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Citation for published version (APA):

Long, X., van der Sanden, E., Prevoo, Y., ten Hoor, L., den Boer, S., Gelissen, J., Otte, R., & Zwartkruis-Pelgrim, E. (2018). An efficient heuristic method for infant in/out of bed detection using video-derived motion estimates. *Biomedical Physics & Engineering Express*, 4(3), [035035]. <https://doi.org/10.1088/2057-1976/aab85f>

Document license:
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DOI:
[10.1088/2057-1976/aab85f](https://doi.org/10.1088/2057-1976/aab85f)

Document status and date:
Published: 16/04/2018

Document Version:
Publisher's PDF, also known as Version of Record (includes final page, issue and volume numbers)

Please check the document version of this publication:

- A submitted manuscript is the version of the article upon submission and before peer-review. There can be important differences between the submitted version and the official published version of record. People interested in the research are advised to contact the author for the final version of the publication, or visit the DOI to the publisher's website.
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To cite this article: Xi Long *et al* 2018 *Biomed. Phys. Eng. Express* **4** 035035

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PAPER

An efficient heuristic method for infant in/out of bed detection using video-derived motion estimates

RECEIVED
16 January 2018

REVISED
8 March 2018

ACCEPTED FOR PUBLICATION
21 March 2018

PUBLISHED
16 April 2018

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Keywords: infant monitoring, video, motion estimation, sleep, in bed, heuristic detection

Abstract

Camera-based infant monitoring has received substantial attention because of its unobtrusiveness, allowing long-term and continuous monitoring. To assess infant sleep, it is required to know whether the infant is in bed or out of bed. This can automate monitoring for analyzing data solely when the infant is in bed, providing accurate assessment of sleep quality. In this work, we propose a method aimed at detecting infant in/out of bed status for a 24 h period using motion estimates derived from an infrared video camera. The method is based on several heuristic decision-making rules to examine the motions between peaky motions that are expected to express activities or events of putting the infant in bed or taking the infant out of bed. For example, when these events are identified, intuitively, if a period between two events has consistently motions (caused by infant's body movements), this period should be detected as infant 'in bed', otherwise as 'out of bed'. Our proposed method would largely increase the efficiency (i.e. reduce the computational load) compared to some advanced computer vision algorithms that try to recognize infant's face or torso. To separate the motions caused by infant body movements and other activities from, for example, parents, a region of interest (ROI) is configured. This ROI can be fixed and customized. 77 datasets of 24 h recordings from five infant participants were analyzed in this study. Experiments were conducted in a free-living environment in the participants' own home. Results show that an average accuracy of 95.8% using a fixed ROI configuration, and that of 96.9% using a customized configuration were achieved. This indicates that our proposed method is reliable for infant in/out of bed detection.

1. Introduction

Objective and continuous tracking of infant sleep is paramount for parents and healthcare professionals for interpreting and evaluating infant's mental and physical development [1, 2]. It could enable tailored coaching and parenting for achieving improved sleep quality of infants [3, 4]. The objective assessment of sleep quality is often done by analyzing sleep patterns or sleep states including wakefulness and different sleep stages as well as several sleep parameters such as sleep efficiency, total sleep time, number of awakenings, and sleep onset latency for both infants and adults [5–8]. More importantly, to obtain reliable measures on sleep patterns, a prolonged monitoring with multiple nights is recommended [9, 10], requiring the use of unobtrusive sleep

monitoring techniques in an in-home scenario [11, 12] in contrast to the gold standard polysomnography recordings [5].

In the past decade, many unobtrusive or minimal-obtrusive devices or systems have been developed, and used for objective infant or baby sleep monitoring based upon various sensing techniques using, for example, ballistocardiography [13], capacitive sensing array [14], actigraphy [10], photoplethysmography [15, 16], and infrared (IR) or thermal video camera [17, 18]. Camera-based baby monitors have been well commercialized in the market (e.g. Philips Avent Smart Baby Monitor and Evoz Baby monitor) because of their primary advantage of unobtrusiveness of monitoring compared with other types of monitors. For example, wearables or other contact monitors, e.g.

