both platforms only move in the horizontal direction.

2) *Lung mechanics simulation:* Tay et al. [16] and Tay et al. [15] developed simulator platforms that reproduce lung

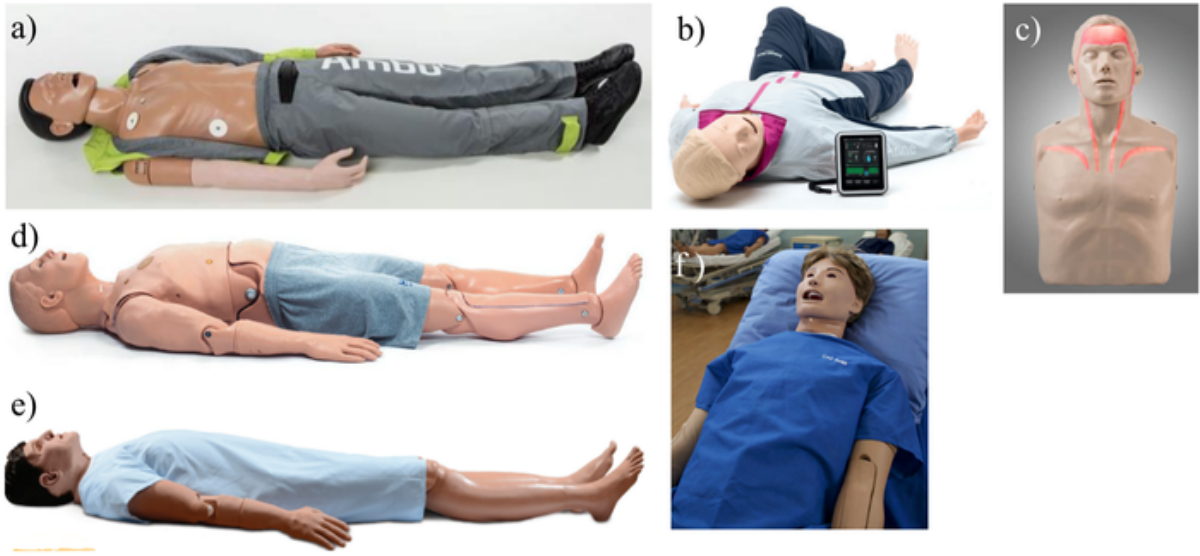


Fig. 4. Off-the-shelf anthropomorphic phantoms for clinical skills training: a) The AmbuMan Advanced [27] b) Laerdal Resusci Anne QCPR [28] c) Brayden CPR training manikin [29] d) The Gaumard HAL Series patient simulator [30] e) CAE training simulator Apollo [31] f) CAE training simulator Ares [32].

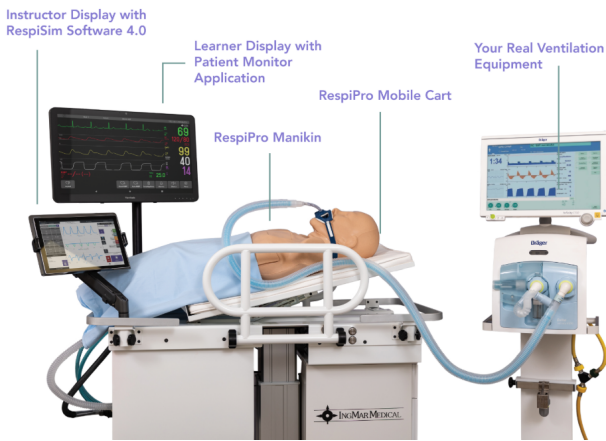


Fig. 5. The IngMar RespiSim System [33]

mechanics by modelling respiratory system compliance, resistance and pressure–volume behaviour. Their CARE Test Lung (Figure 6f) uses two bellows representing the left and right lung. A bellows is a flexible, accordion-like chamber that expands and contracts to move air or fluid. These bellows are driven by a programmable ventilator that controls tidal volume, airway resistance and lung compliance. Instead of prescribing external displacement, thoracic motion arises indirectly from physiologically grounded changes in internal lung volume, allowing more realistic simulation of asymmetric expansion and altered stiffness. Although the CARE Test Lung does not include an anthropomorphic torso, its physiologically driven actuation makes it valuable for studying how variations in lung mechanics influence external motion.

3) *Non-contact sensor validation*: The most relevant category for camera-based detection involves platforms designed for non-contact sensor validation. Jiang and Dahnoun [12] developed a simulator (Figure 6g) which replicates human

cardiorespiratory motion. This is to provide a controlled and noise-free baseline for testing a heart and respiration rate monitoring radar-based system. Similarly, Pentari et al. [17] constructed a moving mechanical target (Figure 6h) to evaluate ultra-wideband radar sensors for detecting heart and respiration rates in clinical or obstructed scenarios. In a similar set-up as Pentari et al. [17] and Jiang and Dahnoun [12], Song et al. [14] designed a programmable mechanical target to accurately simulate realistic cardiorespiratory motion. This device aims to validate human detection, distinguishing between materials and humans to regulate office lighting.

E. Validation studies

The reviewed validation studies highlight information about human kinematics and surface dynamics and their mathematical modelling.

1) *Human kinematics and surface dynamics*: Kaneko and Horie [25] examined the three-dimensional breathing movement distances of the thorax and abdomen in 100 healthy subjects. The aim of this study was to measure three-dimensional distances of specific points on the thorax and abdomen during breathing. Additionally, the study aimed to evaluate the effects of age, posture, and sex on breathing movements. De Groote et al. [24] clarified this kinematic behaviour by quantifying the exact movement vectors of the rib cage and showing how the upper ribs predominantly follow a “pump-handle” pattern while the lower ribs follow a “bucket-handle” pattern².

Johansson et al. [21] focus on quantifying the chest mobility and respiratory movement of patients with a disease. They compared the data of 35 patients with asthma, Chronic Obstructive Pulmonary Disease (COPD) and Sensory Hyper-reactivity (SHR) with those of healthy individuals. In the study by Sameera et al. [19], an analysis is presented regarding the

²These patterns will be further explained in subsubsection I-H1.

