Continuous Movement Quantification in Preterm Infants Using Fiber Mat: Advancing Long-Term Monitoring in Hospital Settings

Zheng Peng, *Member, IEEE*, Yidan Zhao, Deedee Kommers, Henrie van den Boom, Rong-Hao Liang, Xi Long, *Senior Member, IEEE*, Hendrik Niemarkt, Peter Andriessen, and Carola van Pul

***Abstract*— Movement patterns in preterm infants can offer crucial insights into their physiological state including maturational development and sleep. These patterns can also serve as early indicators for potential deteriorations, such as cerebral palsy, sepsis, and epilepsy. In this study, we investigated a novel 2-D optical fiber mat system for the automated monitoring of infant movement, thereby enhancing the efficiency and safety of neonatal care in both the neonatal intensive care unit (NICU) and neonatal medium care unit (NMCU). The 20 preterm infants admitted to both NICU and NMCU were enrolled in the study. They underwent monitoring for a duration of 2–5 h using both an optical fiber mat and a camera which provided valuable movement annotations. The signals from the fiber mat were quantified, selected, and then integrated into a consolidated movement signal. This signal was subsequently transformed into binary states, distinguishing between "movement" and "still" based on the distribution of the movement signal. The proposed fiber mat system achieved a mean [standard deviation (SD)] area under the receiver operating curve (AUC) of 0.91 (0.05), and an *F*-score of 0.73 (0.09), when compared with manually annotated video recordings. This study demonstrates the feasibility of continuous movement monitoring for preterm infants within hospital settings. It illustrates the promising potential to evolve into a predictive tool for monitoring patient deterioration through the fusion of physiological information in both hospital environments and within the comfort of homes.**

***Index Terms*— Motion detection, movement patterns, optical fiber mat, preterm infants.**

Manuscript received 2 October 2023; revised 6 December 2023; accepted 10 January 2024. Date of publication 23 February 2024; date of current version 4 March 2024. This work was supported by Eindhoven MedTech Innovation Center (e/MTIC). The Associate Editor coordinating the review process was Dr. Yuya Koyama. *(Corresponding author: Zheng Peng.)*

Zheng Peng and Carola van Pul are with the Department of Clinical Physics, Máxima Medical Center, 5504 DB Veldhoven, The Netherlands, and also with the Department of Electrical Engineering, Eindhoven University of Technology, 5612 AZ Eindhoven, The Netherlands (e-mail: z.peng@tue.nl).

Yidan Zhao is with the Department of Applied Physics, Eindhoven University of Technology, 5612 AZ Eindhoven, The Netherlands.

Deedee Kommers, Hendrik Niemarkt, and Peter Andriessen are with the Department of Neonatology, Máxima Medical Center, 5504 DB Veldhoven, The Netherlands.

Henrie van den Boom is with Luxisens Technologies, 5612 AZ Eindhoven, The Netherlands, and also with the Department of Electrical Engineering, Eindhoven University of Technology, 5612 AZ Eindhoven, The Netherlands.

Rong-Hao Liang is with the Department of Electrical Engineering and Industrial Design, Eindhoven University of Technology, 5612 AZ Eindhoven, The Netherlands.

Xi Long is with the Department of Electrical Engineering, Eindhoven University of Technology, 5612 AZ Eindhoven, The Netherlands.

Digital Object Identifier 10.1109/TIM.2024.3369135

I. Introduction

MONITORING movements in infants, particularly preterm infants, can provide insights into their physiological conditions throughout various aspects of neonatal care [1], [2]. It plays a vital role in, for example, sleep assessment [3], developmental maturation tracking [4], and early disease detection, such as cerebral palsy, sepsis, and epilepsy [5], [6], [7]. However, the current clinical practice in neonatal intensive care unit (NICU) and neonatal medium care unit (NMCU) relies on subjective and intermittent observations to assess the general movement of preterm infants. This approach may result in missing clinical events because of its discontinuity. Therefore, there is a need to develop continuous and objective approaches for movement monitoring in these infants to effectively document the infant activity and reduce the workload of caregivers. In particular, approaches that are unobtrusive and without direct contact with the skin of infants are desired, because attached sensors or electrodes can increase the risk of infection and the possibility of skin damage [8]. Importantly, these approaches should not limit or change the movement patterns and behavior of the infants.

To address this need, different noncontact or unobtrusive approaches to quantify movement in infants have been explored. As summarized in our recent systematic review [2], video-based motion quantification approaches were most often investigated as a noncontact and less obtrusive monitoring technology in infants, showing promising results on movement and cerebral palsy detection [5], [9]. Specifically, as reported in [9], an average area under the receiver operating curve (AUC) of 0.86 was obtained for general movement detection in preterm infants by using the background substruction method in video recordings. However, challenges related to occlusion, light conditions, and privacy concerns remain obstacles to video-based approaches. An alternative unobtrusive approach involves quantifying movement artifacts within physiological signals from patient monitors as indicators of movement in preterm infants. Zuzarte et al. [4] applied this approach using photoplethysmogram (PPG) signals from five preterm infants, achieving an average sensitivity of 0.79 and specificity of 0.81 in detecting general movements. Further exploration, as reported in our previous study [10], yielded an average

AUC of 0.90 for detecting larger scale movement. Notably, this signal-reusing approach does not impose additional burdens on preterm infants or caregivers but is limited by the placement locations of the physiological sensors and the presence of embedded filters within these sensors.

Given these limitations, several researchers have focused on the development of mat-based solutions with ballistography (BSG) sensors for movement quantification. BSG is a nonintrusive method that measures the mechanical forces generated by the body, including body movement, breathing motion, and the mechanical action of the beating heart [also known as ballistocardiography (BCG)]. Mat-based approaches use BSG sensors to measure the pressure generated by infants, providing an unobtrusive solution that can be positioned beneath a regular patient mattress, thereby mitigating the risk of patient contact and infection. These BSG-based technologies enable the simultaneous measurement of body and chest motion alongside heartbeats, facilitating a comprehensive assessment of the infant's condition.

Different types of mats have been investigated for infant movement monitoring. Joshi et al. [11] used an electromechanical film sensor (EMFi) mat to quantify the movement of ten preterm infants by extracting the signal instability index from BSG, achieving an AUC of 0.90 in general motion detection. However, this film sensor only provides one output, lacking movement location information and making it more susceptible to artifacts or noise outside the infant's lying area. Aziz et al. [12] applied a two-dimensional (2-D) pressure-sensitive mat (XSensor Technology Corporation, Calgary, AB, Canada) to measure BSG signals for infant motion detection. By quantifying infant movement based on the displacement of the center of pressure, they achieved remarkable results with an AUC of 0.97. Nevertheless, their evaluation relied on discrete movement events of five infants, highlighting the need for further validation for real-time applications of movement monitoring in a bigger dataset. In addition, fiber optic sensors offer distinct advantages: they have no electrical conductivity, exhibit immunity to electromagnetic interference, possess multiplexing capabilities, and demonstrate reduced sensitivity to temperature variations [13]. These properties are particularly crucial in the intricate and demanding environment of the NICU. Furthermore, the design of our mat featuring a grid of plastic fiber makes it thinner, simpler, and more cost-effective compared with other fiber optic sensor configurations [14].

