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Evaluation of a Depth Camera as e-Health Sensor for Contactless Respiration Monitoring

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***Abstract*—We evaluate a contact-free method to observe the breathing behavior of persons seated in front of a desktop environment, with an RGB-D camera attached to the screen. Our system monitors the breathing-induced movement of the user's chest, delivering a respiration curve from the camera depth stream by mean- or median-based averaging of single-distances to pixels in the target body region over time. The system was evaluated in an experiment on 8 study participants. The mean-based respiratory rate estimation presented fewer errors and the system works best at close proximity. At 1m distance, it presents a correlation to a respiration belt as ground truth of 0.94 and an absolute error of 0.04bpm. From our data, no influence on the performance of the system was found by gender or different respiration rate. The final system does not require extensive knowledge to set up and operate. The approach allows users to monitor their breathing rate while working, opening up new e-health application areas. They range from self-care and healthcare to managing operators in safety-critical systems such as control rooms, since the respiratory rate is closely linked to a person's state of attention.**

***Index Terms*—non contact respiration monitoring, RGB-D camera, respiratory rate, remote respiration measurement**

I. Introduction

Although the human respiratory rate is an important vital parameter when it comes to monitoring or diagnosing possible physical illness [1], respiration is still under-measured [2], [3]. Apart from clinical environments, the estimation of the human respiratory rate has a wide range of applications, from sports and fitness tracking to meditation, well-being and sleep monitoring. It is closely linked to behavioural and affective states [4] and can even be used as an indicator of wakefulness or rather concentration, deploying the circumstance that the respiratory rate decreases when drifting towards sleep [5].

In this work, we envision an easy to set-up respiration monitoring system that delivers reliable data and can be operated by non-professionals in an everyday environment with the purpose to enable a whole range of e-health applications, be it for sports, meditation, personal or professional health monitoring, or beyond. Asthma patients, to name a concrete example, could benefit from long-term observations of their breathing made at home, without the need to go to a special lab or their doctor's office where only a limited amount of time and space is available [6].

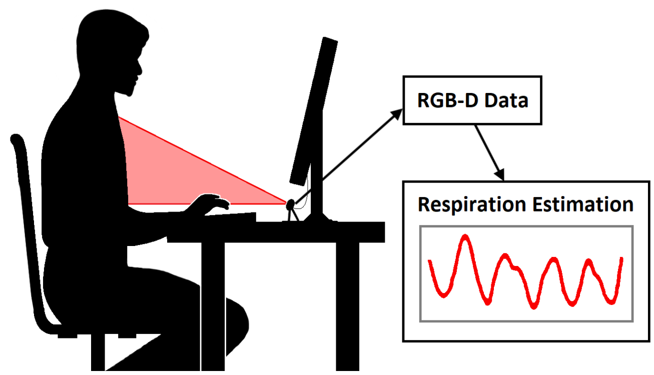

Fig. 1. Overview of our proposed system: An unobtrusive depth camera observes the user's chest to estimate and monitor this user's breathing.

To detect the respiratory rate, a variety of sensors can be used. The most accurate sensors include respiration belts, spirometers, or nasal tubes. However, these contact-based sensors are particularly obtrusive to wear and might hinder people at their occupation or daily routines. Also, in most cases they are not easy to set up or wear and typically require specific equipment and an expert to conduct the measurements. Smaller devices such as pulse oximeters operating on photoplethysmography measure heart rate or SpO2 reliably but lack a reliable and instant respiratory rate estimation [7].

An alternative to such contact-based sensors are the so-called remote respiration estimation methods that inter alia utilize a depth camera to measure subtle chest and torso movements during breathing cycles [8]. Such a system only has little set-up requirements, just a depth camera, e.g. deployed in many modern smartphones, and a user sitting or standing in front of it. Recent respiration estimation methods do not even need a clear line of sight to the user's chest or torso region and are robust to small occlusions and motion artifacts [9]. Such a sensor that does not require extensive arrangements, that delivers reliable data, and can be operated by non-professionals would perfectly fit in the range of e-health applications as discussed above.