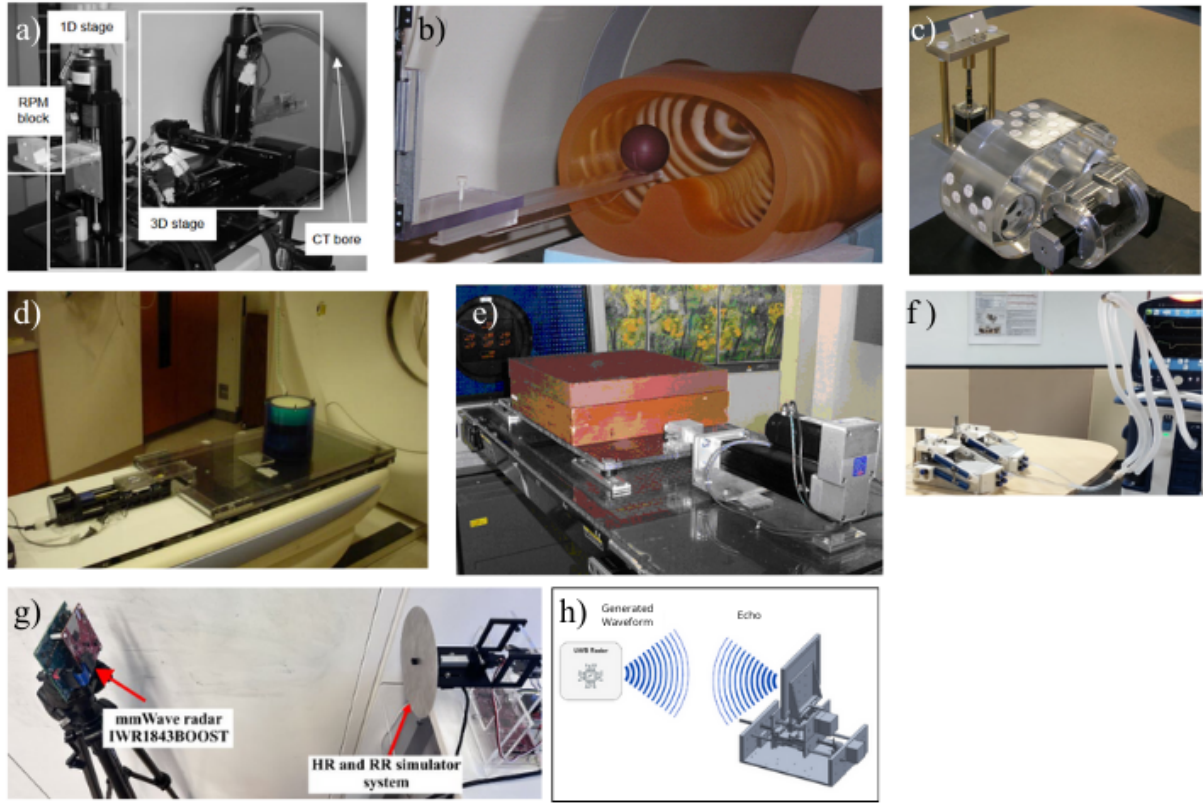


Fig. 6. Mechanical motion platforms: a) 4D Phantom [13] b) Washington University 4D Motion Platform with a sphere attached to it inside the LUNGMAN chest phantom [9] c) Modified QUASAR phantom with the chest-wall platform [11] d) Irregular breathing platform [8] e) Platform for small motions [10] f) CARE Test Lung [15] g) Mechanical thorax motion simulator [12] h) Mechanical target for Radar [17].

movement of the thorax and abdomen during the measurement of respiratory functions with Doppler radar. They propose a theoretical model that considers the contributions of both the thorax and abdomen.

2) *Mathematical modelling*: Calabrese et al. [20], on the other hand, propose a mathematical model based on a lever system. This model illustrates the interaction between the rib cage and abdomen, represented by two springs, while volume changes are described by a damper. It provides the biomechanical basis that physical simulators aim to replicate mechanically. Lujan et al. [23] introduces a probability distribution function to model asymmetric organ motion for radiotherapy, arguing that simple sine waves fail to capture the time spent at exhale. Singh et al. [18] propose a mathematical model that simulates thoracic motion due to cardiorespiratory activity. This model can be used for testing radar-based systems that measure vital signs. And finally, Zhao et al. [22] developed a biomechanical finite element model, which incorporates Hill's active muscle model, to demonstrate how specific muscle contractions cause the motion of the thorax and abdomen.

F. Input signals

While the previous sections focused on the different existing simulators, this section examines the input signals that drive these simulators. The most commonly applied approach defines respiratory motion as a prescribed kinematic displace-

ment of a surface or platform, where position is specified explicitly as a function of time.

1) *Kinematic input signals for prescribed surface motion*: Lin et al. [1] uses sinusoidal waveforms with a period of 5 seconds to simulate a respiratory rate of 12 breaths per minute. Waveforms of varying amplitudes simulating tidal volumes were applied to control the linear actuator. This approach produces only a basic breathing pattern, resulting in a simple periodic movement of the Lapman torso. Jiang and Dahnoun [12] extends this concept by updating the signal dynamically. They model the relationship between surface displacement and time as a sinusoidal function, see Equation 1. To generate the required pulse-width modulation (PWM) signal, the system defines the maximum and minimum duty cycle values ($DutyMax$, $DutyMin$) and the period (T_p). A timer interrupt periodically recalculates the duty cycle using the sinusoidal function, enabling continuous real-time adjustment of the actuator input.

$$DutyCycle = DutyMax + (DutyMax - DutyMin) \cdot (0.5(1 + \sin(2\pi \cdot \frac{time}{T_p}))) \quad (1)$$

Kissick et al. [9] and Litzenberg et al. [10] based their input signals on the work of Lujan et al. [23]. Lujan et al. [23] use a similar equation for determining the position of an organ. It was chosen because it can easily be used to test the velocity

and acceleration characteristics. The modified QUASAR of Dunn et al. [11] is able to use the breathing equations of the Lujan model [23] for creating a breathing movement.

The Washington University 4D Motion Platform with a sphere (see Figure 6b), described by Kissick et al. [9], generates an elliptical motion pattern. The sphere's movement was created by mapping a one-dimensional respiratory motion trace onto an elliptical trajectory, thereby producing simultaneous lateral and longitudinal displacement. The longitudinal (head-to-toe) component of this motion was approximated using Equation 2.

$$x(t) = A \cdot \sin^{2n}(\pi \cdot t/T) \quad (2)$$

A period (T) of 5 seconds was used and an amplitude (A) of 1 cm. The value $n = 2$ in the exponent of the breathing trace was chosen to model the situation for which more time is spent at exhale than inhale, which requires that $n > 1$. This creates a more physiologically realistic movement than a pure sinusoidal [9].

Litzenberg et al. [10] states that sinusoidal movements are not wholly representative of observed clinical anatomic motion, so they use a more complex equation, Equation 3, as input for the modified QUASAR.

$$y(t) = A \cdot \cos^4(\pi \cdot t/T) \quad (3)$$

This equation was tested for amplitudes ranging from 5 mm to 20 mm, and periods of 2, 4, and 6 seconds, over a 45-s measurement period. The previous models were not validated against another model; on the other hand, Song et al. [14] compares a simple sinusoidal model against a "more realistic" model. They use a similar set-up as Pentari et al. [17], which can be seen in Figure 6h. The "more realistic" models for moving the mechanical target consist of a respiration input and a heart rate input, which are shown in Equation 4 and Equation 5.

$$p_R(t) = \sin^p(\pi \cdot f_R \cdot t) \quad (4)$$

$$p_H(t) = e^{t/\tau} + \left[\left(\frac{\sqrt{2}}{\omega_0 \tau} - 1 \right) \sin \frac{\omega_0 t}{\sqrt{2} - \cos \frac{\omega_0 t}{\sqrt{2}}} \right] e^{-\frac{\omega_0 t}{\sqrt{2}}} \quad (5)$$

where f_R is the respiratory frequency and p controls the rounding of the cusp and the general shape of the signal, while the heart signal is modelled with an analog pulse of an exponential $e^{\frac{t}{\tau}}$, with time constant τ , filtered by a critically damped second-order Butterworth filter with cutoff frequency ω_0 . The mechanical target was programmed to oscillate with a combination of the two sinusoidal waveforms at the frequencies of $f_R = 0.25$ Hz and $f_H = 1.25$ Hz and the maximum displacements of 1 cm and 0.03 cm, respectively, which emulate the cardiorespiratory thoracic movement. The other parameters, $\tau = 0.05$, $\omega_0 = 2\pi$ and $p = 3$, were chosen to best represent typical real data. Using this model, Song et al. [14] demonstrates that using a complex model revealed signal harmonic patterns that were not visible when using the simple sinusoidal model. Although these kinematic input signals enable precise control over displacement amplitude and

frequency, they inherently decouple surface motion from underlying lung physiology, motivating the development of input models in which thoracic motion emerges from volumetric respiratory processes.

