2023 IEEE International Conference on E-health Networking, Application & Services (Healthcom) | 979-8-3503-0230-1/23/$31.00 ©2023 IEEE | DOI: 10.1109/HEALTHCOM56612.2023.10472386

Improving Video-Based Actigraphy for Sleep Monitoring of Preterm Infants

Zheng Peng
Clinical Physics
Maxima Medical Centre
and Electrical Engineering
Eindhoven University of Technology
Eindhoven, The Netherlands
z.peng@tue.nl

Dandan Zhang
Electrical Engineering
Eindhoven University of Technology
and Philips Research
Eindhoven, The Netherlands
d.zhang3@tue.nl

Carola van Pul
Clinical Physics
Maxima Medical Centre
and Electrical Engineering
Eindhoven University of Technology
Eindhoven, The Netherlands
c.v.pul@tue.nl

Rong-Hao Liang
Industrial Design
Electrical Engineering
Eindhoven University of Technology
Eindhoven, The Netherlands
J.Liang@tue.nl

Peter Andriessen
Neonatology
Maxima Medical Centre
Veldhoven, The Netherlands
P.Andriessen@mmc.nl

Ronald M. Aarts
Electrical Engineering
Eindhoven University of Technology
Eindhoven, The Netherlands
r.m.aarts@tue.nl

Xi Long
Electrical Engineering
Eindhoven University of Technology
Eindhoven, The Netherlands
X.Long@tue.nl

***Abstract*—Video-based actigraphy is a non-contact technology that measures body movement through video recordings, commonly expressed as activity count. It has been widely used to assess infant sleep. One validated method for video-based actigraphy is the three-dimensional recursive search (3DRS). However, its sleep-wake classification performance in preterm infants is only moderately satisfactory, necessitating methods to improve it. This paper proposes an enhanced approach to compute activity count for video-based actigraphy in evaluating sleep patterns in preterm infants. The proposed technique involves applying exponentially weighted moving average (EWMA) to continuous activity count to reduce abrupt variations and false detection of wakefulness. Additionally, the 3DRS protocol we previously utilized is proprietary, limiting its accessibility to the public and its widespread adoption. To overcome this limitation, we have investigated the efficacy of an open-source algorithm known as background subtraction (BS), which, in our previous work, has demonstrated superior performance in body motion detection in preterm infants. To evaluate the performance of the proposed method, a dataset consisting of video recordings from five hospitalized preterm infants was used. The activity counts obtained from 3DRS, and BS were compared in terms of their ability to classify sleep and wake states using a linear discriminant classifier. The results obtained through leave-one-patient-out cross-validation revealed a significant improvement in the classification of sleep and wake states in preterm infants for both methods when the EWMA were applied to the activity counts. The mean Cohen's kappa coefficients were found to be 0.58 for 3DRS and 0.51 for BS. Despite BS exhibited comparatively lower performance than 3DRS, it can still be considered a viable alternative for acquiring video-based actigraphy data in the assessment of sleep of preterm infants.**

Keywords—actigraphy, motion detection, preterm infants, sleep states classification.

I. Introduction

Sleep plays a critical role in the growth and development of preterm infants, who are particularly vulnerable due to their physiological immaturity. It contributes to brain development, strengthens immune function, and aids in memory consolidation and learning processes [1]. The current practice of assessing infant sleep heavily relies on subjective and intermittent observations made by caregivers. This approach proves challenging in the neonatal intensive care unit (NICU) where preterm infants often experience disrupted sleep due to frequent care events in this high-stress environment [2]. Continuous sleep monitoring in preterm infants in the NICU allows for better prioritization of caregiving, aiming at less sleep disturbance for better brain development. Therefore, to enhance the duration and quality of sleep without creating extra burden for these vulnerable patients, there is a growing need for an automatic and unobtrusive sleep assessment method that can be used to optimize caregiving routines in the NICU.

Actigraphy, a validated and cost-efficient method often measured with a wearable sensor, has been employed to measure activity levels and evaluate sleep patterns in the pediatric population [3]. While actigraphy has been applied in studies assessing infant sleep [4], [5], these approaches typically require physical contact with the infant's skin, introducing risks of skin damage and discomfort. These limitations emphasize the importance of unobtrusive or non-contact assessment methods, such as video-based actigraphy (i.e., actigraphy obtained from video recordings) [6], which can evaluate sleep in preterm infants without compromising their well-being.