This work aims to evaluate and assess the performance of a depth camera employed as a respiration sensor in an everyday environment outside clinics. In particular, it quantifies the precision of the estimation of the current respiratory rate in the presence of possible distorting influences of user characteristics, such as gender or individual clothing. We hereby focus on office-like settings where a user sits in front of a display and does some sort of breathing exercise or simply is monitored by the system over a period of time. A depth camera can be installed on the display like a small webcam with a clear line of sight to the user's upper torso as depicted in Figure 1. We argue that this setup already resembles many, if not most use cases such a respiration sensor would be used in. It for instance allows for long-term respiration monitoring during screen work or while watching TV, or can be used in a more active context like practicing guided respiration exercises in front of a display where the system provides some sort of feedback to the user, the supervisor, or e.g. a doctor. In safety critical functions, e.g. in control rooms or rescue coordination centers, it can serve as a fatigue indicator, or it may be the basis to recognize problematic respiratory events at an early stage, for instance of asthma patients. In this way, it can function as a safety device, recognizing the altered state of the user.

We present in this work a remote respiration estimation system consisting of a small and affordable Intel RealSense D435 depth camera attached to a standard consumer grade PC like a webcam. The system is evaluated on a convenience sample of 8 study participants under a range of varying parameters. The contributions of this work and the developed system are summarized as:

- A benchmark dataset containing force data from a respiration belt together with raw and processed depth data from an Intel RealSense D435 RGB-D camera recorded from the chest from 8 participants, 4 male and 4 female, each recorded in six different settings: at 1m, 2m and 3m distance with a paced respiratory rate of 10bpm or 15bpm respectively.
- The source code for a remote breath monitoring system to be used with an Intel RealSense D435 depth camera. The small dimensions of the device and the possibility of adjustments make it an attractive choice for a wide range of individual work environments, most likely attaching the RGB-D camera like a webcam to a screen.
- An evaluation of the system following the experimental methodology of [10]. Our system to extract the respiratory rate from depth data is compared to the ground truth data from a respiration belt for various conditions, as well as earlier systems with different depth imaging hardware. The influence of participants' gender, different respiration rates and mean- or median-based algorithms is investigated together with causes for possible differing and the effect of individual clothing style.

Our experiment scripts are publicly available at https://github.com/SierraBravo0705/rr-realsense for replication and further experimentation. This paper will in the next sections first position this work among related research, before describing the design and study results. A discussion of the results then leads to our main conclusions.

II. Related Work

The approaches for continuously measuring the respiratory rate can be divided into contact or non-contact systems. As the first-named class is more likely to cause users distractions, only the latter group comes into question.

Recently, much investigated strategies comprise of traditional RGB cameras, RGB-D cameras, thermal imaging, radar and even Wi-Fi. All these contact-free techniques make use of one of two general principles, according to [11].

1) Alteration of the air volume: In a breathing cycle, the chest and abdomen expand during inhalation and contract during exhalation. A displacement is induced in the direction that the body parts are facing.
2) Change in air flow: It causes effects around the nose such as periodic variations in temperature or humidity.

Radio science takes advantage of the Doppler effect. Objects in motion, such as the torso during breathing, cause a Doppler frequency shift [12]. Besides Ultra-Wideband Radar (UWB), Continuous Wave (CW), and Frequency-Modulated Continous Wave (FMCW), even Wi-Fi devices are utilized. Radar systems offer certain advantages. With electromagnetic waves, the respiratory rate behind obstacles is detectable. Sufficient lighting is not needed. Privacy concerns related to image recording cannot arise. However, [12], [13] point out yet unmet challenges: For instance, some of the pre-mentioned techniques require high power. The ones which can operate with less, i.e. Wi-Fi, generally have a lower sensitivity. In general, high effort is needed to approach problems like the multipath effect, motion artifacts corrupting the Doppler shift by the chest, or interference with other medical equipment. Thus, high-precise systems are very complex and costly.