Due to the aforementioned advantages of the optical fiber, it is promising to quantify the general movement in preterm infants using a 2-D optical fiber mat. Recognizing the exceptionally lightweight of preterm infants, we tailored the design of this fiber optic mat specifically for this population. To the best of the author's knowledge, this study represents the pioneering use of a fiber optic mat to detect general movement in preterm infants. In this article, our contributions are as follows.

1) An introduction of a new unobtrusive 2-D optical fiber mat for continuous monitoring of infant movement, which significantly enhances the safety and reliability of measurements.
2) A novel method for quantifying movement, allowing for comprehensive measurements in both continuous and binarized formats.
3) The movement patterns from this measurement can be associated with the maturation and respiratory conditions of infants, holding the potential to better understand their movement behavior and to complement other vital signs for predictive monitoring in preterm infants.

The subsequent sections will describe the development and design of our 2-D fiber mat system, the experimental methodology Section II and performance evaluation Section III, and a discussion Section IV of the implementations and applications based on our findings.

II. Methods

A. Optical Fiber Mat Specifications

The fiber mat used in this study was developed by van den Boom et al. [15]. As shown in Fig. 1, the mat comprises a 2-D grid of polymer optical fibers (POFs), an optoelectronics module, and a data acquisition and control module. Each crossing of the POFs functions as a highly sensitive pressure sensor. Whenever pressure or weight is exerted on a crossing, the pressure can be quantified by detecting the couple-out optical power received by the photodiodes. Subsequently, the measured light signal undergoes conversion and amplification before being stored in a secure digital card (SD card) or computer by the microcontroller (Teensy 3.6) within the data acquisition and control module. Importantly, the light power coupled out of the transmitting fibers due to the measured exertion is minimal, typically less than 0.01%, and the remaining light that continues through the transmitting fiber to the next crossing experiences minimal attenuation. Thus, the sensitivity of each crossing remains largely unaffected by the pressure to other crossings, allowing each crossing to independently measure distinct forces originating from different locations on the mat. The main novelty of this mat lies in the utilization of a pressure-sensitive optical coupling mechanism and the construction of a crossing where the fibers remain in their original, unmodified state. In addition, the design of the crossing exhibits a high degree of tolerance toward alignment errors. This is achieved by incorporating small patches of flexible and scattering material, enhancing sensitivity without the necessity for precise alignment. Varied sensitivity characteristics can be achieved based on the dimensions of the patches. Using larger patches yields logarithmic characteristics, thereby expanding the dynamic range of the system. For more details about this mat, we refer to our previous work [15].

The dimensions of the fiber mat used in this study were $488 \times 316 \times 2$ mm (0.2-mm outside the nodes), integrating an 8×5 POF grid with a resolution of 5 cm. The pressure on the 40 nodes is detected at a rate of 50 Hz. The optical receiver exhibited a sensitivity of 0.4 V/nW with a cladding diameter of 0.5 mm, while the optical power of the red LEDs coupled with the transmitting POFs exceeded 1 mW. We tailored the fiber mat using the silicone rubber patches of 10×10 mm^2 on one side and the hard rigid patches of 30×30 mm^2 on both sides and tested it specifically for our population, ensuring

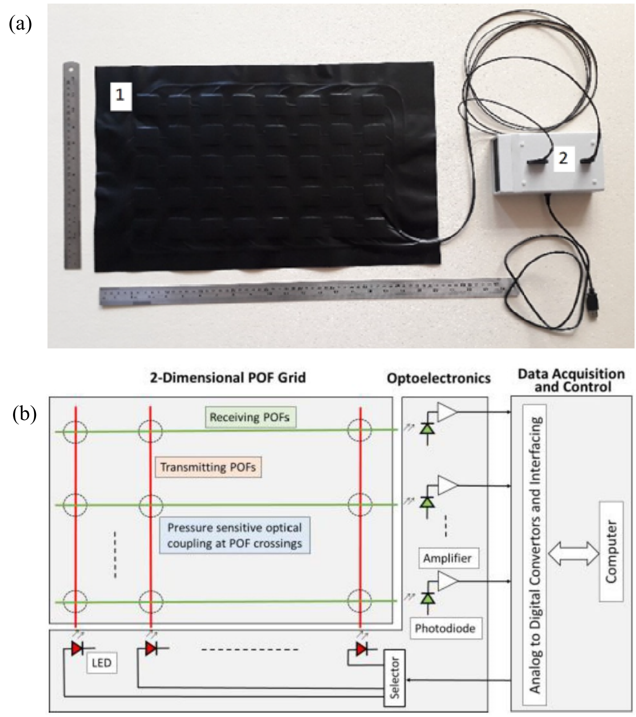

Fig. 1. (a) 1—2-D fiber mat and 2—controller. (b) Block diagram of the 2-D fiber mat.

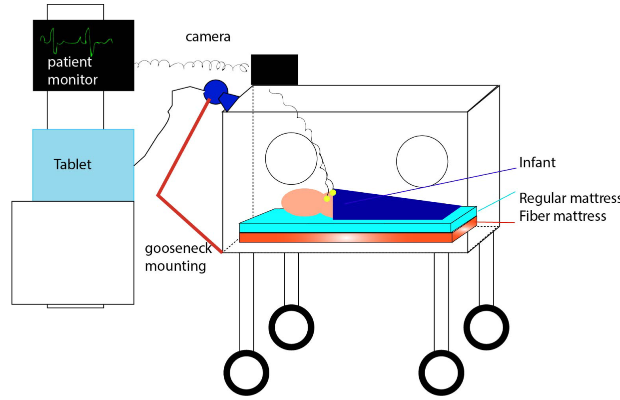

Fig. 2. Schematic of data acquisition setup.

that the measurement range covers the weight of our infants (600–3000 g).

B. Data Acquisition

A cohort of 20 preterm infants admitted to the NICU or NMCU at the Máxima Medical Center, Veldhoven, The Netherlands, were enrolled in this study. As illustrated in Fig. 2, the fiber mat was positioned underneath the regular mattress in the incubator or open bed during each patient's recording session. A camera system (UI-3860LE-C-HQ) with a resolution of 1280 $\times$ 720 pixels and a frame rate of 10 frames/s was mounted on the top of the incubator/open bed to capture the head and upper body of the infant. The BSG signals of the mat and the video recording stored on the tablet were manually synchronized at the start of each recording.

All infants were recorded for 2–5 h during daytime hours to ensure good light conditions for the video recordings. Table I shows the characteristics of all recorded infants and their recordings. The median (range) gestational age (GA), postmenstrual age (PMA), and study weight of the infants on the day of the study were 29.5 (25.3–36.1) weeks, 33.3 (29.3–37.9) weeks, and 1615 (960–2725) g, respectively. The 13 out of 20 infants received noninvasive respiratory support during recordings. Routine care was provided to all infants during recordings. The study protocol received a waiver from the ethical committee because of its unobtrusive nature in accordance with the Dutch law on medical research with humans and written, informed parental consent was obtained prior to infants' participation in the study.