In our prior research [6], we used a proprietary three-dimensional recursive search (3DRS) method [7], [8] to calculate activity counts for video-based actigraphy, demonstrating its feasibility in assessing sleep-wake patterns in preterm infants. However, the performance for identifying sleep and wake states using video-based actigraphy has significant room for improvement. Expanding upon this foundation, this study introduces an improved activity count feature that incorporates temporal association using exponentially weighted moving average (EWMA) to enhance the performance of automatic sleep-wake classification. Furthermore, the 3DRS method we previously utilized is currently not openly available to the public due to its proprietary nature , limiting its availability for unrestricted use. This motivated us to seek a different method that can accurately quantify body movement for measuring video-based actigraphy and thus to monitor sleep. Background subtraction (BS) is a well-known method in motion estimation or detection which is available from the OpenCV library [9]. BS exhibited superior performance in our previous validation study in infant motion detection compared with several other methods such as optical flow, oriented FAST, and rotated BRIEF [10]. In this work, we aimed to 1) enhance the performance of video-based sleep-wake classification in preterm infants using our proposed new activity feature and, 2) to provide a viable and freely accessible alternative to 3DRS for deriving video-based actigraphy for non-contact sleep assessment and compare its performance to 3DRS.

II. Dataset

The dataset used in this study was the same as described in [6]. It consisted of video recordings from five preterm infants who were receiving routine care in the NICU at the Máxima Medical Center in Veldhoven, The Netherlands. The patients had a mean ± standard deviation gestational age (GA) and postmenstrual age (PMA) of 30.1 ± 2.9 and 31.7 ± 2.9 weeks, respectively. For each infant, written informed consent was obtained from the parents.

To collect the recordings, a uEye monochrome video camera (IDS GmbH) was placed inside each infant's incubator, capturing videos at a resolution of 736 × 480 pixels with a frame rate of 8 frames per second.

Behavioral sleep and wake (including caretaking) states were first manually scored by a pediatric sleep expert using Prechtl's rules [11]. The expert reviewed the video recordings and synchronized chest-impedance respiratory signals whenever necessary to ensure accurate scoring according to a modified behavioral sleep annotation framework developed by Otte et al. [12]. On average, a total of 665.8 ± 81.4 non-overlapping 30-s epochs were collected from the five preterm infants. Among these epochs, the wake epochs accounted for 9.9 ± 5.8%. For further information, we recommend referring to the study conducted previously [6].

III. Methods

As mentioned before, to obtain video-based actigraphy, we quantified motion using two video-based motion detection methods (3DRS and BS). In the preprocessing stage, each frame was subsequently normalized using histogram equalization to enhance efficiency and contrast. Both methods estimated motion values based on the video frames, and the resulting quantified motion values were then used to calculate the activity count feature (i.e., video-based actigraphy) for each 30-s epoch. This activity count feature was then evaluated by means of sleep-wake classification in preterm infants.

A. *Three-dimensional recursive search (3DRS)*

3DRS is a spatial-temporal prediction algorithm for motion estimation. It divides each frame into smaller blocks of uniform size, typically 8 × 8 pixels. For each block in the current frame, a search area is defined in the reference frame based on a predicted motion vector derived from previous estimations. The algorithm performs a coarse search within the search area, evaluating the similarity between the current block and the blocks within the search area using a similarity metric. The block with the highest similarity measure is considered the best match, and the differences between the best matching blocks across consecutive frames are measured using a motion vector. The magnitude and direction of the motion vector are quantified as the measure of motion in each frame. In this study, we applied the 3DRS method proposed in [7] where the motion vector candidate sets were modified by adjusting spatial-temporal candidate locations and adding mean motion vectors. The output motion vector for each block was selected from a candidate set based on prediction vectors, including a spatial-temporal neighborhood and the addition of small random values. This adaptation enhances the detection of small movements, such as the limb movements under the blanket.