Thermal imaging-based respiratory rate observation takes advantage of changes in facial temperature induced by respiration. The main disadvantages of systems as presented in [1], [14] are the need to have the subject placed at a very close distance of maximum 1m, to having a clear view of the face, and to dealing with frequent movements of the head. Non-depth based optical respiratory rate monitoring techniques with RGB or near-infrared cameras range from image subtraction as deployed in [15] to optical flow methods as in [16]. They make use of the upward and downward movement of the chest induced by respiration. Although the equipment itself is comparably cheap, implementing these methods requires complex algorithms and thus high computational time.

So far, RGB-D cameras have been used mainly in sleep laboratories or to identify sleep apnea in lying patients, with the camera alone [17], [18] or with the depth camera only to track the position of the subject while radar detects the respiratory rate [19]. For the purpose of monitoring apnea, no high-precise recognition of respiratory rate was necessary. However, high-performance approaches with an error up to just 0.11bpm now exist [10], [20], [21]. All RGB-D methods employ the principle (1), the alteration of the air volume in organs. They can yet be subdivided into two groups: The first group is based on the reconstruction of a quasi-volume

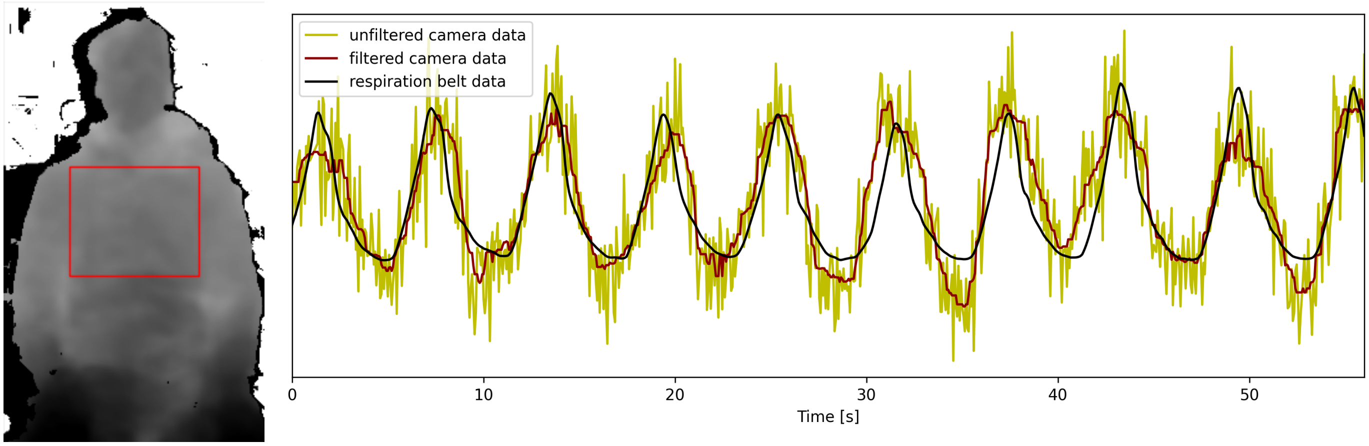

Fig. 2. Left: Grey colour-coded example of a depth frame, as recorded by the D435 RealSense RGB-D camera. The red rectangle in the middle is the region of interest (ROI) contining most depth pixels at the chest. This image was taken from participant 9, at 1m distance. The frame is cut around the participant, focusing only on the participant's upper body. The plot on the right shows exemplary the unfiltered and filtered depth curve as obtained from the depth camera overlayed by data from respiration belt. This data is from participant 1, breathing at 10bpm, taken from 2m distance with the mean averaging mechanism.

of the deforming body part (1.1), while the second group tracks the distance between observed area and camera directly (1.2). Naturally, the latter method must by some means be included in the first one, as the volume change is closely related to the shift in the third dimension. [22] compared volume- and distance-based approach. Their finding was that the volume method is less precise as well as computationally more elaborate, which is why we resorted to method (1.2) in this work.