wrist-, ankle-, or foot-worn devices (e.g. Owlet Smart Baby Monitor), smart jacket [19], and smart accessories (e.g. Mimo Baby Sleep Tracker), are usually not very well accepted by infants because their skin is very sensitive and vulnerable [11, 20]. Additionally, wearables often require constant attention as they require mounting and dismounting upon usage, e.g. to charge the battery or when the infant is put in bath. Therefore, due to the nature of noncontact and ‘install and forget’ monitoring, a video camera is considered one of the most unobtrusive devices to monitor infant sleep. Furthermore, video-based approaches are not only capable of capturing body movements [21] but also, more interestingly, of capturing vital signs such as respiratory movements and heart rate [17, 18], which are of profound significance for classifying different sleep states.

Before assessing infant sleep, it is of importance to know whether the infant is in bed or out of bed. This can automate an infant monitor for analyzing data when the infant is in bed, providing accurate measures of sleep-related statistics and sleep states. With a video camera, advanced algorithms of image processing for human tracking, which attempt to recognize infant’s face/body or parent’s appearance, are expected to work well in identifying the infant in or out of bed status. However, these algorithms are computationally expensive since they need to deal with a large number of video frames, possibly requiring the use of a high-performance computing unit that is difficult and costly to integrate into the camera. To this matter, methods to estimate motions from the video frames (mostly caused by baby’s body movements) should be considered promising. With motion data, intuitively, it is able to identify a baby’s presence and, further, to characterize her/his sleep-wake patterns [9, 10]. Compared to the image processing algorithms, the use of solely motion data can largely reduce the computational load (increase the efficiency), which is more applicable in real applications. Some good-performing motion estimators have been proposed such as block-based gradient descent search [22], four-step search [23], and 3D recursive search (3DRS) [24]. Recently, a dedicated efficient 3DRS motion estimation algorithm from an IR camera has been successfully employed in analyzing human sleep [21, 25].

This paper describes a fast and reliable heuristic method aiming at detecting whether an infant is in bed or out of bed in a free-living environment using IR video-derived motion data. As mentioned, motion estimates are able to quantify infant body movements to some extent, which should highly correlate to the presence of the infant. Therefore, by exploiting motion estimates, detecting the infant in bed or out of bed status would be possible. A simple method described in [26] proposes to categorize the amplitude of video-based motion estimates in three levels (small, intermediate, and large) so that the infant in/out of bed status can be determined. However, brutally

setting motion values to be one of the three discrete levels would likely cause ‘under-representation’ and ‘low resolution’ of the body movements, leading to a bad detection performance. Therefore, instead of motion levels, we analyze continuous raw motion estimates in this study. Moreover, since during sleep infants do not always make body movements, it would be of interest to exploit motions within a certain period, e.g. between the potential ‘events’ of putting the infant to bed and taking the infant out of bed. This actually takes infants’ movement information over time into account. Apart from that, in real applications, various placements and angles of the camera can produce different views of the bed. As a result, the total amount of motions derived from video frames would sometimes be caused by activities from the parent(s) such as cleaning the room or even from other objects such as a door opening/closing, an insect flying by the camera, etc. In this case, considering the total amount of motions might lead to misclassifications in distinguishing between the infant in and out of bed status. In order to improve the detection performance, we propose to configure a region of interest (ROI), serving to analyze as much as possible the motions caused solely by infant body movements during sleep.

2. Materials and methods

2.1. Participants

The study protocol was approved by the Internal Ethics Committee for Biomedical Experiments (ICBE) of Philips Research Eindhoven, The Netherlands (study number: 2015-0079). As the study was observational in nature, no additional approval from an external ethics board was required (the Dutch law on medical scientific research with human beings (WMO) was not applicable). The study was performed in conformity with the declaration of Helsinki.