B. *Background subtraction (BS)*

The BS method identifies regions of motion by comparing the current frame to a pre-defined background model [13]. The model serves as a reference, and any differences between the current frame and the background model indicate motion in corresponding regions. Initially, the background model is constructed using a fixed number of frames and is continuously updated to account for environmental changes. In this study, we utilized a Gaussian mixture model implemented in the OpenCV package, similar to our previous work [10]. This method enables the initialization and continuous adaptation of the background model, allowing for the detection of foreground regions in each frame. However, since BS does not provide a motion vector, we quantified motion by counting the number of pixels identified as foreground in each frame.

C. *Exponentially weighted moving average (EWMA) for video-based actigraphy*

Actigraphy often measures activity count over a certain period. For sleep analysis, video-based actigraphy can be derived by counting the number of motion values (estimated from video data) exceeding a pre-defined threshold for each epoch [6], [14]. For 3DRS, a threshold of 0 was used due to its sparse characteristics. For BS, the threshold was empirically set at 0.2 times the standard deviation of the estimated motion values.

Based on the sleep scoring rules [12], the annotation only accepts changes lasting longer than 3 minutes as a new state to consider the sleep context. The frequent abrupt changes in activity count with a short time (e.g., less than 3 minutes) might be due to fast but not fluent body movements of the monitored infant (such as jerky movements) or other 'high-frequency' external disturbances such as flashing light from the patient monitor. These changes may not lead to sleep wake transitions, hence should not be detected by the algorithm. To accommodate the annotation rules for automatic sleep-wake classification, we therefore smooth the activity count for each epoch using EWMA as following:

$$y_0 = x_0$$
$$y_n = (1-\alpha)y_{n-1} + \alpha x_n$$

where x_n represents the raw activity count of the n^{th} epoch, y_n represents the updated smoothed activity count of the n^{th} epoch. We optimized the weight coefficient α to determine the desired decay rate corresponding to a half-life of two minutes. Notably, this EWMA function only relies on the raw activity count from previous instances, which, from algorithm perspective, still allows for real-time monitoring of body movement in clinical applications.

D. Sleep-wake classification and performance evaluation

In this study, we evaluated the sleep-wake classification performance using different motion detection methods for deriving video-based actigraphy with and without using EWMA. We employed the same linear discriminant classifier as in our previous study [6] to classify preterm infant sleep and wake states using video-based actigraphy. Leave-one-patient-out cross validation was applied for training and testing the classifier. Each round of cross validation involved training the model with data from four infants and testing it on the remaining infant to assess its performance. To provide a comprehensive evaluation for comparing the classification performance, concerning wake as the positive class, multiple evaluation metrics including sensitivity, specificity, positive predicted value (PPV), negative predicted value (NPV), accuracy, Cohen's kappa coefficient, and the area under the receiver-operating-characteristic (ROC) curve (AUC) were reported. Furthermore, we calculated the Pearson’s correlation between the activity counts obtained from 3DRS and BS to gain insights into their relationship.

IV. RESULTS

Table I presents the results of preterm infant sleep-wake classification (mean ± standard deviation) for 3DRS and BS using activity count with and without EWMA. The table demonstrates that, independent of the motion detection method, applying EWMA enhanced the classification performance for all metrics. The best performing method was 3DRS using activity count with EWMA, achieving a Cohen's kappa of 0.58 ± 0.08 and an AUC of 0.94 ± 0.05. It is interesting to note that, although BS performed less than 3DRS, its overall performance using activity count with EWMA was comparable to that obtained using raw activity count for 3DRS. The comparison can also be observed in Fig. 1, where the ROC curve using 3DRS with EWMA activity count outperformed the rest. Fig. 2 provides an example that visually compares different methods in estimating activity counts with sleep annotations, The figure shows that the activity count with EWMA was able to effectively filters out fast changes conveyed in the raw activity count data. Furthermore, the correlation between 3DRS and BS was also increased by applying EWMA to activity count.