In [10] monitoring the displacement of the chest instead of the abdomen or the entire torso as the region of interest (ROI) showed in general better results. A ROI size as large as possible was recommended excluding areas unaffected by breathing. For a distance of up to 2m and sitting study participants, the use of mean or median to average pixels inside the ROI in contrast to more complex approaches like remodeling the chest surface presented the best results. Mean and median can handle occlusions only to a minimum, though.

In [10], [21], as well as in many other related works, mostly the Kinect v2 RGB-D camera was used. However, as claimed by the manufacturer [23] the Intel RealSense D435 outperforms it with higher resolution and frame rate. It is smaller, which simplifies its installation, and the use of stereo technique instead of Time of Flight permits mounting several devices in the same room.

III. System Design and Study Setup

Our system is designed as an open-source repository[1] to facilitate replication by others. It includes a collection of python modules to extract the respiration estimation signal from depth frames. As illustrated in Figure 1 our system consists of an Intel RealSense D435 depth camera connected to a standard computer via USB 3.1. The system filters out all necessary data from individual depth frames, as indicated by the left image in Figure 2 and saves the timestamps and average distance to the chest, each for every single depth frame, together in a CSV-file. The average distance hereby is computed by either the mean or the median of single-depth pixel values inside a predefined region-of-interest (ROI) of the current depth frame. Different distances between person and camera in the later experiment cause the same body region to be described by less or more pixels. The ROI covers only the chest, so its size must be adjusted according to the distance. Both averaging methods, deploying the mean or median, are used on the same data to permit comparison later on. To address camera noise in the depth data, a temporal median filter with a kernel size of 18 for mean averaged depth data and 14 for median averaged depth data is implemented. Furthermore, depth pixels with a depth value of 0m, i.e. no depth value could be derived, are excluded from the averaging mechanism.

For the evaluation of our system in the conducted experiments, the setup is extended. While their breathing induced chest motion was recorded by the depth camera, users wore a respiration belt for ground truth measures, registering expansion and contraction of the chest as a varying force signal. From the force and depth data a respiration rate is extracted, respectively. In the end, the quality of the camera derived respiration rate is quantified by the Pearson Correlation Coefficient (PCC) and error resulting from the comparison to the exact respiration belt respiratory rate. The PCC is computed on each whole sequence by Fisher's z and with a confidence interval of 99%.

The simultaneous beginning and end of the recordings for both sensors could not be automatically determined or accurately synchronized during the experiment. Therefore, an alignment mechanism was added that relies on shifting the shorter dataset for the maximum delay period step-wise over the other one. The combination with the highest PCC between the respiration belt and depth camera would be taken, and their timescale correctly adjusted. The plot to the right in Figure 2 is

[1] https://github.com/anonymized/anon-realsense

an example of the aligned respiration curves from the camera and respiration belt data. It also illustrates the noise reducing effect of the median filter on the raw averaged depth data inside the ROI (yellow curve and red curve).

To derive the respiratory rate inside a sliding window of nearly 60 seconds, the upper peaks of the respective signal are detected, and their timestamps are saved. Next, the mean time intervals between the peaks is identified. This value equals the periodic time and allows one to calculate the respiratory rate via its reciprocal. The PCC for the considered camera and respiration belt data is known from alignment. The Absolute Error is defined by the difference between the camera-based estimation of respiratory rate and the respiration belt's respiratory rate. The Relative Error is the quotient of the Absolute Error divided by the respiration belt's ground truth respiratory rate. As will be seen in more detail, different respiration rates were tested. The Relative Error was introduced as a parameter that permits the comparison of deviations from different basis values.