Participants were five infants (three females) aged 14.4 ± 2.7 months (range 10–16 months). They were born at term with appropriate birth weight as confirmed by the parents. Their parents had been recruited both through the researchers’ own network, and with the help of a recruitment agency specialized in recruiting subjects for scientific studies. Recruitment took place in March and April, 2016. Inclusion criteria were that the infants needed to sleep (most of the time) in their own bed, in their own bedroom, and be below 18 months at the start of the study. Exclusion criteria were health problems, or problems related to feeding, sleeping or infant development (this information was provided by the parents). Before consenting to have their baby participate, all steps of the study were explained in full to the participants’ parents. If they agreed to let their baby participate, both parents signed an informed consent form in accordance with the declaration of Helsinki. Participants’ parents were reimbursed an hourly rate of €10 for the time we asked

Figure 1. (a) Philips Avent uGrow baby monitor and (b) an example of an IR camera video frame view placed in the baby room. The head and face of the infant are covered to be invisible because of privacy concerns.

them to invest in study participation. In addition, they could keep the Philips Avent uGrow baby monitor (figure 1(a)) that was used during the study.

2.2. Data acquisition

Data acquisition was performed in the participants' own home. In order to obtain representative data from actual use cases, parents were asked to place a Philips Avent uGrow baby monitor (figure 1(a)) in their baby room so they could see their infant's bed. There were no other specific requirements regarding camera placement except for ensuring the view of the infant. A laptop was placed in the room to collect and store raw IR video stream images through an external LAN. The parents were asked to behave as usual depending on their habitual daily routine. An example of an IR video frame from the baby monitor from a participant is shown in figure 1(b).

In this work, 77 recordings (24 h each) from the five infants were used for data analysis. The frame rate or sampling frequency of the video recordings was 15 Hz and the images were 320×180 pixels. The infant in/out of bed detection was conducted for each continuous 24 h recording, starting from each day at 12:00 PM until the next day at 12:00 PM. On average over all 24 h recordings, the total in-bed time accounted for $43.9 \pm 18.8\%$ per day from all participants. For infant in/out of bed detection, each recording was divided into non-overlapping 30 s epochs, as is usual for sleep staging according to the AASM standard [5]. Note that each 24 h recording could be shorter than 24 h due to the presence of missing data, caused by technical problems such as device or the local internet disconnection, frame loss, and system reboot. On average, the missing data accounted for about $17.0 \pm 5.7\%$ (4.1 ± 1.4 h) for each 24 h recording. Of the 77 recordings, 38 recordings from two participants were used to train the in/out of bed detector and the other 39 recordings from the other three participants were used to test the detector. Manual annotation by human raters was used as ground-truth of the infant in/out of bed status. The annotations were

straightforward and done through visual inspection in a simple tool in which raters could use a slide to indicate at what point in time a baby was in versus out of bed. Note that, in this work, we used a temporal resolution of 30 s epoch in infant in/out of bed detection.

2.3. Video-based motion estimation

Motion caused by infant body movements, parents or other disturbances (e.g. from flying insects or spinning toys) can indicate their behaviors, or 'events', in a room. This is important information that can tell whether the infant is in bed or not, enabling further the automated analysis of infant sleep. In this work, the 3DRS motion estimation algorithm was employed to quantify motions from IR videos [21, 25, 27]. The algorithm has been shown to be robust to scene changes (or more specifically in this case, light changes), meaning that the effect of daytime light can be eliminated.

The IR video recording and its corresponding raw 3DRS motion estimates have a frame rate (or sampling rate) at $f_s = 15$ Hz that is apparently too high for in/out of bed detection with 30 s basis. Thus, we converted the motion data into continuous non-overlapping 30 s epochs by computing the sum of the raw motion estimates for each epoch. Figure 2 shows an example including four IR camera video frames within a video recording over 24 h (from 12:00 PM to 12:00 PM the next day), the derived motion estimates and the corresponding epoch-based motion sums. Note that a larger estimated motion value usually corresponds to a large body movement or more body movements.