C. Annotations for Movements

To validate the feasibility of our proposed algorithm in detecting infant movement using the fiber mat, we used manually annotated video recordings as the reference for comparison. Because of the low luminance conditions and camera malfunction, one continuous segment lasting roughly 1 h was chosen from the recorded video of each infant to construct and assess our motion detection algorithm. The three infants (infant numbers 9, 15, and 19) had to be excluded due to their excessively dark video recordings, which could not be properly annotated. As a result, we had a total of 16.2 h of annotated videos from 17 infants.

For the annotations, similar to our previous work [10], the selected video recordings were imported into MATLAB's Video Labeler tool. A human annotator, who is one of the authors, performed the annotations according to the following scheme: 1) the video recording was divided into nonoverlapping epochs of 10 s each; 2) within each epoch, the annotations were categorized as either still, gross movement (involving torso or chest movement), or fine movement (isolated movements of the head, hands, arms, fingers, or facial expressions), unless it was not possible to determine one of these three main categories; 3) other categories including intervention, camera motion, and unsuitable view were annotated in parallel with the three main categories; and 4) subcategories were also used to annotate specific limb and head movements when they were visible. For this study, we focused on the three main annotation categories still, gross movement, and fine movement. Epochs that could not be distinguished (such as instances when the infant was out of bed or sometimes during parental and caregiver interventions) were excluded from the motion detection analysis. Notably, after the motion detection algorithm was evaluated by these annotated videos, the full continuous recordings from the fiber mat of each infant were examined to assess whether the optimized algorithm could identify associations between infant ventilator support status and movement patterns.

D. Movement Quantification

The fiber mat was used to measure the light coupling out of the fiber caused by the pressure or weight exerted by the infant on it. This light signal was converted to an electronic signal as BSG. When there is no movement, the BSG signal obtained from each node of the mat remains relatively stable, accompanied by white noise that corresponds to the weight

TABLE I
INFANT AND RECORDING CHARACTERISTICS

Infant	GA (weeks)	PMA (weeks)	Birth weight (g)	Study weight (g)	Gender	Position	Respiratory support	Duration (hours)	Bed type
1	31.6	32.3	1650	1560	female	Supine	No	2.71	Incubator
2	27.3	31.6	1150	1440	female	Lateral	Yes	4.06	Incubator
3	30.7	33.0	1335	1990	male	Supine	Yes	2.42	Open bed
4	36.1	36.7	1790	1810	male	Lateral	No	2.53	Incubator
5	33.6	34.3	2210	1985	female	Supine	No	3.96	Incubator
6	32.7	33.6	2180	2190	male	Lateral	No	2.93	Incubator
7	33.1	33.6	2300	2230	female	Lateral	No	4.28	Incubator
8	33.1	34.0	2370	2310	female	Supine	No	3.27	Incubator
9	32.3	33.6	1440	1410	male	Supine	No	2.59	Incubator
10	32.3	34.0	990	1150	male	Lateral	Yes	4.31	Incubator
11	27.1	36.0	1070	2500	male	Prone	Yes	4.62	Open bed
12	27.1	36.7	1080	2725	male	Supine	Yes	2.90	Open bed
13	25.3	31.7	860	1380	male	Lateral	Yes	2.06	Incubator
14	26.0	37.9	400	1830	male	Supine	Yes	2.88	Incubator
15	26.1	29.9	800	960	female	Supine	Yes	3.50	Incubator
16	28.7	29.7	1170	1230	male	Supine	Yes	4.06	Incubator
17	28.7	30.4	1100	1100	male	Lateral	Yes	3.51	Incubator
18	30.3	31.7	1660	1670	male	Lateral	Yes	4.21	Incubator
19	27.4	29.3	990	1010	female	Lateral	Yes	3.89	Incubator
20	28.1	30.0	1410	1395	male	Lateral	Yes	3.99	Incubator
Median (range))	29.5 (25.3-36.1)	33.3 (29.3-37.9)	1252.5 (400-2370)	1615 (960 -2725)	—	—	—	3.51 (2.06-4.62)	—

applied to each node. However, when the infant moves, the stability of the signals is disturbed due to the shifting pressure, resulting in nonstationary fluctuations. We used these fluctuations to identify and quantify infant movements.

To accomplish this, we developed an algorithm that uses the BSG signals from the fiber mat to quantify the movements of the infant in real time, as illustrated in Fig. 3. First, recognizing that the BSG signals contain not only movement but also components related to respiration and heartbeats, we applied bandpass filtering to each node's BSG signal within the frequency range from 0.001 to 0.4 Hz. This filtering process served to minimize the influence of cardiorespiratory elements. Next, to highlight the fluctuations generated by movements and keep the same sample rate, we proceeded to calculate the dynamic changing range using a moving window of 1 s with a moving step of one sample (0.02 s). Furthermore, the nonnegative nature of this changing range enables a more meaningful interpretation of the quantified movement signal. Afterward, the utilization of the 2-D outputs of the mat enables the identification that artifacts or noise typically manifest in specific nodes rather than uniformly affecting the entire mat. For instance, when the mat is obstructed by the door of the incubator, the nodes located at the corners retain elevated values due to the applied pressure from the door. To eliminate this noise and consider the fact that signals associated with movements tend to exhibit higher energy levels and greater sparsity because of the random occurrence when compared with signals without any movements, we consequently applied an evaluation of the energy and sparsity characteristics of each signal to discern these movement signals. The energy of each signal was determined by evaluating its SD, which indicates the signal's variability. As for the sparsity assessment, we applied the Gini index, as it satisfies the majority of properties associated with sparsity [16]. By using these metrics, we were able to effectively identify and prioritize the signals that exhibited both high energy and sparsity, reflecting the presence of movements. Specifically, the multiplication of these two min–max normalized metrics (energy and sparsity) was used to rank the signals, and the top 20 nodes in the ranking were subsequently selected for subsequent processing in movement quantification. Since typically infant movement is considered to change over several seconds, the selected 20 signals underwent additional smoothing using a third-order Savitzky–Golay filter [17] to comply with this characteristic and eliminate noise spicks that could potentially lead to false detection of movements. Finally, the signals were averaged to generate a consolidated movement signal.

E. Binarization for Quantified Movement Signal

To further process the (averaged) continuous movement signal into a binary signal that explicitly indicates infants' movement status which is often required and easy to interpret by clinicians, two binarization methods were implemented in this study. The first method involved setting a threshold based on the amplitude of the normalized movement signal. For the second method, an automatic threshold was specialized for each infant, taking into account the distribution of the estimated movement signal values from the beginning of the signal.