2) *Volume-based physiological input models:* In contrast to purely kinematic approaches, volume-based physiological input models describe respiration in terms of lung volume, pressure and airflow. The internal volumetric changes cause the thorax and abdomen to rise and fall. Singh et al. [18] argues that the shape of the thoracic motion pulse varies considerably and cannot be simplified to a sinusoidal model. Their model is based on optimal chemical-mechanical respiratory control to create waveforms that create inhalation and exhalation patterns. The displacement of the thorax, is assumed to be proportional to the variation in lung volume $V(t)$. Therefore, the pattern of thoracic movement $x(t)$ follows the variations in lung volume during a breathing cycle. The equation of motion is expressed as:

$$P(t) = \dot{V}(t) \cdot R_{rs} + V(t) \cdot E_{rs} \quad (6)$$

where $P(t)$ is the isometric respiratory pressure, $V(t)$ is the instantaneous lung volume, $\dot{V}(t)$ is the instantaneous airflow, R_{rs} is the total resistance of the respiratory system and E_{rs} represents the elastance of the lungs, chest wall and airways.

The model considers only two phases of the breathing pattern as repeating inhale and exhale phases. The empirical equations for lung volume variation pattern and, consequently, the thoracic movements for a breathing cycle during inhalation and exhalation periods, can be derived as follows:

- **Inspiration phase** ($0 \leq t \leq t_1$):

$$V(t) = \frac{\tau_{rs}}{R_{rs}} \left[A_1 t^2 + A_2 t + A_3 (1 - e^{-t/\tau_{rs}}) \right] + V_0 e^{-t/\tau_{rs}} \quad (7)$$

- **Expiration Phase** ($t_1 \leq t \leq t_1 + t_2$):

$$V(t) = \frac{P(t_1)}{R_{rs}} \left(\frac{1}{\tau_{rs}} - \frac{1}{\tau} \right) \left[e^{(t-t_1)/\tau} - e^{-(t-t_1)/\tau_{rs}} \right] + V(t_1) e^{-(t-t_1)/\tau_{rs}} \quad (8)$$

In these equations, t_1 and t_2 denote the duration of inspiration and expiration, respectively. The system time constant is defined as $\tau_{rs} = R_{rs} \cdot C_{rs}$, while τ represents the rate at which inspiratory activity declines. The parameters A_1, A_2, A_3 are functions of pulse shaping parameters.

During a normal breath, thorax motion comprises two components: the displacement from respiration activity and, second, the displacement due to cardiac activity. For simulating this cardiac activity, they use the theory of a relaxation oscillator, specifically the Van der Pol oscillator. The oscillating behaviour is described by the non-linear differential equation:

$$\frac{d^2 x}{dt^2} - \alpha(1 - x^2) \frac{dx}{dt} + \omega^2 x = 0 \quad (9)$$

where x represents the displacement, α is the pulse-shaping parameter, and ω determines the frequency of the heart rate. A higher value of α results in a waveform that is less

sinusoidal and more representative of the distinct peaks found in physiological cardiac signals.

The displacement of the thorax caused by heart activity is captured during a breath-hold condition. Because the motion due to heart activity was too small (0.2–0.5 mm) compared to the motion due to respiration (3–12 mm). Therefore, the dataset of thoracic motion due to heart activity only was extracted from the breath-hold duration and used to perform the similarity analysis. The time profile of the thoracic movement due to respiratory and cardiac activity obtained from the simulation was compared with the human thorax experimental data from Shafiq and Veluvolu [35].

As can be seen in Figure 7a, the exhale–inhale pattern closely follows the experimental dataset function. The pulse duration and respiration rate are consistent for both the simulated signal and the referenced signal. The similarity between the simulated waves and the signals from the dataset was assessed. The researchers tested their hypothesis that thoracic movement cannot be simplified to a sinusoidal model; so they also compared a sinusoidal model to their dataset. In the free-breathing scenario, the maximum correlation coefficient approached 0.97 for their model. A similar pattern was observed for irregular and post-exercise breathing as well. However, the similarity index between the sinusoidal model and the dataset waveforms ranged from a correlation coefficient of 0.68 to 0.84. As shown in Figure 7b, the simulated cardiac cycle closely aligns the experimental dataset wave. When comparing the simulated waves from the real breath-hold data (where only heart motion is visible), the relaxation oscillator model achieved a median correlation coefficient of around 0.93, compared to only 0.70–0.84 for the sinusoidal model. This suggests that thoracic displacement during respiration is more accurately represented by the proposed simulation model than by the assumption of sinusoidal motion.

3) *Composite cardiorespiratory motion signals*: Not only Singh et al. [18] included the cardiac activity when simulating breathing movement, several studies extend their models by incorporating cardiac activity. These models represent thoracic motion as the superposition of respiratory and cardiac components with distinct frequencies and amplitudes, which becomes particularly relevant for high-sensitivity, non-contact sensing systems.

As mentioned previously, Song et al. [14] developed a programmable mechanical target driven by a signal combining a non-sinusoidal respiratory waveform with a higher-frequency, lower-amplitude cardiac component.

The study of Pentari et al. [17] aims to measure the respiratory and heart rate with a radar based on their displacement³. Although primarily applied to radar-based sensing, this representation remains relevant for camera-based systems, particularly when detecting shallow breathing.

Taken together, the reviewed input signal strategies range from simple prescribed displacement profiles to physiologically grounded and composite cardiorespiratory models. For camera-based respiration-rate detection, this progression illustrates that input signal flexibility and variability are more

critical than adherence to any single waveform, as robust visual algorithms must generalise across diverse and irregular breathing patterns.

G. Mechanisms for motion generation

Building on the input signal strategies discussed in the previous section, this section examines the mechanical mechanisms used to translate these signals into physical respiratory motion. The focus lies on how different actuation principles influence the resulting surface deformation relevant for visual respiration-rate detection. The included literature identifies three categories of mechanisms used to simulate visible thoracic and abdominal excursions:

- Motor-driven kinematic motion systems
- Volumetric expansion-based systems
- Hybrid systems.

1) *Motor-driven kinematic motion systems*: These systems use motors to push or pull specific anatomical regions or platforms. They have precise control over displacement amplitude and frequency, often used for calibrating sensors.

Dunn et al. [11] modified the QUASAR phantom (Figure 6c) by replacing a DC motor with a programmable stepper motor. It features a decoupled “chest-wall” motion platform (the platform in the left corner) driven by a second stepper motor. The chest motion platform has a maximum speed of 16 mm/s with a maximum translation of 60 mm and a minimum translational step size of 0.001875 mm.