2.4. Region of interest (ROI)

As stated, the total amount of motions from the video frames could be the combination of motions caused by, for example, infant body movements, parental activity such as putting infant in bed or taking infant out of bed, parental visit, and other disturbances. In this case, the motion estimates could not characterize and separate these activities or behaviors very well,

leading to an unreliable detection of the infant being in or out of bed. An ROI is therefore set in the video frames, aimed to specify motions from the infant and other subjects or objects. Afterwards, the motions within the ROI (IROI) area and outside the ROI (OROI) area can be calculated separately. The IROI and the OROI area are expected to only include motions caused by the infant movements and other activities (i.e. parental activity or visit), respectively, ideally allowing the separation between them. In this work, we propose two different ROI configurations: (i) fixed ROI and (ii) customized ROI, as depicted in figure 3. It is assumed that the length (horizontal axis) and the width (vertical axis) of a video frame is x and y , respectively. Of the entire frame, the IROI area for the fixed configuration is a rectangular, accounting for a certain percentage constrained by $a = \theta \cdot x$ and $b = \theta \cdot y$. For the customized ROI configuration, the IROI area is selected to include only the mattress within the bed frame.

Intuitively, the customized ROI seems able to better distinguish between the motions from the infant when in bed and from others activities compared to the fixed ROI. However, the disadvantage is that this configuration requires either a user's effort (manual selection) or a dedicated mattress/bed-frame detector based on recorded video frames, increasing the

computational load. Besides, the customized ROI configuration usually needs adjustment in case camera placement or angle changes during recording. The fixed configuration would not encounter these problems but it is apparently less adequate than the customized one. In this study, two ROI configurations were applied, which are:

- i. A fixed ROI with $\theta = 0.9$ as shown in figure 3(a) (i.e. 81% of the recorded video area in the center), where θ was empirically chosen to produce good detection performance, and
- ii. A customized ROI (manually set) including mattress area only, as shown in figure 3(b).

2.5. In/out of bed detection

With video-derived motion estimates, a fast and simple heuristic detection method is proposed in this paper to detect infant in/out of bed status. By visually checking some videos and their corresponding motion data, we found that the peaky motions (with very high amplitudes) often corresponded to the 'events' where the infant was put to bed or taken out of bed. These events are considered transitions between infant in bed and out of bed status. Thus, events should be detected before determining the in/out of bed status.

In the following list, several heuristic conditions are designed to identify events based on 30 s epoch-based motion estimates.

- The motions less than a certain percentile of the motion values in the IROI area and in the OROI area throughout the entire 24 h recording should not be events. Hence, the motions of those epochs are set to be zeros, i.e. they are ‘filtered out’. This is because infant body movements, instead of transitions (i.e. the two parent’s activities) that usually produce relatively large motions, often cause relatively small-amplitude motions. Given an epoch, let m and n represent the IROI motion and the OROI motion, respectively, we have

$$m = 0, \quad n = 0 \quad \text{if } m < m_\alpha \text{ and } n < n_\beta. \quad (1)$$

where m_α is the α percentile of the motion values and n_β the β percentile of the motion values over the entire recording. Thereafter, this results in new IROI motion value m' and new OROI motion value n' at that epoch.

- The motions in both areas (IROI and OROI) should be larger than zero, designating that the motions should be sufficiently large (i.e. there should be transitions happening) when the parent is putting the baby to bed or taking the baby out of bed.
- The ratio between the motions in the IROI in the OROI area should be less than a certain value r (see equation (2)). This is because the motion in the OROI area is expected to not be too small compared with that in the IROI area when the parent is putting the infant in bed or taking the infant out of bed, otherwise it is likely the baby is making large body movements

$$EVENT = \begin{cases} 1, & m' > 0 \text{ and } n' > 0 \text{ and } \frac{m'}{n'} < r \\ 0, & \text{Otherwise,} \end{cases} \quad (2)$$

where $EVENT = 1$ means that the epoch is identified as being an event, $EVENT = 0$ means that the epoch is identified as not being an event.

As long as events are localized, the original epoch-based motions in the IROI can be analyzed to detect infant in/out of bed. The basic hypothesis is that, between two events, the motions in the IROI area are infant body movements (in bed) while lack of motions is caused by infant absence (out of bed). Therefore, we propose two heuristic rules to detect the infant in/out of bed status as described below:

- If the maximum motion amplitude in the IROI area over a 24 h recording is too small (less than a global threshold T_g), the motions are likely caused by noise or some small disturbances such as insect flying. In this case, the entire recording is detected to be

‘infant out of bed’; otherwise, we examine the following rule. Here T_g of 100 was experimentally chosen to maximize the detection accuracy.