For the first method, we empirically established a threshold of amplitude of 160 based on the evaluation of thresholds observed in the half cohort. This means that once set, the threshold remained unchanged and applied to determine the onset and offset of the movements in all infants. As the baseline may differ across patients, we developed the second method to automatically determine the threshold for each infant. Specifically, due to the absence of a theoretical distribution for movement signals in preterm infants, and to refrain from making strong assumptions, we applied kernel

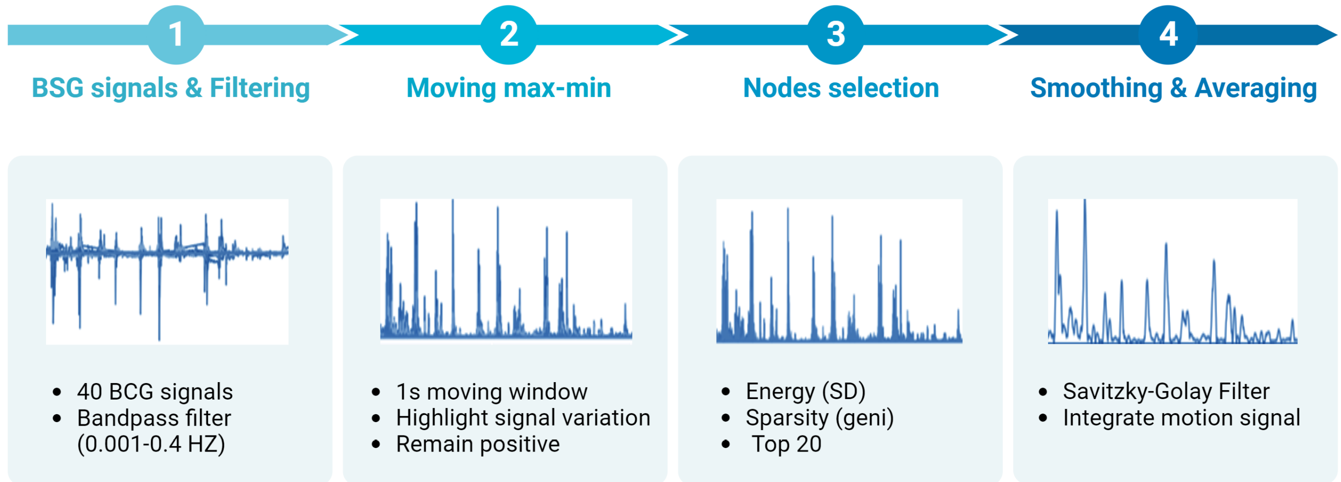

Fig. 3. Signal processing workflow for movement quantification.

density estimation (KDE) to estimate this distribution, using the initial 5-min window of movement signal values from each infant. The bandwidth for the estimation was automatically determined using Silverman's rule [18]. Since movements can have three distinct distributions, namely, still, fine movement, and gross movement which have overlapping areas between each other, we assumed that the distribution of still was included within the first local minimum of the estimated distribution. Using this first local minimum, we conducted a grid search from 0.1 to 1 in increments of 0.1 in the half cohort to optimize coefficients proportional to the number of local minima (distributions) for establishing the threshold between still and movements. In cases where the number of local minima exceeded three (indicating an estimation of more than three distributions), we averaged the first two local minima. This process yielded the following equation to eventually determine the threshold T:

$$T = \begin{cases} 0.1 * \text{minima}_1, & \text{if } n = 1 \\ 0.3 * \text{minima}_1, & \text{if } n = 2 \\ 0.6 * \text{minima}_1, & \text{if } n = 3 \\ (\text{minima}_1 + \text{minima}_2)/2, & \text{if } n >= 4 \end{cases}$$

where minima_1 and minima_2 denote the values of the first and second local minima in the estimated distribution, and n indicates the number of local minima present.

F. Evaluation for Quantified Movement Signal

To detect the presence of infant movement, we included all the 10-s epochs having one of the three main categories of annotations (still, fine movement, and gross movement) and further categorized them into either still or movement by merging fine movement and gross movement for binary classification. This categorization can assist clinicians in determining infant movement status related to certain clinical conditions, for example, quiet sleep and lethargy.

We first used the AUC, a threshold-independent metric, to evaluate the overall performance of the estimated continuous movement signal. Subsequently, in line with the annotation scheme, we segmented the derived binary movement signal into nonoverlapping epochs of 10 s to assess the performance of the derived binary movement signals generated by two thresholding algorithms. A movement epoch was defined as any duration of derived movements, while a still epoch denoted the absence of derived movements. We evaluated the derived binary movements with the annotated binary movements using various threshold-dependent metrics, including sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and F-score. These metrics allowed us to assess and compare the performance of the two thresholding algorithms generating the binary movement signal. Afterward, the changes in performance across different study weights of infants were analyzed to examine the sensing ability of the fiber mat. Finally, to evaluate the ability of movement location detection, a visual example of real-time infant movement location monitoring using the 2-D outputs of the fiber mat was illustrated.

G. Movement Pattern Analysis on Infant Mature

A potential utilization of this optical fiber mat can be an examination of the developmental progress of the motion patterns as infants mature. Inspired by the analysis of Zuzarte et al. [4], we analyzed the total hourly duration of movements lasting shorter than 5 s and longer than 30 s of the recording hours in 20 infants. Pearson's correlation was calculated to analyze the relationship between the movement duration and both the GA and PMA of infants. In addition to investigate if the noninvasive respiratory support may influence the infant movement behavior, a Wilcoxon rank-sum test [19] was used to examine the statistical difference in movement duration between infants receiving noninvasive respiratory support and those without.

III. RESULTS

Fig. 4 presents the duration of annotated videos of the three categories (still, fine movement, and gross movement) with

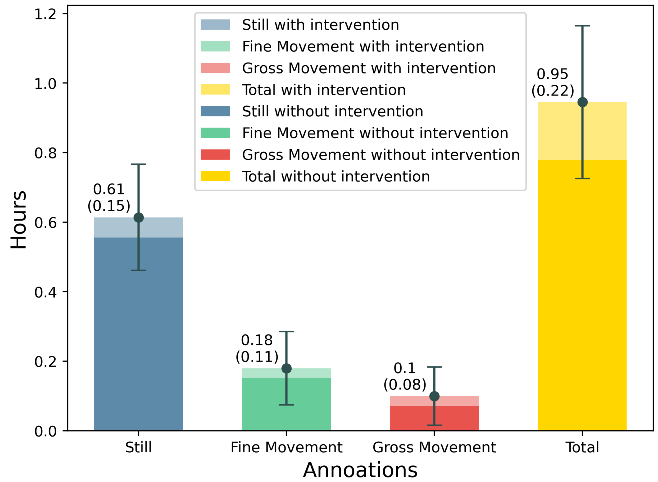

Fig. 4. Duration of annotated videos and three main annotations with and without interventions.

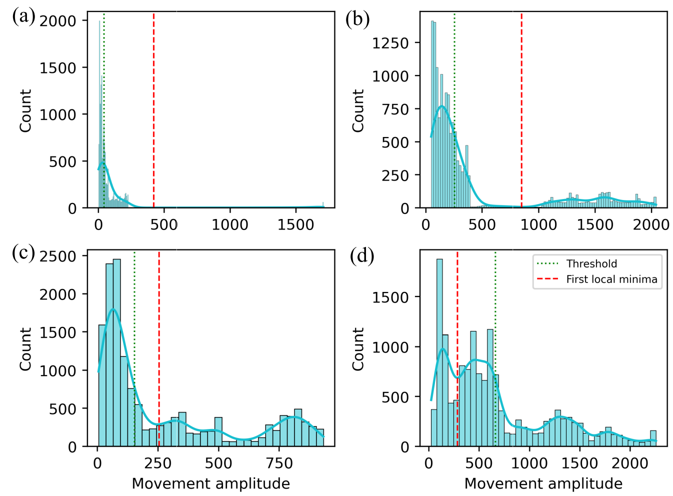

Fig. 5. Specialized threshold and distribution of 5-min movement signal in automatic thresholding method. (a) Estimated distribution with one local minima. (b) Estimated distribution with two local minima. (c) Estimated distribution with three local minima. (d) Estimated distribution with four local minima. The blue line shows the distribution of the KDE. The red dashed line is the estimated threshold. Background colors represent the estimated distribution of still and movement based on the first local minima.