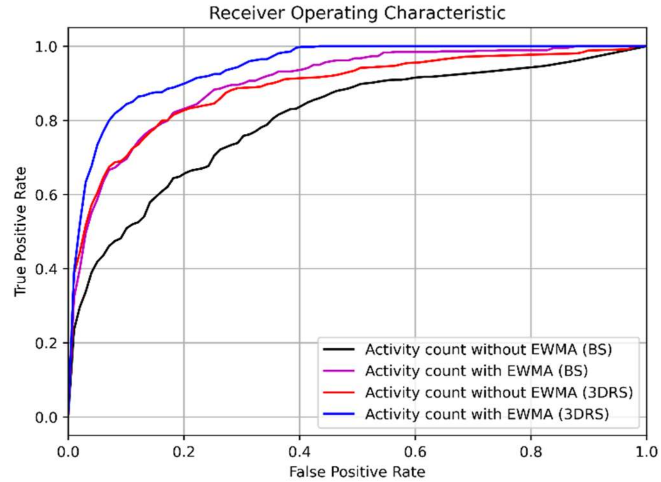

Fig. 1. Receiver operating characteristic (ROC) curve of different methods for preterm infant sleep-wake classification.

TABLE I. SLEEP-WAKE CLASSIFICATION PERFORMANCE BASED ON VIDEO-BASED ACTIGRAPHY DERIVED USING 3DRS AND BS WITH AND WITHOUT EWMA. THE RESULTS ARE PRESENTED IN MEAN ± STANDARD DEVIATION.

Evaluation metric	*3DRS activity count without EWMA*	*BS activity count without EWMA*	*3DRS activity count with EWMA*	*BS activity count with EWMA*
Kappa	0.51 ± 0.15	0.39 ± 0.13	0.58 ± 0.08	0.51 ± 0.16
AUC	0.89 ± 0.06	0.80 ± 0.06	0.94 ± 0.05	0.90 ± 0.07
Accuracy	0.92 ± 0.05	0.90 ± 0.05	0.93 ± 0.03	0.90 ± 0.07
Sensitivity	0.53 ± 0.20	0.41 ± 0.12	0.64 ± 0.17	0.62 ± 0.13
Specificity	0.97 ± 0.03	0.96 ± 0.02	0.97 ± 0.02	0.92 ± 0.07
PPV	0.62 ± 0.17	0.54 ± 0.23	0.65 ± 0.13	0.57 ± 0.21
NPV	0.94 ± 0.05	0.93 ± 0.05	0.95 ± 0.04	0.95 ± 0.03
Correlation	0.84 ± 0.19 *		0.91 ± 0.12 **	

* Correlation between 3DRS and BS with raw activity count.
** Correlation between 3DRS and BS with EWMA activity count.

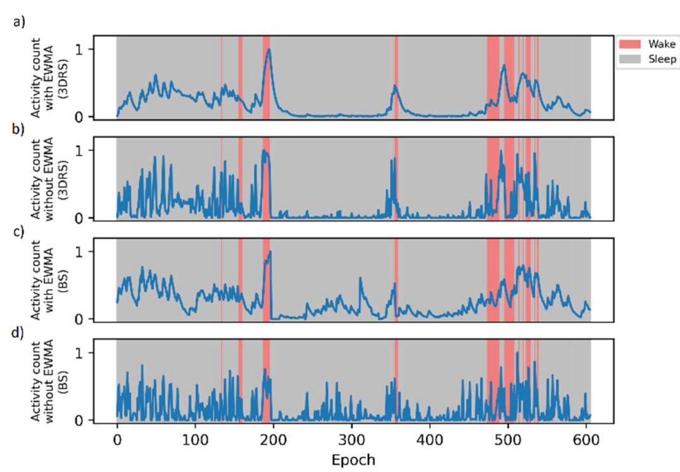

Fig. 2. Activity count obtained using different motion detection methods over time (30-s epoch), with background colored by corresponding annotations (Wake and Sleep). (a) Activity count with EWMA from 3DRS. (b) Activity count without EWMA from 3DRS. (c) Activity count with EWMA from BS. (d) Activity count without EWMA from BS.