The irregular breathing platform (Figure 6d) of Fitzpatrick et al. [8] utilised a single-axis sliding platform driven by a stepper motor to simulate superior–inferior⁴ motion. The movable platform is mounted to a base using precision linear bearings to restrict the platform to a displacement of approximately 5 cm along a straight line with very little friction.

To manage loads up to 27 kg, Litzenberg et al. [10] utilised an AC servo motor with a ball screw. While rotary induction motors provide accurate cyclical motion at constant speed, they are limited to sinusoidal movements. Conversely, stepper motors offer high-resolution incremental motion but can experience “slippage” at higher speeds when the torque is insufficient to overcome the load’s inertia. This slippage can be reduced by lowering the phantom’s weight or decreasing the motion profile’s velocity and acceleration. Implementing a closed-loop feedback mechanism can also help correct slippage, ensuring the desired position is reached, though it may take longer than expected [10].

Some complex systems, like the 4D Phantom (Figure 6a) from Malinowski et al. [13], use different stages for their operations. They have a 3D stage to track the movement of internal tumours and a separate 1D stage to control external breathing aids. It is powered by four independent rotary stepper motors, which are connected to lead screws within slide assemblies to produce linear motion. Three motors are connected orthogonally to move a stage in three dimensions. Additionally, the system can execute trajectories that specify the positions of the axes at 20-millisecond intervals. In this

³Further details are explained in subsection I-H4.

⁴Superior–inferior is head-to-toe, see Figure 13 in Appendix B.

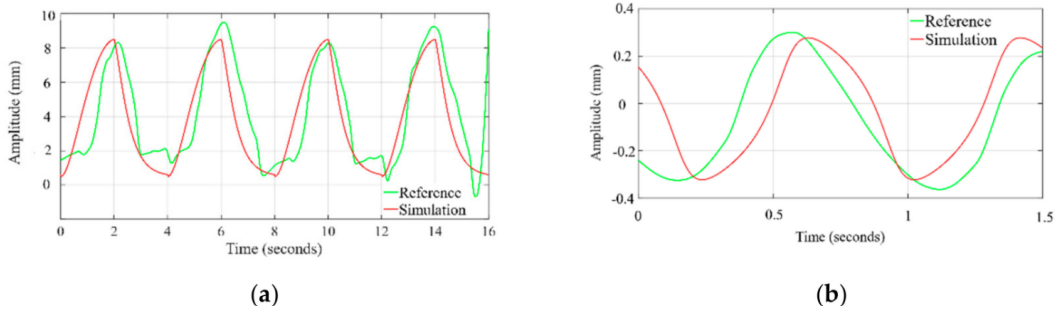


Fig. 7. Thoracic motion due to (a) respiration and (b) heartbeat patterns of the model compared with the dataset of human thoracic movement during breathing [18].

dynamic positioning mode, the motion controller card smooths the paths between the commanded positions. This allowing for the replication of more complex breathing patterns.

The radar simulator (Figure 6h) of Pentari et al. [17] uses two stepper motors. The rotary movements of the motors are converted into linear movements via a trapezoidal screw with an 8mm lead, which corresponds to a maximum resolution of 0.005mm per step.

Thus, DC motors are easy to use but lack the precision for realistic motion reproduction. AC servo motors offer smooth, accurate motion with high-resolution feedback, yet they are mainly designed for repeatable trajectories and may have difficulty with irregular or patient-specific breathing patterns unless specifically programmed. Whereas stepper motors offer high positional resolution and can reproduce micrometre-scale displacements, making them suitable for both tidal and deep breathing simulation. Their primary limitation lies in potential step loss when load or acceleration demands exceed available torque. Although the risk of missed steps can be mitigated through closed-loop operation, reduced velocity, or lower inertia, it introduces constraints that may affect the fidelity of dynamic, non-sinusoidal breathing profiles.

2) *Volumetric expansion-based systems*: This mechanism is commonly used in commercial high-fidelity manikins. These systems utilise internal compressors or external ventilators to inflate artificial lungs or airbags located beneath the chest skin, resulting in visible expansion.

The CAE Apollo & Ares [31][32] simulators utilise an internal pneumatic system to create spontaneous breathing. They have two separate lungs, which provide the possibility of asymmetric thoracic movement⁵. This provides critical training data for abnormal breathing patterns, such as bronchial occlusion⁶.

The Gaumard HAL (S3201 & S1000) [34][30] simulators also feature programmable airways and two lungs that support spontaneous chest rise and fall. They offer dynamic airway resistance and lung compliance, allowing the simulator to mimic gasping or tension pneumothorax⁷ with asymmetric thoracic rise.

⁵With asymmetric thoracic breathing, one side of the thorax rises while the other doesn't or moves symmetrically.

⁶Bronchial occlusion is a blockage in the right or left bronchi.

⁷Pneumothorax is the phenomenon before having a collapsed lung

The DATPHA phantom (Figure 2a) of Abdollahi et al. [4] uses a custom-made pump system and dedicated software to cyclically inflate and deflate lungs. This system of inflation and deflation causes synchronised movements in the thorax and diaphragm, mimicking human respiratory dynamics.

Lin et al. [1] also uses a pump to simulate breathing movement of the Lapman torso (Figure 3a). This was done by connecting it to a computer-controlled pump driven by a linear actuator and flexible bellows, see Figure 8. This allows for the generation of complex, programmable breathing waveforms that physically expand the silicone chest wall of the phantom. The linear actuator was selected to have a maximum linear stroke of 200mm and a maximum linear speed of 150mm/s. Coupled to a flexible bellows, the linear actuator can simulate human breathing up to 20 breaths per minute with tidal volumes ranging from 0 ml to 1500 ml.

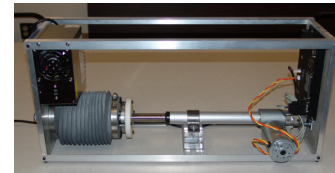


Fig. 8. The pump assembly for the modified Lapman torso with the bellows (left) and the linear actuator (right). [1]

The mechanical model (Figure 2b) by Brosch et al. [6] uses one-liter IV bags to represent the maximum tidal volume consistent with the capacity of human lungs, which were within a saline-filled (mixture of sodium chloride and water) manikin. The expansion of these bags displaced saline into a container located on the abdomen, effectively simulating the respiratory volumetric changes of a supine patient. Two tubes were connected to the lungs and extended through the neck of the manikin. The inflation and deflation of the bags were managed using a portable large animal respirator, providing a constant breathing rate and volume. Before experimentation, a resting volume of air (1000-1200 ml in total) was established in the two lungs because humans naturally have a resting volume of air in their lungs, even after complete exhalation.

In the dynamic ALDERSON phantom (Figure 2c) of Chrysanthou-Baustert et al. [2], a controller regulated the air valves that inflated lung-shaped balloons, achieving specific tidal volumes for normal and deep breathing patterns. The

breathing phantom consists of humansized inflatable lungs. At end-expiration, the air volumes of the left and right lungs were 510 and 565 mL, respectively. This is because the left lung of a human is also smaller due to the placement of the heart. Each lung was covered with a 1-mm-thick thermoplastic structure. The respiratory cycle was set to 6 sec and the tidal volumes were set to 450 and 550 mL for the normal and deep breathing, respectively.