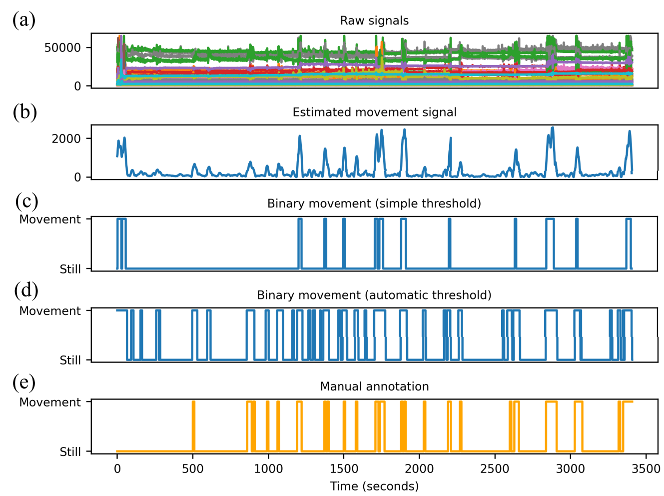

Fig. 6. Estimated and binary movement signals. (a) Raw signals from 40 nodes of a fiber mat. (b) Estimated movement signal derived from the movement quantification algorithm. (c) Binary movement signal based on automatic thresholding method. (d) Binary movement signal based on a simple thresholding method. (e) Manual annotation based on the video.

and without caregiver interventions for all infants included in the movement detection analysis. Upon excluding the indistinguishable epochs (due to the occlusion of the camera view field), it can be observed that still occupied the majority of the recorded time with a mean (SD) of 0.61 (0.15) hours per infant, followed by fine movement with 0.18 (0.11) hours per infant and gross movement with 0.1 (0.08) hours per infant. Interventions account for a significant part of each annotation.

Regarding the binary classification between still and movement, Fig. 5 presents the instances using the automatic threshold derived from the first 5-min movement distribution of 1–4 local minima, respectively. The red dashed line represents the first local minima in the estimated distribution, serving as a baseline to distinguish still from movement. The adjusted automatic threshold (depicted by the green dotted line), derived from this local minima, efficiently truncates the tail of the estimated distribution (representing the category of still) to discern it from the remaining movement signals. In Fig. 6, examples of signals spanning 1 h are displayed, including raw BSG signals from 40 nodes of a fiber mat, the estimated movement signal derived from the movement quantification algorithm, the binary movement signal obtained through the automatic thresholding method, and the simple thresholding method, and the manual annotation based on video analysis (serving as reference). It can be seen that the estimated movement signal highlights the fluctuation in raw signals, but not all the fluctuations correspond to the movement in the manual video-based annotation. Table II displays the evaluation results of infant movement detection using the fiber mat, including both thresholding methods. The estimated movement signal had a mean (SD) AUC of 0.91 (0.05) when compared with the annotations. Notably, on average the binary movement signal derived through the automatic thresholding method outperforms its counterpart derived through the simple thresholding method in terms of performance (indicated by a larger mean) and robustness (indicated by a smaller SD) in almost all the metrics (sensitivity, specificity, PPV, NPV, and F-score). While this automatic method achieves a good balance between sensitivity and specificity, as well as PPV and NPV in the majority of preterm infants, it is noteworthy that the threshold is excessively high for infants 5 and 6, and relatively low for infants 16 and 17. Furthermore, the changes in performance in terms of AUC and F-score over different weights of infants are shown in Fig. 7. The asterisks denote the performance obtained from infants in the open bed with a thicker mattress. It can be seen that the movement detection performance of the fiber mat has no significant correlation with the weight of infants ($r = -0.28$, $p = 0.27$, and $r = 0.33$, $p = 0.19$ for AUC and F-score, respectively) [20] and the thickness of mattress has little influence on performance.

Fig. 8 displays a visual example of infant movement location monitoring using 2-D outputs of the fiber mat. The left heat map shows the movement location detected by the specific

TABLE II
PERFORMANCE OF INFANT MOVEMENT DETECTION USING SIMPLE AND AUTOMATIC THRESHOLDING METHODS

Infant	Sensitivity		Specificity		PPV		NPV		F-score		AUC
	Simple	Auto	Simple	Auto	Simple	Auto	Simple	Auto	Simple	Auto	
1	0.92	0.92	0.91	0.91	0.64	0.66	0.98	0.98	0.76	0.77	0.99
2	1	1	0.64	0.80	0.42	0.57	1	1	0.60	0.73	0.96
3	0.86	0.74	0.65	0.81	0.67	0.76	0.85	0.79	0.75	0.75	0.88
4	0.62	0.76	0.97	0.87	0.84	0.61	0.90	0.93	0.71	0.68	0.93
5	0.23	0.60	1	0.92	1	0.98	0.16	0.25	0.38	0.74	0.81
6	0.81	0.48	0.74	0.93	0.81	0.91	0.74	0.56	0.81	0.63	0.85
7	0.79	0.80	0.71	0.70	0.79	0.79	0.71	0.72	0.79	0.79	0.83
8	0.76	0.64	0.78	0.92	0.49	0.68	0.92	0.90	0.60	0.66	0.91
9	\	\	\	\	\	\	\	\	\	\	\
10	0.82	0.60	0.92	0.98	0.90	0.96	0.85	0.74	0.86	0.74	0.94
11	0.37	0.76	0.97	0.87	0.92	0.83	0.66	0.82	0.53	0.79	0.91
12	0.68	0.76	0.98	0.92	0.98	0.91	0.73	0.77	0.80	0.83	0.95
13	0.93	0.77	0.52	0.72	0.37	0.46	0.96	0.91	0.53	0.57	0.85
14	0.91	0.83	0.86	0.92	0.82	0.88	0.93	0.89	0.86	0.86	0.96
15	\	\	\	\	\	\	\	\	\	\	\
16	0.96	1	0.74	0.46	0.59	0.42	0.98	1	0.73	0.59	0.96
17	0.80	0.95	0.95	0.73	0.79	0.47	0.95	0.98	0.80	0.63	0.94
18	0.92	0.73	0.65	0.92	0.68	0.88	0.91	0.81	0.78	0.80	0.94
19	\	\	\	\	\	\	\	\	\	\	\
20	0.83	0.88	0.78	0.71	0.87	0.84	0.72	0.77	0.85	0.86	0.88

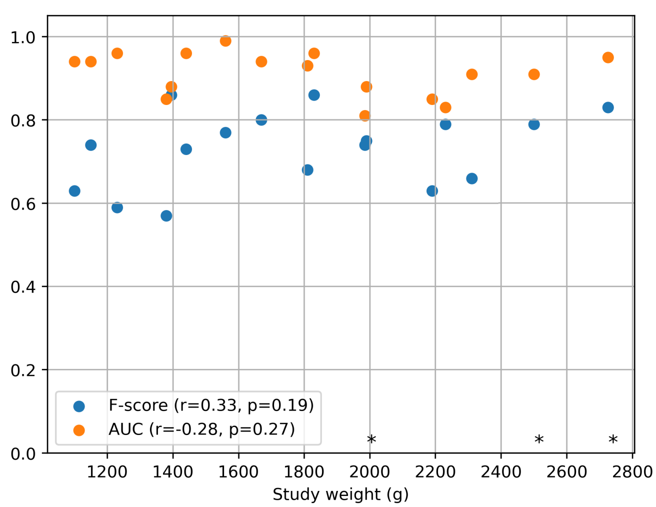

Fig. 7. Performance of F-score and AUC over study weight. Asterisks denote the performance obtained from infants in open beds.

node in the mat. The right heat map shows the raw signal of each node, indicating the weight location of the infant. It is clear that at that measured moment, the head and shoulder of the infant were moving and the infant was lying on the upper right corner of the fiber mat.