Eight people, aged 21 to 57 years (4 male, 4 female), participated in this indoor experiment. Their study-relevant personal information is summarized in Table I. They sat down in an upright position on a chair of 0.5m standard height, facing the RealSense D435 depth camera. The camera was mounted on a tripod with a horizontal view on the complete chest for all distances tested, 1m, 2m, and 3m. Below the camera, a paced breathing visualization was shown which participants were asked to follow to decrease user specific breathing behaviors in this work. According to [24] the normal respiratory rate of an adult lies between 12 bpm and 20 bpm. The first paced respiratory rate was 15 bpm (0.17 Hz) while the second respiratory rate simulated a more relaxed state with 10 bpm (0.25 Hz). In total, each participant was recorded in six settings, on three distances with two respiratory rates each.

Participants wore a Vernier GoDirect respiration belt around their chest and below their shirts or pullovers to provide respiration ground truth. The sample rate of the respiration belt and depth camera was set to their minimum of 10 Hz and 15 Hz respectively to reduce the necessary memory and processing time later. Still, with 10 Hz the modified Sample Theorem $f_{sample} = 2.2 * f_{max}$ is generously met so that Aliasing is avoided [25]. The ROI is set manually within the RealSense SDK and can be extracted from the metadata of the captured depth stream. Furthermore, the clothing of the participants was noted to allow an assessment of the possible influence of personal clothing style. Textiles were divided into the two classes tight-fitting and loose-fitting. The latter fabrics were believed to not reflect the characteristic chest displacement during a breathing cycle due to the intermediate space between the thorax and the textile.

IV. Study Results

In Figures 3 and 4, the 48 data sets of the 8 participants in their 6 settings are grouped according to four different parameters: Gender, distance, respiratory rate, and the whole compilation. Figure 3 hereby shows the mean-based averaging method for depth pixels, and Fig. 4 shows the median-based approach.

TABLE I

Gender, age, and clothing style of participants. "t" or "l" represent "tight-fitting" or "loose-fitting" respectively.

Participant	1	2	3	4	5	6	7	8
gender	f	f	f	m	f	m	m	m
Age	27	57	26	27	25	21	57	24
Clothing Style	l	l	t	t	l	t	l	l

With a median PCC of 0.86, the mean averaging method shows a high correlation. It decreases from 0.94 for 1m over 0.83 for 2m to 0.66 for 3m distance. With an overall Absolute Error (Abs Err) of 0.11 bpm or 0.77% Relative Error (Rel Err), the proposed system presents low errors. They develop similarly to the PCC and increase at higher distances. The Abs Err ranges from 0.04 bpm at 1m via 0.12 bpm at 2m to 0.28 bpm at 3m. It stands out positively that there are just few data outliers. Taking into account PCC and both error measures, the male and female groups, as well as 10 bpm and 15 bpm group perform similarly to their counterparts. This behavior remains the same for the median-based calculation method.

Although the PCC for the median-based approach remains comparable for the 1m distance with 0.92, further distances are clearly outperformed by the mean-based method. The median PCC at 2m already is as low as 0.63 and decreases to 0.39 at 3m. Overall, the PCC for all groups is only 0.69. The error displays the same behavior. From the 1m distance, its median lies at 0.04 bpm and increases to 0.44 bpm at 3m. Again, for the 1m distance resulted an Abs Err of 0.04 bpm or rather a Rel Err of around 0.3% which is nearly the same as with the prior method. The errors amplify to 0.21 bpm and 2.15% for 2m, and 0.44bpm and 3.25% for 3m. All in all, the median approach can compete with the mean approach at the shortest distance, but suffers more at higher distances.

For the evaluation of individual clothing style, the data provided by the mean approach were considered. Comparing the PCC and errors from those participants with loose-fitting textiles to all participants, the values were hardly diverging, even for the 3m distance.

V. Discussion

The negative impact of elevated distances between the user and the RGB-D camera on the estimation of the respiration rate is not surprising, as previous work such as [10], [20], [21] faced the same problem. It is mainly caused by the higher noise level on higher distances. Also, the more distant the user is, and thus the ROI is located, the smaller the ROI appears in a frame if it is kept strictly covering the chest. Consequently, the same anatomical area is less accurate because it is described by fewer pixels. A Rel Err around 0.3% and a PCC of up to 0.94 makes the system applicable at close range with the mean approach or with the median approach. The first one can deal rather well with a further distance between person and sensor, the median approach performs more poorly in these situations.