The Wilhelm phantom (Figure 2d) of Bolwin et al. [7] uses two-component silicone air bags, with volumes of 2 litres and 0.5 litres, to represent the left and right lungs. A piston connected to the torso's membrane translates movement into volume changes. The lungs are pressurised before the torso is filled with water and made airtight, after which the lung air valves are opened. Moving the piston causes the membrane to shift the inner torso's volume, resulting in the inflated and deflated motion of the lungs, thanks to the rigid shell and incompressible water inside.

The SimVep phantom (Figure 3b) of Valencia et al. [3] includes two independently functioning lungs of 0.6 litres, allowing the simulation of different conditions in each lung. The system is designed to be used together with a mechanical ventilator. The ventilator allows precise control, enabling the simulation of various clinical conditions. All parameters can be adjusted, allowing for realistic replication of both normal and pathological respiratory mechanics. Thus, volumetric expansion-based systems offer a physiologically grounded method of simulating respiration by generating motion through internal pressure or volume changes. This enables them to reproduce natural breathing movement. But their accuracy relies heavily on simple bellows and pump systems, which struggle with fine control, due to delays and limited responsiveness to rapid components. While these systems capture realistic breathing behaviours and biomechanical relationships, they lack the precision and repeatability of kinematic actuators. Thus, volumetric expansion offers high physiological realism but lower controllability, making it ideal for scenarios requiring natural motion rather than precise trajectory reproduction.

3) *Hybrid systems*: The CARETestLung system (see Figure 6f), designed by Tay et al. [15] and Tay et al. [16], employs a hybrid pneumatic and electromechanical design to simulate a linear single-compartment lung model. Air from the ventilator passes through a network of pneumatic tubes, where airway resistance (R_{rs}) is adjusted using tubes of varying lengths and diameters. The lung compartment features a flexible PVC hose supported by a fixed base and a movable upper platform that acts as a diaphragm. An electric servo motor operates a lifting mechanism to create negative pressure for air intake, while a spring system provides passive lung elastance (E_{rs}). Just as the ASL 5000 respiratory simulator of the IngMar RespiSim system (Figure 5) employs a piston-in-cylinder mechanism to create precise, realistic breathing profiles. The piston mechanism enables highly repeatable motion with fine temporal resolution, making it suitable for validating ventilator performance, modelling patient-ventilator interaction and simulating rapid perturbations such as coughs or asynchronous breaths.

The torso motion simulator (Figure 2e) of Ulrich et al. [5]

creates both thoracic and abdominal breathing. The abdominal motion is generated by a DC-motor with a rotary encoder as control feedback and the thorax is lifted and lowered with three servomotors. The thorax is simulated as a rotatory movement by the servomotors, whereas the abdomen has a linear up-and-down motion.

While the actuation mechanisms determine how respiratory motion is generated, the visual characteristics observed by camera-based systems are ultimately governed by the resulting surface dynamics, which are examined in the following section.

H. Surface dynamics

Having examined the actuation mechanisms that generate respiratory motion, the next section focuses on the resulting thoracic and abdominal surface dynamics and incorporates the influence of the heartbeat.

1) *Thoracic movement*: The thoracic movement consists of movements in different directions. When the upper ribs are elevated, the anteroposterior⁸ dimension of the thorax increases, a movement often referred to as the "pump-handle" movement. The ribs move in a ventral⁹ and cranial¹⁰ direction. Meanwhile, the middle parts of the lower ribs move laterally¹¹ when they are elevated, which increases the transverse dimension, a movement known as the "bucket-handle" movement. Because the ribs are shaped like hoops, this upward rotation increases the diameter of the chest cavity. These movements are visualised in Figure 9 and Figure 10.

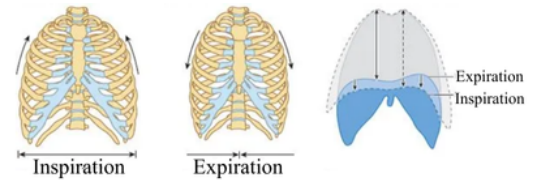


Fig. 9. The thorax widens during inspiration as the ribs are elevated. And the thorax narrows during expiration as the ribs are depressed. The primary movement of inspiration is contraction of the diaphragm, which increases the vertical dimension of the thoracic cavity. [36]

De Groote et al. [24] researched the kinematics of breathing in **seated** positions of healthy subjects. They found no clear-cut difference in the ratio of ventral to lateral displacement between the upper rib cage and the lower rib cage. Instead, both compartments moved primarily in the cranial and ventral directions, with lateral displacements being significantly smaller (averaging 1–2 mm) compared to ventral displacements (averaging 3–5 mm).

As explained in subsubsection I-F1, the motion platform of Kissick et al. [9] moves in an ellipse. The lateral and caudal¹²

⁸Anteroposterior direction is from the front to the back, see Figure 13 in Appendix B.

⁹Ventral is the front, see Figure 13 in Appendix B.

¹⁰Cranial is towards the head, see Figure 13 in Appendix B.

¹¹Lateral is the direction away from the middle, see Figure 13 in Appendix B.

¹²Caudal direction is the direction towards the tail, see Figure 13 in Appendix B.

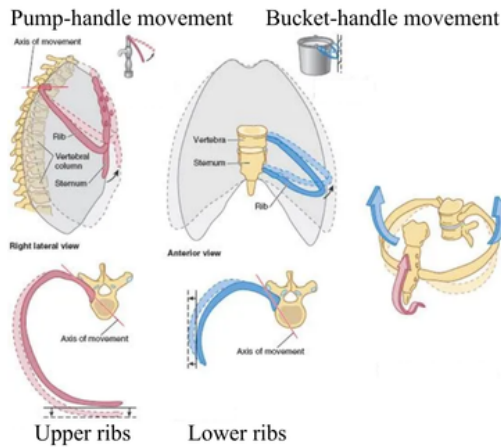


Fig. 10. The red movement shows the pump-handle movement when the upper ribs are elevated. And the blue movement shows the bucket-handle movement, where the middle parts of the lower ribs move laterally when they are elevated. [36]

motions are equal in magnitude at 1.0 cm peak-to-peak, but the anteroposterior motion is significantly less at 2.5 mm peak-to-peak.

Lin et al. [1] tracked the thoracic movement using different pump strokes, explained in subsubsection I-G2 and shown in Figure 8. The Lapman torso required larger-than-average human tidal volumes to achieve similar thoracic displacements. This is because it is constructed out of several centimetres of solid silicone, resulting in a rather low compliance boundary for the lung cavity. However, the larger tidal volume required does not affect the effectiveness of this platform as a validation tool, because it can be accurately compensated for the difference in volumes to achieve human-like motion.