Fig. 9 represents the interplay among GA, PMA, respiratory support status, and movement duration of infants. Applying a Wilcoxon rank-sum test on movement duration in two groups of respiratory status (with and without support), we observed a significant difference in infants receiving respiratory support, specifically regarding the movement durations lasting longer than 30 s ($p < 0.01$). However, no significant difference was found in shorter bursts (less than 5 s) between the two groups. Furthermore, we can also observe a significant negative correlation between GA and the longer movement duration with a correlation coefficient of -0.43 ($p < 0.01$). Such correlation with PMA was not significant.

Fig. 8. Visual example of movement and location monitoring using 2-D outputs of the fiber mat. The left heat map shows the movement detected by the specific node. The right heat map shows the raw signal of each node.

IV. DISCUSSION

In this study, we have introduced a novel approach for quantifying movement in preterm infants using a 2-D fiber mat, aiming to provide safe and robust movement monitoring for the optimal care of infants in the NICU and NMCU. As reported in our recent systematic review [2], continuous and unobtrusive movement monitoring can offer valuable insights into infants' movement patterns, which are essential for assessing their physiological status and developmental progress. This movement-based vital sign can complement traditional physiological parameters and enable a more holistic understanding of the condition of infants, allowing for timely intervention and early detection of clinical pathologies, such as sepsis and seizure [6], [7].

One notable advantage provided by our optical fiber mat compared with other mat-based solutions is that its 2-D independent output enables node selection based on target signal properties, enhancing signal reliability. In this study, our algorithm used energy and sparsity to characterize movement signals for node selection. These selection criteria can be tailored to periodic properties in applications such as estimating respiration and heart rate. Furthermore, as shown in

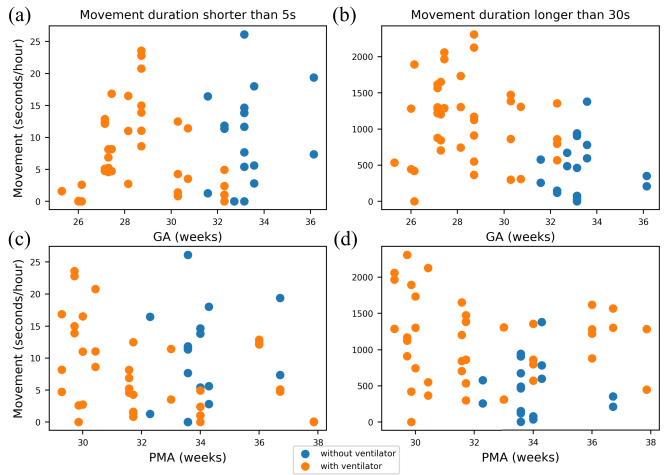

Fig. 9. Movement duration over GA and PMA. (a) Movement duration lasting shorter than 5 s over GA of infants with and without respiratory supports. (b) Movement duration lasting longer than 30 s over GA of infants with and without respiratory supports. (c) Movement duration lasting shorter than 5 s over PMA of infants with and without respiratory supports. (d) Movement duration lasting longer than 30 s over PMA of infants with and without respiratory supports.

Fig. 8, the movement and its location information captured by this 2-D mat can provide relevant clinical information without compromising privacy and have the potential to further recognize the detailed limb movements which can contribute to the prediction of neurological and motor impairments of infants [21], [22]. In addition, the high sensitivity of the fiber mat makes the measurement unaffected by the weight of infants (as displayed in Fig. 7). This is particularly useful for preterm infants because of their extremely light weights. However the measured signals may easily reach saturation when the sensitivity of optical receivers is too high, this needs further investigation in future applications.

Another advantage of our approach is the flexibility it offers to clinicians in choosing customized thresholds for movement detection. As presented in Fig. 5, instead of using the automatic thresholds, the clinicians can also determine the thresholds based on the specific characteristics of each infant's movement distribution to simplify the movement signal into "movement" and "no movement" states or detect gross movement from stillness and fine movement according to specific clinical applications (e.g., sleep assessment). Furthermore, the movement distribution itself may also provide valuable clinical information to clinicians. In addition to this, regarding the performance of general movement detection in preterm infants, our approach demonstrates the competitive performance when compared with the state-of-the-art approaches using various technologies for the same objective [4], [9], [10], [12].

The examination of movement patterns in conjunction with infant maturation and respiratory support status revealed a statistically significant negative correlation in long bursts over GA, but no statistically significant correlation was observed with PMA. This observation may be attributed to the increased complexity of health issues among younger infants, potentially leading to discomfort and consequently a greater occurrence of long bursts. In addition, the results demonstrated a noteworthy difference in long movement bursts between infants receiving respiratory support and those without such support. This difference may be attributed to more intervention of caregivers and an impact of respiratory support on infant sleep, thereby resulting in a higher frequency of long movements. Conversely, the long movements may increase with the maturational increase as reported in other studies [23], [24]. Nonetheless, further exploration is needed to augment comprehension of the intricate interplay between respiratory function and movement patterns.

Several 2-D pressure-sensitive mats with different technologies have been explored to assess infant physiological status. Harada et al. [25] used piezoresistive polymer film sensors, which is also a very interesting technique but may introduce electrical safety concerns necessitating further safety testing in NICU environments. The capacitive sensors (LX100:100.100.05, XSensor Technology Corporation) used in studies of Kyrollos et al. [26], [29], [30] have higher sensing resolution but can be susceptible to electromagnetic interference. Donati et al. [14] developed another fiber mat, but their sensor points with the LED and detector are placed on a PCB with a thickness exceeding 7 mm. In contrast, our fiber mat comprises a grid of plastic fiber, making it thinner and more straightforward in design. Apart from infant maturation and respiratory status, the 2-D mat-based monitoring of infant movement can be further applied to cerebral palsy detection [27], arm movement assessment [28], and posture classification [14]. Interestingly, the activity score developed by Harada et al. [25] is also worth to investigate for our population (preterm infants), although their evaluation relied solely on visualization in two postterm infants, leaving the generalizability of their method uncertain. Moreover, within the realm of advanced infant monitoring, the prospect of precise movement tracking and pose monitoring using pressure mats in the NICU is a promising solution. Kyrollos et al. [26] delved into this area by exploring location mapping between video and mattress, head localization [29], and infant pose estimation [30], presenting promising outcomes. However, their validation of infant pose estimation relied on a Mannequin Lying pose dataset, necessitating further validation using real preterm infants.