- If the maximum IROI amplitude over the entire recording is not less than the threshold T_g , the in/out of bed status is then determined by exploiting whether there are sufficient infant body movements between two events. Considering the IROI motion data between two consecutive events having a total of k epochs, only the epochs in the middle within a certain period are taken into account and the epochs that are too close to the events should be disregarded. This is because parental activities (putting the infant to bed and taking the infant out of bed) could also result in motions appearing in the IROI area, and these activities often last for several minutes. Hence, to avoid the influence of those activities, a percentage p of epochs at the beginning and the end of the k epochs are excluded. Assuming $\mathbf{m} = m_1, m_2, \dots, m_k$ are the motion values of k epochs between two events, the motion values in the middle period are

$$\mathbf{mc} = m_{[k \cdot p] + 1}, m_{[k \cdot p] + 2}, \dots, m_{[k \cdot (1 - p)]}. \quad (3)$$

The percentage P of non-zero epochs (epochs with motions) within that period are then quantified as

$$P = \frac{\#(\mathbf{mc} > 0)}{k \cdot (1 - 2p)}, \quad (4)$$

in which $\#(\mathbf{mc} > 0)$ computes the number of non-zero epochs in $\mathbf{mc}$. Afterwards, the entire period is detected as ‘infant in bed’ if P is larger than a local threshold T_b , otherwise as ‘infant out of bed’, such that

$$STATUS = \begin{cases} 1, & P > T_b \\ 0, & P \leq T_b \end{cases} \quad (5)$$

where $STATUS = 1$ and $STATUS = 0$ correspond to infant in bed and infant out of bed within a given period between two events, respectively.

The method described above might produce very short periods of ‘infant in bed’ or ‘out of bed’ for only a few epochs. However, practically, these short periods do not (or are rather unlikely to) happen in real life. Therefore, a post-processing mechanism is used to smooth the detection results aiming at filtering out those very short periods. Here a median filter with a sliding window (at a window size $w = 21$ epochs) is adopted, where the window size value was experimentally set so it led to maximal detection accuracy. The procedure of the infant in/out of bed detection method is demonstrated in figure 4.

To evaluate the detection performance, the mean and standard deviation (std) accuracy results are obtained and compared for both training and test sets. In addition, we also present the confusion matrix with true positives (TP, number of correctly identified in bed epochs), true negatives (TN, number of correctly identified out of bed epochs), false positives (FP, number of out of bed epochs misclassified as in bed epochs)

and false negatives (FN, number of in bed epochs misclassified as out of bed epochs).

3. Results and discussion

The detector parameters need to be experimentally optimized based on training data to maximize the infant in/out of bed detection accuracy. The parameter optimization was done through an exhaustive search by looking for the best combination of parameters from all combinations. In figures 5 and 6, the optimization performances for some parameters for the fixed and the customized ROI are shown, respectively, where the detection results (accuracy, %) are provided when using different parameter values. It can be seen that the optimal parameter values are mostly consistent between the training and the test data set. For the fixed ROI configuration, the optimized parameters are $\alpha = 85$, $\beta = 97$, $r = 4$, $P = 0.01$, $T_l = 0.03$; for the customized ROI configuration, the optimized parameters are $\alpha = 81$, $\beta = 97$, $r = 20$, $P = 0$, $T_l = 0.03$.

Figure 7 illustrates an example of achieving infant in/out of bed detection with the customized ROI configuration. It can be seen in the figure that the detection results fit very well to the annotation, visually indicating the validity of our proposed method. The training and test detection results (offline) are presented in table 1. As expected, the performance with the customized ROI configuration is slightly but significantly better than that with the fixed ROI configuration, where the significance of difference was examined with a paired t-test at $p < 0.05$. Yet with both configurations, we achieved high performance in infant in/out of bed detection using motion estimates derived from IR videos. In addition, the optimal

parameters in the training and in the test data set are comparable, indicating that the parameter estimation in our proposed method should be sufficiently reliable and robust.