2) *Human studies about thoracic and abdominal movement:* Zhao et al. [22] uses a three-compartment model, including the pulmonary rib cage (RCp), the abdominal rib cage (RCa) and the abdomen. Eight markers were then selected to measure the expansion and contraction displacement (normal and tangential displacement) of each area on the horizontal and vertical planes of the thorax and abdomen during breathing. Twelve subjects were selected, between 23 and 30 years old and with a body mass index (BMI) of 25.1 ± 7.7 . All subjects were in good health and had no history of respiratory diseases. The researchers found that when the subject was in supine position, gravity caused a decrease in the abdomen's anteroposterior¹³ diameter and an increase in its right-to-left diameter. Similarly, De Groote et al. [24] reported that in seated positions, subjects' tidal breathing produced predominantly cranial and ventral rib cage motion, with lateral displacements being substantially smaller. Taken together, these observations underscore that thoracic and abdominal movement patterns are influenced not only by respiratory mechanics but also by posture-dependent gravitational deformation of soft tissues. This indicates that a robust visual respiration rate detection system should be

trained on three-dimensional surface deformation data rather than on linear displacement alone.

Kaneko and Horie [25] determined the 3-dimensional distances of observational points on the thorax and abdomen during breathing in healthy subjects and assessed the effects of age, posture, and sex. The study included 100 healthy participants, 50 females and 50 males, with ages ranging from 20 to 74 years (44.8 ± 16.8), all with a BMI under 30. Thirteen markers were placed on the participants' thorax and abdomen and they were tracked by eight infrared cameras. The participants were observed during quiet breathing and deep breathing in both supine and sitting positions. The researchers found that the average distances the markers moved during quiet breathing were less than one-third of the distances measured during deep breathing. They noticed that the movement of the upper thorax significantly decreased with age and that the thoracic movement distances decreased with age during deep breathing in the supine position. In terms of gender differences, females generally exhibited less abdominal movement than males. During deep breathing in the supine position, males showed significantly greater distances for lower thoracic and abdominal markers compared to females. However, during quiet breathing in the supine position, females demonstrated significantly greater thoracic marker distances and shorter abdominal marker distances compared to males. This aligns with observations from other studies that females often have a wider rib cage contribution and lower abdominal contribution to tidal volume during quiet breathing. When comparing the two positions during quiet breathing, the mean respiratory rates were significantly higher in the sitting ($15.4 \pm 3.6 \text{ breaths/min}$) than in the supine position ($14.6 \pm 3.7 \text{ breaths/min}$). But, no significant differences in the respiratory rates were found between the sex and age groups.

Disease-specific variations in thoracic and abdominal motion were investigated by Johansson et al. [21]. In the study of Johansson et al. [21], thirty-five patients diagnosed with SHR¹⁴, 19 with COPD¹⁵, 32 with asthma and 28 control subjects were included. Their thoracic and abdominal expansion was measured with a measuring tape and their movement with light sensors. The participants were in a supine position on a treatment bench with cushions under their head and knees, relaxing and closing their eyes during measurements. They showed that patients with COPD had lower expansion ability compared to the other three groups. The COPD patients also demonstrated lower thoracic flexion values than both the asthma and the control group. Lastly, the thoracic extension ability of the COPD patients was lower than that of the control subjects. During quiet breathing, both COPD and asthma patients exhibit higher values of lower thoracic and abdominal movement compared with the SHR group. In the COPD group, these values were even higher than in the control group. During deep breathing, the abdominal movement values were lower in the SHR group than in the asthma patients and control subjects. However, in the COPD group, the abdominal and lower thoracic movement values

¹³Anteroposterior direction is from the front to the back, see Figure 13 in Appendix B.

¹⁴Sensory Hyperreactivity

¹⁵Chronic Obstructive Pulmonary Disease

were lowered only compared with the control group. Thus, it is important to include abdominal movement to simulate these diseases.

3) *Models for abdominal breathing*: To understand the mechanics of abdominal breathing, Calabrese et al. [20] propose a dynamic model based on a lever system, see Figure 11.

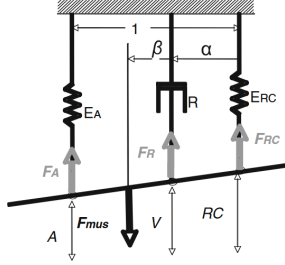


Fig. 11. The lever system where E_{RC} , F_{RC} , RC and E_A , F_A , A are the elasticity of the springs, the elastic tension forces and the displacement of the ribcage and abdomen. R is the resistance of the damper, F_R its force and V its displacement. F_{mus} is the respiratory muscle force, α is the distance between the damper and the rib cage spring and β is the distance between the damper and the application point of F_{mus} . [20]

The volume changes (V) are represented by the vertical displacement of a damper. The constraints of the parameters are as follows $0 < \alpha < 1$ and $\alpha - 1 < \beta < \alpha$. The relationship between total lung volume and the vertical displacement of the abdomen and rib cage is defined as:

$$V = \alpha A + (1 - \alpha)RC \quad (10)$$

To account for dynamic factors, the elastance of the rib cage compartment (E_{RC}) and the abdominal compartment (E_A) were included and they derived a differential equation based on the moment equilibrium of the lever bar. This results in an expression for airflow ($\frac{dV}{dt}$) as an equation of the positions of the abdomen and rib cage:

$$\frac{dV}{dt} = K_A A + K_{RC} RC \quad (11)$$

To validate the lever model, eleven healthy participants were recorded to gather data. The group of participants included eight females and three males, with ages ranging from 19 to 55 years old (28.5 ± 12.6). Their weights varied from 46 to 87 kg (61.6 ± 10.6) and their heights spanned from 154 to 185 cm (168 ± 10). Their breathing was measured by pneumotachography¹⁶. The model was validated by 40% of the recorded breaths (1,193 out of 2,971), achieving a determination coefficient of $R^2 \geq 0.70$. The results confirm that airflow can be modelled as a linear combination of abdominal and rib cage displacements.

Sameera et al. [19] uses Equation 4 of Song et al. [14] to create an equation to describe the thoracic and abdominal motion during respiration. They assume that the movement is scaled with a factor X .

$$x_R(t) = X \sin^p(\pi \cdot f_R \cdot t) \quad (12)$$

¹⁶Pneumotachography is a method for measuring airflow.

The abdomen and thorax displacements are defined as $x_1(t)$ and $x_2(t)$ respectively, using Equation 12. They assume that $\frac{x_1}{x_2} = 2$, so the displacement of the abdomen is twice as big as the thorax. They also assume that the total phase difference between the abdomen and thorax is about 20 degrees. The total phase delay between the two components determines how they add to produce a signal measured by radar. The comparison of the results of the experiment is shown in Figure 12. They include Doppler radar data collected simultaneously with infrared cameras tracking thirteen markers attached to the skin.

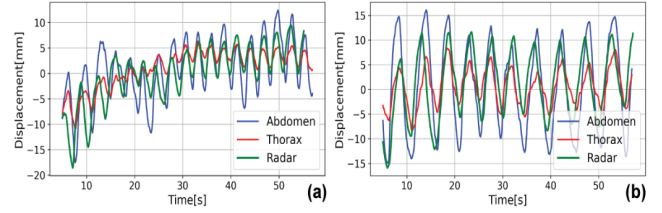


Fig. 12. Displacement results comparing thorax marker and abdomen marker for (a) normal breathing and (b) deep breathing with radar-estimated displacement [19].