Several limitations of our study must be acknowledged. The manual annotation of movement events introduces potential errors such as inaccurate timing of the movement onsets and offsets. The limited field of view provided by the camera system might lead to underestimation of certain movements, particularly those occurring in the legs' area and under the blankets. These missing movement events may lead some detected true positives into false positives, underestimating the performance of the fiber mat in movement quantification. In addition, although we included a wide range of patients in different GA and weights, the relatively small dataset used for this study might restrict the generalizability of the findings. Addressing these limitations through larger datasets, automated annotation methods, and improved camera placement could enhance the robustness and applicability of our approach.

This feasibility study yields promising results on movement monitoring using the 2-D fiber mat. Its inherent safety, cost-effectiveness, and absence of privacy concerns make it applicable across various clinical applications. Enhancements in performance can be achieved by incorporating more nodes and dynamic sensitivity adjustment of optical receivers in future iterations. Furthermore, upcoming research will explore additional functionalities, such as respiration and heart rate estimation, further solidifying the fiber mat's potential as an unobtrusive vital sign monitor in preterm infants. Ultimately, it could evolve into a predictive tool for monitoring patient deterioration through the fusion of physiological information.

ACKNOWLEDGMENT

This study was done within the framework of the Eindhoven MedTech Innovation Center (e/MTIC), Eindhoven, The Netherlands, and the collaboration with Luxisens Technologies.

REFERENCES

[1] H. Chen, M. Xue, Z. Mei, S. B. Oetomo, and W. Chen, "A review of wearable sensor systems for monitoring body movements of neonates," *Sensors*, vol. 16, no. 12, p. 2134, 2016.

[2] Z. Peng et al., "Continuous sensing and quantification of body motion in infants: A systematic review," *Heliyon*, vol. 9, no. 7, 2023, Art. no. e18234.

[3] S. F. Schoch, O. G. Jenni, M. Kohler, and S. Kurth, "Actimetry in infant sleep research: An approach to facilitate comparability," *Sleep*, vol. 42, no. 7, pp. 1–9, 2019.

[4] I. Zuzarte, P. Indic, D. Sternad, and D. Paydarfar, "Quantifying movement in preterm infants using photoplethysmography," *Ann. Biomed. Eng.*, vol. 47, no. 2, pp. 646–658, 2019.

[5] Q. Wu et al., "Automatically measure the quality of Infants' spontaneous movement via videos to predict the risk of cerebral palsy," *IEEE Trans. Instrum. Meas.*, vol. 70, 2021, Art. no. 5019511.

[6] Z. Peng et al., "A continuous late-onset sepsis prediction algorithm for preterm infants using multi-channel physiological signals from a patient monitor," *IEEE J. Biomed. Health Informat.*, vol. 27, no. 1, pp. 550–561, Jan. 2023.

[7] J. R. Martin et al., "Optical flow estimation improves automated seizure detection in neonatal EEG," *J. Clin. Neurophysiol.*, vol. 39, no. 3, pp. 235–239, 2022.

[8] D. L. August, R. A. Ray, Y. Kandasamy, and K. New, "Neonatal skin assessments and injuries: Nomenclature, workplace culture and clinical opinions—Method triangulation a qualitative study," *J. Clin. Nursing*, vol. 29, nos. 21–22, pp. 3986–4006, 2020.

[9] Z. Peng et al., "A comparison of video-based methods for neonatal body motion detection," in *Proc. 44th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Jul. 2022, pp. 3047–3050.

[10] Z. Peng et al., "Body motion detection in neonates based on motion artifacts in physiological signals from a clinical patient monitor," in *Proc. 43rd Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Nov. 2021, pp. 416–419.

[11] R. Joshi et al., "A ballistographic approach for continuous and non-obtrusive monitoring of movement in neonates," *IEEE J. Translational Eng. Health Med.*, vol. 6, pp. 1–10, 2018.

[12] S. Aziz, Y. S. Dosso, S. Nizami, K. Greenwood, J. Harrold, and J. R. Green, "Detection of neonatal patient motion using a pressure-sensitive mat," in *Proc. IEEE Int. Symp. Med. Meas. Appl. (MeMeA)*, Jun. 2020, pp. 1–6.

[13] P. Roriz, O. Frazão, A. B. Lobo-Ribeiro, J. L. Santos, and J. A. Simoes, "Review of fiber-optic pressure sensors for biomedical and biomechanical applications," *J. Biomed. Opt.*, vol. 18, no. 5, 2013, Art. no. 050903.

[14] M. Donati, F. Cecchi, F. Bonaccorso, M. Branciforte, P. Dario, and N. Vitiello, "A modular sensorized mat for monitoring infant posture," *Sensors*, vol. 14, no. 1, pp. 510–531, 2014.

[15] H. van den Boom, O. Raz, and T. Koonen, "A robust and low-cost 2-dimensional pressure sensing system using polymer optical fibre," in *Proc. Eur. Conf. Opt. Commun. (ECOC)*, Dec. 2020, pp. 1–4.

[16] N. Hurley and S. Rickard, "Comparing measures of sparsity," *IEEE Trans. Inf. Theory*, vol. 55, no. 10, pp. 4723–4741, Oct. 2009.

[17] M. J. E. Savitzky and A. Golay, "Smoothing and Differentiation," *Anal. Chem.*, vol. 36, no. 8, pp. 1627–1639, 1964.

[18] B. W. Silverman, *Density Estimation for Statistics and Data Analysis*, vol. 26. CRC Press, 1986.

[19] H. B. Mann and D. R. Whitney, "On a test of whether one of two random variables is stochastically larger than the other," *Ann. Math. Statist.*, vol. 18, no. 1, pp. 50–60, Mar. 1947.

[20] C. J. Kowalski, "On the effects of non-normality on the distribution of the sample product-moment correlation coefficient," *J. Roy. Stat. Soc., C (Appl. Statist.)*, vol. 21, no. 1, pp. 1–12, 1972.

[21] C. Marcroft, A. Khan, N. D. Embleton, M. Trenell, and T. Plötz, "Movement recognition technology as a method of assessing spontaneous general movements in high risk infants," *Frontiers Neurol.*, vol. 6, p. 284, Jan. 2015.

[22] K. Raghuram et al., "Automated movement recognition to predict motor impairment in high-risk infants: A systematic review of diagnostic test accuracy and meta-analysis," *Developmental Med. Child Neurol.*, vol. 63, no. 6, pp. 637–648, 2021.

[23] M. Fukumoto, N. Mochizuki, M. Takeishi, Y. Nomura, and M. Segawa, "Studies of body movements during night sleep in infancy," *Brain Develop.*, vol. 3, no. 1, pp. 37–43, 1981.

[24] D. Holditch-Davis, D. H. Brandon, and T. Schwartz, "Development of behaviors in preterm infants: Relation to sleeping and waking," *Nursing Res.*, vol. 52, no. 5, pp. 307–317, 2003.

[25] T. Harada, A. Saito, T. Sato, and T. Mori, "Infant behavior recognition system based on pressure distribution image," in *Proc. Millennium Conf. IEEE Int. Conf. Robot. Automat.*, vol. 4, Apr. 2000, pp. 4082–4088.