Although the customized ROI configuration performs slightly better than the fixed ROI configuration, from an application perspective the fixed ROI configuration is recommended. The reason is that, as mentioned earlier, the customized ROI requires either manual effort or an additional image processing algorithm to locate the bed mattress area. Manual setting of the ROI by end-users would probably reduce the usability, user acceptance or compliance of the device, potentially leading to user dropout. More importantly, since the camera view may change due to the changes in, e.g. camera angle or placement, the ROI setting needs to be adjusted accordingly. This would require real-time tracking on video frame to capture the changes in bed-frame, necessitating storage and processing of massive amounts of image data. Also, using additional dedicated real-time image processing algorithms to automatically locate the mattress area is expected to be computationally intensive, degrading its applicability when there are limited computing resources in the device (e.g. memory, CPU, etc). An alternative approach is to detect infant's body torso or head via computer vision algorithms (e.g. [28–30]), which might result in a better performance compared to our approach, but this, too, would cause the utility of much more computing resources. However, this approach does merit further investigation.

By analyzing the misclassifications, cases in which the algorithm drew a different conclusion about the infant's in or of bed status compared to the ground-truth, we found two major types of activities or disturbances that would lead to difficulty in correctly

Table 1. Results of ‘offline’ infant in/out of bed detection.

ROI configuration	Data set	Overall accuracy (mean $\pm$ std)	Confusion matrix (pooled)			
			TP	TN	FP	FN
Fixed ROI	Training	95.6 $\pm$ 5.7%	27 701	60 179	2075	1968
	Test	96.0 $\pm$ 4.2%	40 953	46 906	2946	793
	All	95.8 $\pm$ 4.9%	68 654	107 085	5021	2761
Customized ROI	Training	96.4 $\pm$ 4.2%	27 143	61 519	735	2526
	Test	97.3 $\pm$ 1.9%	40 941	48 174	1678	805
	All	96.9 $\pm$ 3.3%	68 084	109 693	2413	3331

Note. TP, true positive; TN, true negative; FP, false positive; FN, false negative. The in bed status was considered positive class.

detecting the infant’s in/out of bed status. First, our method would likely miss the infant’s ‘in-bed’ epochs because of the absence of motion data during that period. This can occur when the infant was lying in bed without moving for a relative short period after having been put to the bed, and before being taken out of the

bed by his or her parent. Another reason is that the camera view does not cover the whole bed so that the infant is (partially) hidden or invisible, and thus motions by a body part outside the camera view cannot be observed. For example, figure 8 illustrates a period of misclassifications (circled) where half of the bed

was not visible. Second, if external disturbances or activities are consistently occurring in both ROI areas when there is no infant in bed, our method would classify these periods to be 'infant in bed'. For example, figure 9 illustrates a misclassification period (circled) by its corresponding video frames, where the door

opened and closed and the mother spent a relatively long time (>15 min) to prepare the bed before putting her baby to bed. As a consequence, very large motions are present in both ROI areas. By visually inspecting all the misclassification periods, >60% of them were caused by the two types of problems (~24% and ~37%

for the first and the second problems, respectively). Further studies on methods with regard to how to overcome these problems are required. For example, multiple ROI areas (>2) can be configured to separate motions caused by infant body movements, parental activities, and other disturbances. Adaptive adjustment of the camera angle can be applied to capture the entire bed.

As stated, an important objective of this work was to automate the infant sleep stage monitoring. Thereby, the epoch length of 30 s was chosen in infant in/out of bed detection because 30 s is considered the standard epoch length for sleep stage analysis according to the AASM guidelines [5]. In practice, the activities by parent(s) of putting baby in bed and taking baby out of bed can last from half minute to more than ten minutes. Moreover, it is often difficult to identify the real 'transition' moment precisely between infant in bed and out of bed statuses, even by manual annotation. In this work, we therefore considered 30 s to be a reasonable value that should be sufficient in infant in/out of bed detection based on our experience. Nevertheless, the sensitivity of epoch length to the task of in/out of bed detection needs further study.