The thorax marker had a much smaller displacement than the lowest marker on the abdomen. For both cases, the displacement measured by the radar is observed to be between the displacements of the abdomen and the thorax. These results confirm the hypothesis that radar-measured respiratory displacement is composed of abdomen and thorax contributions, with some phase delay between the two. Taken together, this demonstrates that thoracic and abdominal motions contribute differently to the overall breathing signal, often exhibiting phase delays and amplitude differences.

4) *Influence of the heartbeat*: Pentari et al. [17] used the set-up, which can be seen in Figure 6h. They use Equation 13 for measuring the difference in distance between the radar and the "human chest".

$$d(t) = d_0 + a_r \sin(2\pi \cdot f_r t) + a_h \sin(2\pi \cdot f_h t) \quad (13)$$

In this context, d_0 represents the nominal distance, while a_r and a_h represent the average displacements of the "human chest" resulting from respiratory and heartbeat activities, respectively. The variables f_r and f_h correspond to the respiratory and heartbeat frequencies, which are the quantities they want to estimate. The respiratory rate is evidenced by the noticeable movement of the thorax during breathing. This displacement typically varies between 4 mm and 12 mm, corresponding to a frequency range of 0.2 Hz to 0.34 Hz (translating to 12 to 20 breaths per minute). Additionally, this movement contributes to the assessment of the heart rate, as the heart's operation induces a smaller displacement of 0.2 mm to 0.5 mm on the thorax surface with a frequency range of 1 Hz to 1.34 Hz (equivalent to 60 to 80 beats per minute).

Mentioned previously in the study of Singh et al. [18] in subsection I-F2, both respiratory activity and cardiac activity cause the motion of the thorax. The displacement due to cardiac activity is significantly smaller than that of respiration. In their study, the respiratory motion resulted

in thoracic wall displacement ranging from 3 to 12 mm. In contrast, displacement caused by the heartbeat was only between 0.2 and 0.5 mm. Jiang and Dahnoun [12] simulated this by combining a long-stroke linear actuator for respiration with a high-precision micro-linear stepper motor to replicate the subtle thoracic wall displacements caused by the heartbeat. This dual-actuator approach allows for the generation of complex, multi-frequency surface vibrations that are critical for training robust detection algorithms.

Thus, the dynamics of surface movements during breathing arise from complex interactions among thoracic motion, abdominal displacement, gravitational effects and superimposed cardiac activity. Although these interactions are complicated, studies indicate that it is possible to model this behaviour.

II. DISCUSSION

This literature review set out to determine which existing respiratory simulators can reproduce realistic, visually observable breathing patterns for adults in a supine position and which components are most critical for developing and training a camera-based visual respiration-rate detection system. Across the included literature, three simulator categories emerged:

- Anthropomorphic phantoms
- Mechanical motion platforms
- Validation studies

Each category contributes distinct but complementary insights into input signals, mechanics for motion generation and its surface dynamics. Integrating these findings highlights that no single simulator category fully meets the needs of camera-based algorithm training. Instead, the most suitable solution requires a combination of these and depends on the accuracy of the respiratory motion detection of the camera-based system.

A. Input signal

The literature consistently demonstrates that simple sinusoidal input signals are inadequate for representing realistic respiratory motion. Song et al. [14] shows that algorithms trained or validated exclusively on sinusoidal motion fail to capture harmonic structures present in physiological breathing patterns. Similarly, Fitzpatrick et al. [8] and Litzenberg et al. [10] emphasise the importance of simulating irregular breathing patterns to simulate patient-specific trajectories.

Rather than identifying a single “optimal” waveform, this review highlights that input signal flexibility is the critical requirement. This capability allows camera-based systems to be trained on the variability and irregularity that characterise real-world respiration.

B. Mechanisms for motion generation

The reviewed literature demonstrates that air-driven lung systems embedded within anthropomorphic phantoms provide the highest visual realism. Different off-the-shelf simulators illustrate that independent left–right lung control and adjustable lung compliance are critical features. These features create the ability to simulate asymmetric breathing patterns, which are

clinically relevant for conditions such as pneumothorax¹⁷ or bronchial occlusion¹⁸.

Additionally, if the camera-based system can detect very small movements, it is important to include the physiological resting lung volume, as highlighted by Brosch et al. [6]. Furthermore, it is also needed to include lung asymmetry, since the left lung is smaller due to the position of the heart [2].

Fluid-filled torso designs, as demonstrated by Brosch et al. [6], mark a significant advancement in technology. This design converts changes in internal lung volume into interconnected surface movements. This connection more accurately represents human biomechanics, where the thoracic and abdominal structures interact with one another through incompressible tissues. As a result, movement occurs when the lungs expand or contract.

A key practical consideration is whether to control the lung volume using a mechanical ventilator or a linear pump system. Ventilator-driven simulators, such as SimVep [3] and the CARE Test Lung [15], [16], reproduce realistic pressure–volume–flow behaviour and allow simulation of clinically relevant scenarios. In contrast, linear pump or actuator systems, such as the pump¹⁹ of the modified Lapman torso [1] or the DATPHA phantom [4], offer greater flexibility in generating model-derived breathing waveforms. This suits better for algorithm training where a wide range of controlled surface motions is required. For camera-based respiration-rate detection, where visible breathing motion is the primary outcome, the pump-driven systems offer a slight advantage in experimental flexibility. Lastly, purely electromechanical systems based on linear actuators or stepper motors are inherently limited, as they typically generate motion along a single axis. This limitation is also present in most motor-driven platforms, indicating that linear displacement alone is insufficient for realistic visual respiration modelling. Notable exceptions include the simulator developed by Ulrich et al. [5], which combines rotary thoracic motion with linear abdominal movement, the 4D Phantom of Malinowski et al. [13], which uses three motors connected orthogonally and the elliptical motion platforms described by Kissick et al. [9]. These designs represent important intermediate solutions, as they partially approximate the multi-directional nature of human breathing.

C. Surface movement

A central conclusion of this review is that thoracic and abdominal motion should be considered as distinct yet interacting components. Simulators that treat the torso as a single rigid surface fail to accurately replicate these dynamics and may train camera algorithms on unrealistic motion patterns. It is essential for a camera system to be able to differentiate between these regions. A crucial feature of a simulator is the ability to generate these two motions independently or with a programmable phase delay.

Ulrich et al. [5] demonstrates that anatomically correct surface geometry combined with programmable displacement

¹⁷Pneumothorax is the phenomenon before having a collapsed lung

¹⁸Bronchial occlusion is a blockage in the right or left bronchi.

¹⁹see Figure 8

amplitudes is essential for correlating camera-derived signals with reference measurements. Lin et al. [1] further shows with the Lapman torso that, although thicker and less compliant shells necessitate larger internal tidal volumes to achieve human-like external displacement, realistic external motion can still be accomplished through careful calibration. Together, these findings underscore the importance of shell compliance and regional decoupling in simulator design.

Kaneko and Horie [25] highlights that it is important to include the difference between females and males, because their study shows that females exhibit greater thoracic contribution and reduced abdominal motion compared to males. Johansson et al. [21] confirms that you need to include independent control of thoracic and abdominal displacement amplitudes and phase relationships to simulate the breathing for patients with asthma, SHR²⁰ and COPD²¹.