[26] D. G. Kyrollos, R. Hassan, Y. S. Dosso, and J. R. Green, "Fusing pressure-sensitive mat data with video through multi-modal registration," in *Proc. IEEE Int. Instrum. Meas. Technol. Conf. (I2MTC)*, May 2021, pp. 1–6.

[27] T. Kulvicius et al., "Infant movement classification through pressure distribution analysis," *Commun. Med.*, vol. 3, no. 1, p. 112, 2023.

[28] A. Rihar, M. Mihelj, J. Pašič, J. Kolar, and M. Munih, "Infant trunk posture and arm movement assessment using pressure mattress, inertial and magnetic measurement units (IMUs)," *J. Neuroeng. Rehabil.*, vol. 11, no. 1, pp. 1–14, 2014.

[29] D. G. Kyrollos, K. Greenwood, J. Harrold, and J. R. Green, "Transfer learning approaches for neonate head localization from pressure images," in *Proc. IEEE Int. Symp. Med. Meas. Appl. (MeMeA)*, Jun. 2022, pp. 1–6.

[30] D. G. Kyrollos, A. Fuller, K. Greenwood, J. Harrold, and J. R. Green, "Under the cover infant pose estimation using multimodal data," *IEEE Trans. Instrum. Meas.*, vol. 72, 2023, Art. no. 5007212.

Zheng Peng (Member, IEEE) received the B.Eng. degree in electrical engineering from Shandong University, Jinan, China, in 2012, and the M.Sc. degree in electrical engineering from Eindhoven University of Technology, Eindhoven, The Netherlands, in 2018, where he is currently pursuing the Ph.D. degree in electrical engineering, mainly focusing on physiological signal processing and patient monitoring for preterm infants using machine learning.

From 2012 to 2016, he was with State Grid Corporation of China, Chongqing, China, as an Automation Engineer. He was a Data Scientist with Prodrive Technologies, Eindhoven, from 2018 to 2020.

Yidan Zhao received the B.Sc. degree in physics from the University of Science and Technology of China, Hefei, China, in 2021, and the M.Sc. degree in applied physics from Eindhoven University of Technology, Eindhoven, The Netherlands, in 2023.

Her research interests include signal processing and data analysis.

Deedee Kommers received the bachelor's and master's degrees in medicine from Utrecht University, Utrecht, The Netherlands, in 2009 and 2013, respectively, and the Ph.D. degree (cum laude) in industry design from Eindhoven University of Technology, Eindhoven, The Netherlands, in 2018.

She is currently serving as a Physician Researcher at the Máxima Medical Center, Veldhoven, The Netherlands, focusing on enhancing the well-being of newborns by increasing parent–child bonding through extended closeness and developing more parent–child friendly methods for monitoring newborns.

Henrie van den Boom received the M.Sc. degree in electrical engineering from Eindhoven University of Technology, Eindhoven, The Netherlands, in 1984.

Since then, he has been an Assistant Professor with the Electro-Optical Communication Systems Group, Eindhoven University of Technology. He has been involved in many national and international research projects on high-capacity optical fiber data communication systems and networks and polymer optical fiber communication systems and networks for in-home and short-range data communication. He is currently with Luxisens Technologies, Eindhoven, investigating robust and low-cost 2-D sensor applications with polymer optical fiber and is CTO of a start-up company in this field.

Rong-Hao Liang received the M.S. degree in electrical engineering and the Ph.D. degree in computer science from National Taiwan University, Taipei, Taiwan, in 2010 and 2014, respectively.

He is currently an Assistant Professor with Eindhoven University of Technology, Eindhoven, The Netherlands, holding joint appointments at the Department of Industrial Design and the Department of Electrical Engineering. He was an Assistant Research Fellow at the Intel-NTU Research Center, Taipei, from 2014 to 2016. His research centres on user interface technology, including sensing systems for ubiquitous computing and embodied human–computer interaction.

Xi Long (Senior Member, IEEE) was born in China, in 1983. He received the B.Eng. degree (Hons.) in electronic information engineering from Zhejiang University, Hangzhou, China, in 2006, and the M.Sc. and Ph.D. degrees (cum laude) in electrical engineering from Eindhoven University of Technology, Eindhoven, The Netherlands, in 2009 and 2015, respectively.

From 2010 to 2011, he was with Tencent, Shenzhen, China, working on data mining and user research. He has more than ten years of research and development experience in healthcare industry, with Philips Research, Eindhoven, where he has been a Senior Scientist and an AI Leader. He is currently an Associate Professor with the Signal Processing Systems Group, Department of Electrical Engineering, Eindhoven University of Technology. He has published over 120 articles and reports in these fields and his inventions led to more than 15 patent applications. His research interests include signal processing and machine learning in healthcare and medical applications.

Hendrik Niemarkt was born in 1978.

He is trained as a Pediatrician and a Neonatologist with Maastricht University Medical Center, Maastricht, The Netherlands. He works as a Consultant Neonatologist and a Clinical Researcher with the Máxima Medical Center, Veldhoven, The Netherlands, and Eindhoven University of Technology, Eindhoven, The Netherlands. His research interests include "less invasive approaches toward diagnosis and therapy in preterm infants."

Peter Andriessen received the Medical Doctor degree (cum laude) from the Faculty of Medicine, University of Maastricht, Maastricht, The Netherlands, in 1989, and the Ph.D. degree in baroreceptor reflex function in neonates from the University of Maastricht, in 2004.

From 1991 to 1996, he followed his training in Pediatrics at the Radboud University Hospital, Nijmegen, The Netherlands, and Máxima Medical Center, Veldhoven, The Netherlands. From 1996 to 1998, he followed a 30-month Clinical Fellowship in Neonatology at the Máxima Medical Center and the Free University of Amsterdam, Amsterdam, The Netherlands. Since 1999, he has been a Neonatologist with the Máxima Medical Center. Since 2002 onward, he co-supervises master's and Ph.D. students of Eindhoven University of Technology, Eindhoven, The Netherlands, who carry out research projects in the Neonatal Intensive Care Unit, Máxima Medical Center, in close collaboration with the Department of Clinical Physics, Máxima Medical Center. From 2014 to 2024, he was involved as a Co-Supervisor for many Ph.D. projects on neonatal monitoring. Since 2018, he has been the National Project Leader of the Extremely Preterm Infants: Dutch Analysis on Follow-Up Study, a survey on long-term outcomes in extremely preterm infants, carried out throughout all neonatal intensive care units in The Netherlands. His major research interests are patient monitoring, integrative physiology, and long-term follow-up of preterm infants.

Carola van Pul received the M.Sc. degree in applied physics from the Delft University of Technology, Delft, The Netherlands, in 2000, and the Ph.D. degree in applied physics from Eindhoven University of Technology, Eindhoven, The Netherlands, in 2004.

She works at the Máxima Medical Center, Veldhoven, The Netherlands, as a Medical Physicist and one day per week as a Professor Medical Physics at Eindhoven University of Technology. Her topic is physics for diagnosing and monitoring, with a special focus on patient monitoring and alarms for (neonatal) intensive care. In the last decade, her work has focused on the development and implementation of new sensor and monitoring techniques for clinical practice and on artificial intelligence approaches are also being investigated to predict deterioration in these small infants in an earlier stage.