The heuristic infant in/out of bed detection method we described before is performed after collecting the entire 24 h recording. This can only be feasible for 'offline' rather than 'online' (i.e. real-time) detection. However, it would be interesting to have an infant monitoring system in a timely manner, which could allow a better understanding on infant activity and, in particular, real-time analysis of sleep patterns to offer tailored parenting. To achieve that, for the current day, our proposed method can be applied using the motion data to calculate some parameters (e.g. α and β) that require the entire recording's motions from the past day or recording (24 h) instead of that from the current day, allowing the online detection of infant in/out of bed status. However, for a given epoch, the in or out of bed status can only be determined until the next event is identified. The 'offset tolerance' of detecting the events (transitions between infant in and out of bed status) for offline use can be relatively high, where an offline system does not require real-time parenting by parents or healthcare professionals but an overview of in/out bed and sleeping pattern. Yet for an online system, the temporal offset misclassifications (FP and FN values) should be carefully addressed to optimize the parameters and decision-making threshold. The online detection should be investigated in future work.

4. Conclusion

This paper demonstrates the feasibility of a heuristic method for 'infant in bed' or 'out of bed' detection with IR video-derived motion estimates. The method

proposes a model to make decision of infant in/out of bed status based on several heuristic rules by analyzing motions caused by, for example, infant body movements and parental activities such as putting the infant to bed and taking the infant out of bed. By configuring a region of interest (ROI) on the video frames, the motion data inside and outside the ROI were analyzed, where the ROI can be fixed or customized (manually set). A set of parameters in the heuristic rules were tuned to optimize the detection performance. An average accuracy of 95.8% using the fixed ROI configuration and that of 96.9% using the customized ROI configuration were achieved. This indicates that the proposed method, with a low computational complexity, is reliable in detecting infant in/out of bed status. As being important (basic) information about infant sleep and development, automated infant in/out of bed status could be used to assist further long-term monitoring of sleep such as sleep staging, sleep quality assessment, and activity rhythm, allowing tailored parenting and reassurance.

Acknowledgments

This work is funded by Philips Group Innovation, part of Philips Electronics Nederland B.V. At the time of writing all authors were affiliated and/or employed by Philips.

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References

- [1] Bayer J K, Hiscock H, Hampton A and Wake M S 2007 Sleep problems in young infants and maternal mental and physical health *Journal of Paediatrics and Child Health* **43** 66–73
- [2] Mindell J A, Telofski L S, Wiegand B and Kurtz E S 2009 A nightly bedtime routine: impact on sleep in young children and maternal mood *Sleep* **32** 599–606
- [3] Sadeh A, Tikotzky L and Scher A 2010 Parenting and infant sleep *Sleep Medicine Reviews* **14** 89–96
- [4] Ball H L 2002 Reasons to bed-share: why parents sleep with their infants *Journal of Reproductive and Infant Psychology* **20** 207–21
- [5] Berry R B, Brooks R, Gamaldo C E, Harding S M, Lloyd R M, Marcus C L and Vaughn B V 2017 *The AASM Manual for the Scoring of Sleep and Associated Events: Rules, Terminology & Technical Specifications—Version 2.2* (Darien, IL: American Academy of Sleep Medicine)
- [6] Carno M-A, Hoffman L A, Carcillo J A and Sanders M H 2003 Developmental stages of sleep from birth to adolescence, common childhood sleep disorders: overview and nursing implications *Journal of Pediatric Nursing* **18** 274–83
- [7] Fonseca P, Long X, Radha M, Haakma R, Aarts R M and Rolink J 2017 Sleep stage classification with ECG and respiratory effort *Physiol. Meas.* **36** 2027–40
- [8] Long X, Fossier J, Fonseca P, Haakma R and Aarts R M 2014 Analyzing respiratory effort amplitude for automated sleep stage classification *Biomed. Signal Process. Control* **14** 197–205
- [9] Acebo C, Sadeh A, Seifer R, Tzischinsky O, Wolfson A R, Hafer A and Carskadon M A 1999 Estimating sleep patterns with activity monitoring in children and adolescents: how many nights are necessary for reliable measures? *Sleep* **22** 95–103