D. Limitations

This review has several limitations related to the studies included and the methods used. Only one identified system, by Ulrich et al. [5], explicitly incorporates camera-based validation for respiratory gating. This suggests that most simulators were not designed for camera-based detection systems. Conclusions about surface dynamics and motion characteristics were partially based on radar-based sensing, radiotherapy motion platforms, and biomechanical modelling studies. Although these methods are grounded in the same underlying physiological principles, differences in sensing technologies may limit the direct applicability of the findings. Because it was conducted by a single reviewer, there is a risk of selection and interpretation bias, despite the use of a structured search strategy and explicit inclusion criteria. Furthermore, the literature search was restricted to the PubMed and Scopus databases and to English-language publications, which may have resulted in the omission of relevant studies indexed elsewhere or published in other languages.

E. Implications and future research

Several research gaps remain. First, the extent to which cardiac-induced surface motion is detectable by camera-based systems remains unclear. Breath-hold experiments could isolate cardiac motion and determine whether it introduces noise or additional diagnostic information. Second, studies are needed to show how the accuracy of the simulator influences algorithms perform to real patients.

Future work should focus on developing modular anthropomorphic simulators, including an abdomen, which can provide different sizes, sexes and breathing patterns. Such simulators would enable standardised benchmarking of camera-based respiration algorithms and facilitate the creation of large, ethically and representative training datasets.

In conclusion, this review demonstrates that training camera-based respiration-rate detection systems requires simulators that prioritise externally visible biomechanical realism over simplified motion generation. By explicitly defining the components and motion characteristics necessary for visual fidelity, this work provides a foundation for the development of respiratory simulators for camera-based detection systems.

²⁰Sensory Hyperreactivity

²¹Chronic Obstructive Pulmonary Disease

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APPENDIX A SEARCH QUERIES

Scopus search query:

TITLE-ABS-KEY ((breath OR respirat* OR "breathing pattern" OR "respiration rate" OR RR) AND (simulat* OR imitat*) AND (("thorax" W/3 (movement OR motion OR kinematic* OR expansion)) OR ("rib" W/3 (movement OR motion OR kinematic* OR expansion)) OR ("chest" W/3 (movement OR motion OR kinematic* OR expansion)) OR manikin OR mannequin OR mannikin OR manakin)) AND NOT ventilat* AND NOT computat* AND NOT compress* AND NOT thermal AND NOT tissue*

PubMed search query:

((breath[tiab] OR respirat*[tiab] OR "breathing pattern"[tiab] OR "respiration rate"[tiab] OR "RR"[tiab]) AND (simulat*[tiab] OR imitat*[tiab])) AND (("thorax"[tiab] AND (movement[tiab] OR motion[tiab] OR kinematic*[tiab] OR expansion[tiab])) OR ("rib"[tiab] AND (movement[tiab] OR motion[tiab] OR kinematic*[tiab] OR expansion[tiab])) OR ("chest"[tiab] AND (movement[tiab] OR motion[tiab] OR kinematic*[tiab] OR expansion[tiab])) OR manikin[tiab] OR mannequin[tiab] OR mannikin[tiab] OR manakin[tiab]) NOT (ventilat*[tiab] OR ventilation[tiab] OR ventilator*[tiab]) NOT (computat*[tiab] OR computational[tiab] OR computer*[tiab]) NOT (compress*[tiab] OR compression[tiab]) NOT thermal[tiab] NOT tissue[tiab]*

APPENDIX B ANATOMICAL DIRECTIONS

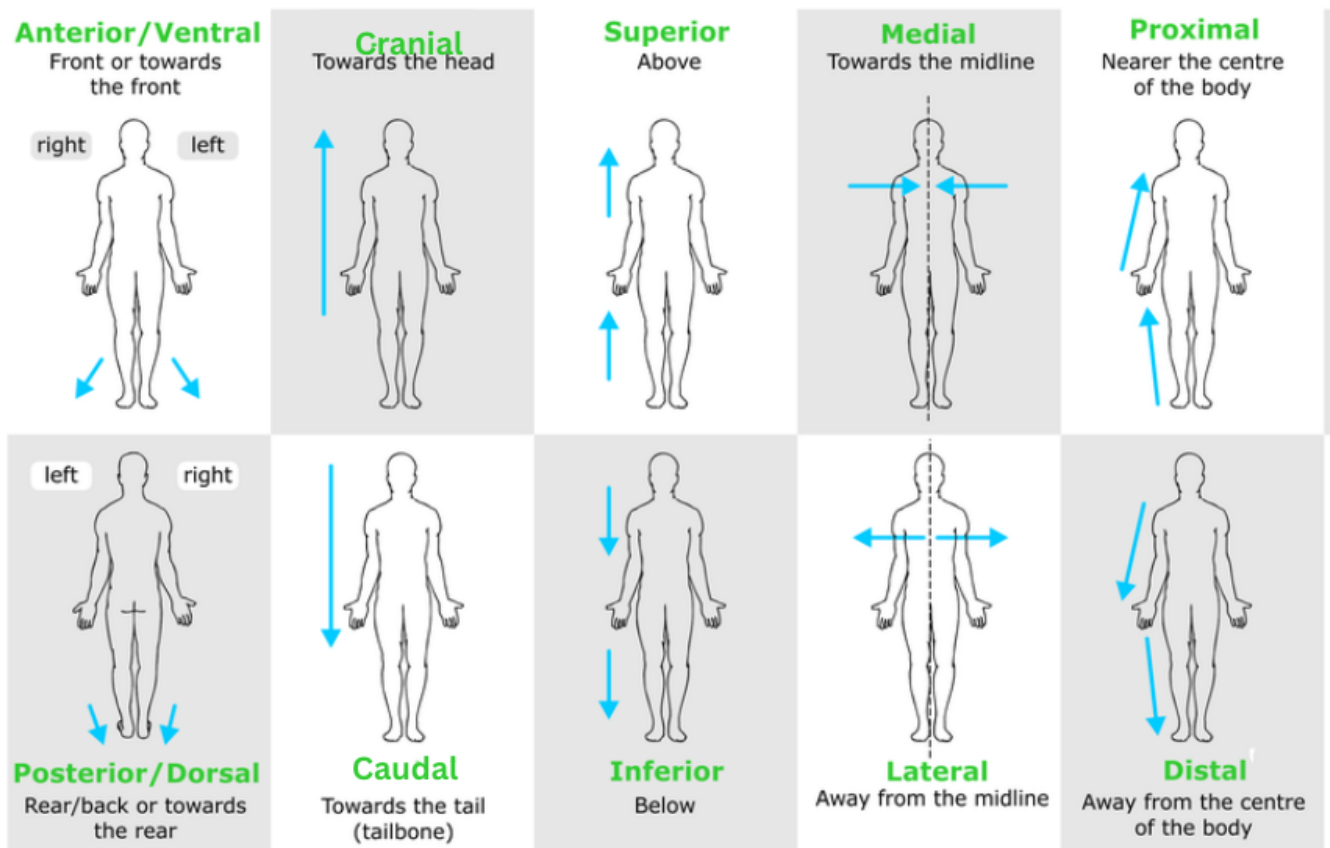


Fig. 13. Anatomical directions [37]