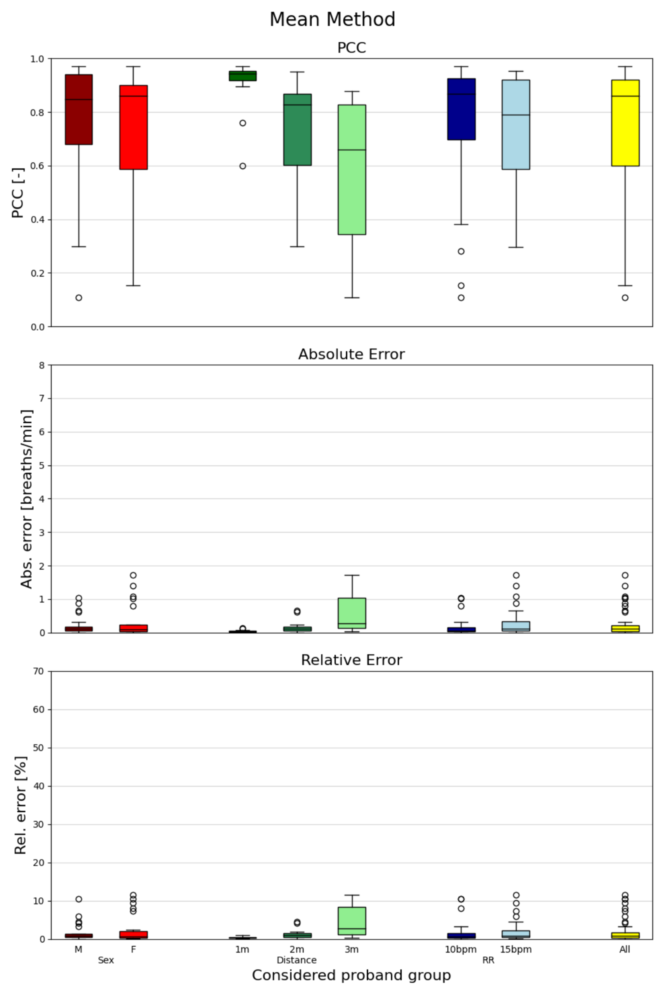

Fig. 3. From top to bottom: Pearson Correlation Coefficient (PCC), Absolute Error and Relative Error w.r.t. ground truth signal for the Mean method. Boxplots show median (middle bar) with whiskers marking 1.5 IQR and with outliers, grouped by (from left to right): Gender, Distance, Respiratory Rate, and the overall performance with no split in the dataset.