V. Discussion

This paper introduces an improved video-based actigraphy approach that considers the temporal association of activity counts. In addition to an existent motion estimation method (3DRS), we also assessed an open-source method (BS, freely available from the OpenCV library) for video-based sleep monitoring in preterm infants in a NICU. The results demonstrated that activity count with EWMA significantly increased the classification performance for both methods. Additionally, as shown in Fig. 2, 3DRS exhibited greater robustness to high-frequency noise when compared to BS, making it more reliable in measuring fluent, larger body movements that are related to wake state instead of jerky, smaller movements that are most likely involuntary and random corresponding to sleep [12]. The superior performance of 3DRS compared to BS can be attributed to several factors. Firstly, in 3DRS, the search area based on the spatial-temporal prediction allows it to consider several consecutive frames instead of only the next frame as in BS [7]. This makes 3DRS more robust to abrupt changes caused by jerky movement or external disturbances, which may lead to false detections using BS. Additionally, the adaptive selection process and precise representation of motion with magnitude and direction in 3DRS contribute to accurate quantification of motion in each frame. In contrast, BS relies on the number of pixels identified as foreground, which may not capture fine motion details as effectively. However, it is worth noting that with the improved activity count feature, BS can achieve a similar performance to 3DRS with raw activity count. Nonetheless, considering the more efficient calculation and free availability of BS, it remains a viable alternative for infant sleep assessment, particularly in home scenarios where the requirement for accuracy may be less stringent.

While the findings of this study are promising, some limitations should be addressed in future research. The dataset used in this study was small, comprising recordings from only 5 preterm infants. Therefore, larger and more diverse datasets should be considered to validate the findings and ensure their generalizability. Furthermore, the study primarily focused on activity count as the only feature for sleep-wake classification, which limits the ability to distinguish between the wake state with reduced activity and the sleep state with increased activity [3]. Future studies can explore the incorporation of other motion-related features [15] or investigate more advanced video-based methods such as deep learning [16] to minimize this limitation. Additionally, the sleep stage annotation in this study was based on a behavioral approach, which was validated by the golden standard (polysomnography, PSG) in a small dataset [12], but this annotation approach should be further validated. As there are various of behavioral sleep stage annotation approaches and they used different criteria for sleep annotations, the performance comparison between studies is limited [17].

To achieve continuous sleep assessment, it is essential to address factors such as caregiving events, movement in background, and camera movement, which may lead to false-positive detections. Therefore future studies should explore the integration of automatic infant body segmentation and intervention detection to improve the reliability of sleep monitoring [18], [19]. Moreover, conducting motion analysis of specific body regions, such as limb movements, we can gain deeper insights into the nuances of sleep-related movement patterns and enhance the accuracy of sleep monitoring. Furthermore, integrating video-based approaches with the capabilities of vital sign monitoring [20] opens up new avenues for advanced sleep assessment, in particular for identifying different sleep states such as active and quiet sleep [21], [22]. The combination of information from video motion analysis and vital signs can enable a more comprehensive understanding of sleep physiology, uncover valuable insights and refine the assessment of sleep quality and health in preterm infants. This integration of multiple modalities has the potential to revolutionize sleep assessment and contribute to improved care and outcomes for these vulnerable patients.

VI. Conclusion

This study presents an improved video-based actigraphy approach for sleep assessment in preterm infants. The use of the activity count with EWMA significantly improved the sleep-wake classification performance for both video-based motion detection methods verified in this work (3DRS and BS). 3DRS outperformed BS in quantifying body movement and detecting sleep/wake states. Nevertheless, using activity count obtained based on BS yielded moderate performance in classifying sleep and wake states, on par with the result reported in our previous work. The proposed video-based actigraphy approach may provide a cost-effective and non-contact method for sleep monitoring of preterm infants admitted in a NICU.

Acknowledgment

This research was performed within the framework of Eindhoven MedTech Innovation Center (e/MTIC) and was partially supported by the China Scholarship Council (Grant No. 201806170049).