- [10] Sadeh A, Lavie P, Scher A, Tirosh E and Epstein R 1991 Actigraphic home-monitoring sleep-disturbed and control infants and young children: a new method for pediatric assessment of sleep-wake patterns *Pediatrics* **87** 494–9
- [11] Werth J, Atallah L, Andriessen P, Long X, Zwartkruis-Pelgrim E and Aarts R M 2017 Unobtrusive sleep state measurements in preterm infants - a review *Sleep Medicine Reviews* **32** 109–22
- [12] Werth J, Long X, Zwartkruis-Pelgrim E, Niemarkt H, Chen W, Aarts R M and Andriessen P 2017 Unobtrusive assessment of neonatal sleep state based on heart rate variability retrieved from electrocardiography used for regular patient monitoring *Early Human Development* **113** 104–13
- [13] Lee W K, Yoon H, Jung D W, Hwang S H and Park K S 2015 Ballistocardiogram of baby during sleep *EMBC: Proc. 37th Ann. Int. Conf. IEEE Eng. Med. Biol. Soc.* pp 7167–70
- [14] Atallah L, Serteyn A, Meftah M, Schellekens M, Vullings R, Bergmans J W M, Osagiator A and Bambang O S 2014 Unobtrusive ECG monitoring in the NICU using a capacitive sensing array *Physiol. Meas.* **35** 895–913
- [15] Johansson A, Oberg P A and Sedin G 1999 Monitoring of heart and respiratory rates in newborn infants using a new photoplethysmographic technique *J. Clin. Monit. Comput.* **15** 461–7
- [16] Grubb M R, Carpenter J, Crowe J A, Teoh J, Marlow N, Ward C, Mann C, Sharkey D and Hayes-Gill B R 2014 Forehead reflectance photoplethysmography to monitor heart rate: preliminary results from neonatal patients *Physiol. Meas.* **35** 881–93
- [17] Aarts L A M, Jeanne V, Cleary J P, Lieber C, Stuart Nelson J, Bambang Oetomo S and Verkruysse W 2013 Non-contact heart rate monitoring utilizing camera photoplethysmography in the neonatal intensive care unit—a pilot study *Early Human Development* **89** 943–8
- [18] Abbas A K and Leonhardt S 2014 Intelligent neonatal monitoring based on a virtual thermal sensor *BMC Medical Imaging* **14** 1–13
- [19] Bouwstra S, Chen W, Feijs L and Bambang Oetomo S 2009 Smart jacket design for neonatal monitoring with wearable sensors *Proc. 6th Int Workshop on Wearable and Implantable of Body Sensor Networks* pp 162–7
- [20] Zhu Z, Liu T, Li G, Li T and Inoue Y 2015 Wearable sensor systems for infants *Sensors* **15** 3721–49
- [21] Heinrich A, Geng D, Znamenskiy D, Vink G and de Haan G 2014 Robust and sensitive video motion detection for sleep analysis *IEEE Journal of Biomedical and Health Informatics* **18** 790–8
- [22] Liu L-K and Feig E 1996 A block-based gradient descent search algorithm for block motion estimation in video coding *IEEE Transactions on Circuits and System for Video Technology* **6** 419–22
- [23] Po L-M and Ma W-C 1996 A novel four-step search algorithm for fast block motion estimation *IEEE Transactions on Circuits and System for Video Technology* **6** 313–7
- [24] Braspenning R and de Haan G 2004 True-motion estimation using feature correspondences *SPIE Proc.* **5308** 369–407
- [25] Heinrich A, Aubert X and de Haan G 2013 Body movement analysis during sleep based on video motion estimation *Proc. IEEE Healthcom* 539–43
- [26] Heinrich A, van Bree K C and Jeanne V 2015 A baby monitoring device *Patent Application* WO 20152015091582 A1
- [27] Heinrich A, van der Vleuten R J and de Haan G 2014 Perception-oriented methodology for robust motion estimation design *IEEE Journal of Selected Topics in Signal Processing* **8** 463–74
- [28] Viola P and Jones M J 2004 Robust real-time face detection *Int. J. Comput. Vis.* **57** 137–54
- [29] Johnson M H, Senju A and Tomalski P 2015 The two-process theory of face processing: modifications based on two decades data from infants and adults *Neuroscience & Biobehavioral Reviews* **50** 169–79
- [30] Saeijs R W J J, Ten W E T A and de With P H N 2016 Densehog-based 3D face tracking for infant pain monitoring *Proc IEEE Int. Conf. on Image Processing ICIP* pp 1719–23