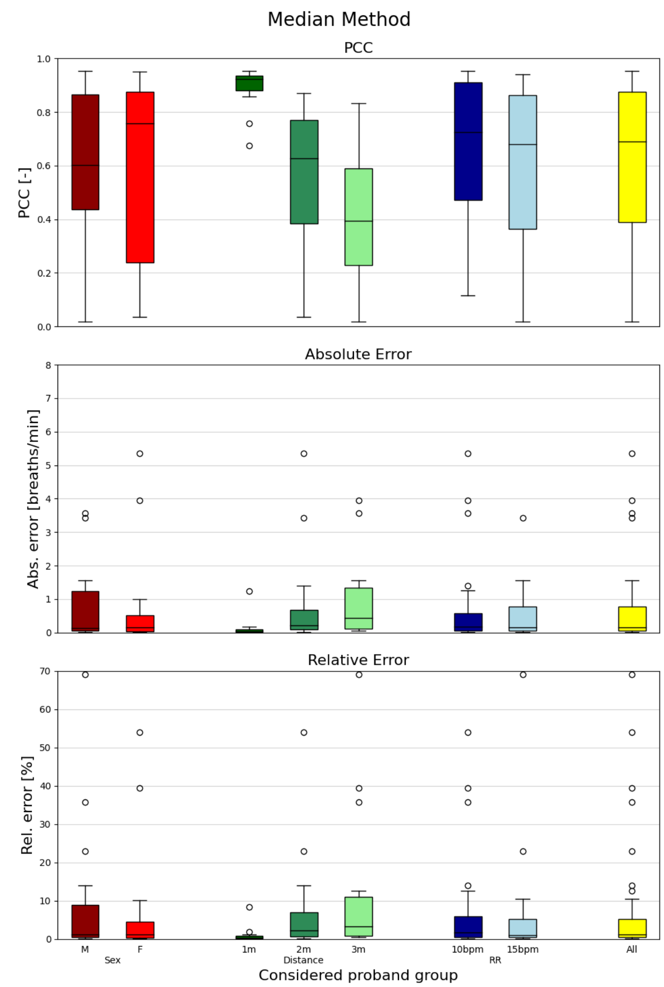

Fig. 4. From top to bottom: Pearson Correlation Coefficient (PCC), Absolute Error and Relative Error w.r.t. ground truth signal for the Median method. Boxplots show median (middle bar) with whiskers marking 1.5 IQR and with outliers, grouped by (from left to right): Gender, Distance, Respiratory Rate, and the overall performance with no split in the dataset.

TABLE II
SELECTED MEDIAN VALUES DERIVED FROM THE RESULT PLOTS FOR THE METHODS MEAN AND MEDIAN

		Method	
Parameter	Group	Mean	Median
PCC [-]	All	0.86	0.69
	1m	0.94	0.92
	2m	0.83	0.63
	3m	0.66	0.39
Abs Err [bpm]	All	0.11	0.16
	1m	0.04	0.04
	2m	0.12	0.21
	3m	0.28	0.44
Rel Err [%]	All	0.77	1.13
	1m	0.33	0.27
	2m	0.95	2.15
	3m	2.77	3.25

From our exploratory survey on clothing style, for the system in use, no work wear related specifications can be derived. However, the distorting effect of a limited sample must be taken into account. Furthermore, if the proposed system is to be used in a clinical context, an experimental comparison of the detectability of respiratory rates between patients with and without respiratory issues is indispensable.

VI. CONCLUSIONS

This work evaluated the use of a small-scale depth camera attached to the monitors of desk workers for the estimation of respiratory rates. Our evaluation process followed the methodology as described in [10] to allow comparison with other depth camera studies. The results show that the mean method works best at 1m distance between camera and user, with errors of 0.33% or 0.04 bpm and a PCC of 0.94. It can convincingly compete with comparative approaches using a D435 or a Kinect v2 [10], [20], [21], given a sitting experimental environment and focusing on close range. Enlarging the distance from the camera to the user results in precision loss. We argue here however that it is not critical in our scenario where we expect users to sit at a desk. This constraint may even be beneficial to avoid recording of the respiratory rate of bystanders or coworkers. Neither gender, nor different frequencies of paced respiratory rate played a negative role in the proposed system with the test group. The system worked reliably without requiring participants to adjust their clothes. The results show that such a system is indeed feasible and allows for daily life respiration estimation in the context of e-health.

A crucial step towards the deployability of the proposed system in clinical environments would be the interface with dedicated medical databases. The constant comparison of significant artefacts from the live respiration signal to the database could potentially allow for a preliminary diagnosis.

Affordability, small size, range of installation height, and compatibility make the D435 ideal for many environments, though its use is limited to a static scenario here where persons are located close to the camera. A precondition for the system to be used and deployed by inexperienced users would be the addition of an interface, for instance through a smartphone App. Further research could also aim at the automatic placement of the ROI, a mechanism as proposed in previous state-of-the-art work to similarly deal with self-occlusions and enabling the system to track its user. Since our proposed system is with the depth pixel averaging method computationally effective, no time lags are expected during the processing of depth frames.

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