References

[1] L. Bennet, D. W. Walker, and R. S. C. Horne, "Waking up too early – the consequences of preterm birth on sleep development," J. Physiol., vol. 596, no. 23, pp. 5687–5708, 2018

[2] J. Park, "Sleep Promotion for Preterm Infants in the NICU," Nurs. Womens. Health, vol. 24, no. 1, pp. 24–35, 2020

[3] M. Sung, T. M. Adamson, and R. S. C. Horne, "Validation of actigraphy for determining sleep and wake in preterm infants," Acta Paediatr. Int. J. Paediatr., vol. 98, no. 1, pp. 52–57, 2009

[4] 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

[5] H. Y. Lan, L. Yang, K. H. Hsieh, T. Yin, Y. C. Chang, and J. J. Liaw, "Effects of a supportive care bundle on sleep variables of preterm infants during hospitalization," Res. Nurs. Heal., vol. 41, no. 3, pp. 281–291, 2018

[6] X. Long, J. Espina, R. A. Otte, W. Wang, R. M. Aarts, and P. Andriessen, "Video-based actigraphy is an effective contact-free method of assessing sleep in preterm infants," Acta Paediatr. Int. J. Paediatr., vol. 110, no. 6, pp. 1815–1816, 2021

[7] A. Heinrich, X. Aubert, and G. De Haan, "Body movement analysis during sleep based on video motion estimation," 2013 IEEE 15th Int. Conf. e-Health Networking, Appl. Serv. Heal. 2013, no. Healthcom, pp. 539–543, 2013

[8] G. de Haan, P. W. A. C. Biezen, H. Huijgen, and O. A. Ojo, "True-Motion Estimation with 3-D Recursive Search Block Matching," IEEE Trans. Circuits Syst. Video Technol., vol. 3, no. 5, pp. 368–379, 1993

[9] G. Bradski, "The OpenCV Library," Dr. Dobb's J. Softw. Tools, 2000

[10] Z. Peng et al., "A Comparison of Video-based Methods for Neonatal Body Motion Detection," Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. IEEE Eng. Med. Biol. Soc. Annu. Int. Conf., vol. 2022, pp. 3047–3050, 2022

[11] H. F. R. Prechtl, "The behavioural states of the newborn infant (a review)," Brain Res., vol. 76, no. 2, pp. 185–212, 1974

[12] R. A. Otte, X. Long, and J. Westerink, "A behavioral approach to annotating sleep in infants: Building on the classic framework," Physiol. Rep., vol. 10, no. 3, 2022

[13] Z. Zivkovic and F. Van Der Heijden, "Efficient adaptive density estimation per image pixel for the task of background subtraction," Pattern Recognit. Lett., vol. 27, no. 7, pp. 773–780, May 2006

[14] X. Long, R. Otte, E. van der Sanden, J. Werth, and T. Tan, "Video-based actigraphy for monitoring wake and sleep in healthy infants: A laboratory study," Sensors (Switzerland), vol. 19, no. 5, pp. 1–10, 2019

[15] J. Ranta, M. Airaksinen, T. Kirjavainen, S. Vanhatalo, and N. J. Stevenson, "An Open Source Classifier for Bed Mattress Signal in Infant Sleep Monitoring," Front. Neurosci., vol. 14, no. January, pp. 1–11, 2021

[16] H. Korkalainen et al., "Deep learning enables sleep staging from photoplethysmogram for patients with suspected sleep apnea," Sleep, vol. 43, no. 11, pp. 1–10, 2020

[17] A. Bik et al., "A scoping review of behavioral sleep stage classification methods for preterm infants," Sleep Med., vol. 90, pp. 74–82, 2022

[18] C. H. Antink et al., "Fast body part segmentation and tracking of neonatal video data using deep learning," Med. Biol. Eng. Comput., vol. 58, no. 12, pp. 3049–3061, Dec. 2020

[19] S. Chaichulee et al., "Cardio-respiratory signal extraction from video camera data for continuous non-contact vital sign monitoring using deep learning," Physiol. Meas., vol. 40, no. 11, 2019

[20] L. Maurya, P. Kaur, D. Chawla, and P. Mahapatra, "Non-contact breathing rate monitoring in newborns: A review," Comput. Biol. Med., vol. 132, no. January, p. 104321, 2021

[21] E. R. de Groot et al., "The value of cardiorespiratory parameters for sleep state classification in preterm infants: A systematic review," Sleep Med. Rev., vol. 58, p. 101462, 2021

[22] J. Werth, L. Atallah, P. Andriessen, X. Long, E. Zwartkruis-Pelgrim, and R. M. Aarts, "Unobtrusive sleep state measurements in preterm infants – A review," Sleep Med. Rev., vol. 32, pp. 109–122, 2017