2021 43rd Annual International Conference of the
IEEE Engineering in Medicine & Biology Society (EMBC)
Oct 31 - Nov 4, 2021. Virtual Conference

Body Motion Detection in Neonates Based on Motion Artifacts in Physiological Signals from a Clinical Patient Monitor

Zheng Peng, Ilde Lorato, Xi Long , Rong-Hao Liang, Deedee Kommers, Peter Andriessen, Ward Cottaar, Sander Stuijk and Carola van Pul

Abstract— **Motion patterns in newborns contain important information. Motion patterns change upon maturation and changes in the nature of motion may precede critical clinical events such as the onset of sepsis, seizures and apneas. However, in clinical practice, motion monitoring is still limited to observations by caregivers. In this study, we investigated a practical yet reliable method for motion detection using routinely used physiological signals in the patient monitor. Our method calculated motion measures with a continuous wavelet transform (CWT) and a signal instability index (SII) to detect gross-motor motion in 15 newborns using 40 hours of physiological data with annotated videos. We compared the performance of these measures on three signal modalities (electrocardiogram ECG, chest impedance, and photo plethysmography). In addition, we investigated whether their combinations increased performance. The best performance was achieved with the ECG signal with a median (interquartile range, IQR) area under receiver operating curve (AUC) of 0.92(0.87-0.95), but differences were small as both measures had a robust performance on all signal modalities. We then applied the algorithm on combined measures and modalities. The full combination outperformed all single-modal methods with a median (IQR) AUC of 0.95(0.91-0.96) when discriminating gross-motor motion from still. Our study demonstrates the feasibility of gross-motor motion detection method based on only clinically-available vital signs and that best results can be obtained by combining measures and vital signs.**

I. INTRODUCTION

Nowadays, more than 30 million newborns suffer from low birthweight (<2500 g), prematurity or small gestational age each year [1]. Due to physiological immaturity, these infants are often hospitalized in a neonatal intensive care unit (NICU) or a medium care unit (MCU) where physiological data are continuously monitored, such as electrocardiogram (ECG), chest impedance (CI) and photo plethysmography (PPG). This data provides real-time vital sign information of heart rate, breathing rate and pulse rate. Additionally, clinical observations of patient status (including motion patterns) are performed as part of the routine care.

Body motion in newborns has shown to be an important predictor for critical clinical events. For instance, research shows that lethargy, the lack of spontaneous motion, is predictive for onset of sepsis [2][3]. Adding motion measures to sepsis prediction models in infants improves the model performance [4]. Other studies report that motion bursts are related to respiratory instability and apneic events [5]. Infants' maturation is also associated with the occurrence of short and long motion bouts [6]. Therefore, continuous motion monitoring can be as important as other vital signs, implying the need for automatic motion measurement in this population.

A challenge for continuous motion monitoring is that in NICU/MCU environments, the use of additional sensors is limited due to the fragility of infants' skin. Non-obtrusive or contactless techniques like camera-based techniques, may suffer from limited light conditions and visual disturbances, e.g. motion detection would be complex when parents or caregivers block the field of view.

Instead of using additional sensors or cameras, some research focuses on measuring motion using motion artifacts in routinely used sensors in clinical practice. For instance, Zuzarte et al. [7] used a continuous wavelet transform (CWT) based method to extract motion from PPG. In our previous study, a signal instability index (SII) based approach was applied on vital signs and compared to a more sensitive non-obtrusive ballistographic signal (BSG) [8]. Both algorithms show promising results for body motion detection.

In this study, we focus on determining motion detection performance using existing vital sign sensors in daily clinical practice. First, we optimized and compared the CWT-based and the SII-based motion estimation algorithms on three routinely used signals acquired from a patient monitor. Second, the performance of the combined measures and signal modalities was evaluated.

II. METHODS

A. Experimental Data

The patient population in our study consisted of 15 infants in the MCU of the neonatal ward in the Maxima Medical Center (MMC) in Veldhoven, the Netherlands. The median (IQR) postmenstrual age of the infants on the day of the study was 35.9(34.9-38.0) weeks. Video recordings were acquired using three thermal cameras (FLIR Lepton 2.5) positioned

Zheng Peng and Ward Cottaar are with the Department of Applied Physics at Eindhoven University of Technology, Eindhoven, The Netherlands. z.peng@tue.nl

Ilde Lorato and Sander Stuijk are with the Department of Electrical Engineering at Eindhoven University of Technology, Eindhoven, The Netherlands.

Xi Long is with the Department of Electrical Engineering at Eindhoven University of Technology and the Philips Research, Eindhoven, The Netherlands.

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

Deedee Kommers and Peter Andriessen are with the Department of Applied Physics at Eindhoven University of Technology and the Department of Neonatology, Maxima Medical Centre, Veldhoven, The Netherlands.

Carola van Pul is with the Department of Applied Physics at Eindhoven University of Technology and the Department of Clinical Physics, Maxima Medical Centre, Veldhoven, The Netherlands.

around the infants' bed. In total, 40-hour video data was recorded for 15 infants. Infants with different lying positions were filmed when possible to evaluate the robustness of the algorithms for all lying positions.

The signals ECG, PPG and CI (which shared sensors with ECG) were acquired from neonatal patient monitors (Philips IntelliVue MX 800, Germany) via a data warehouse (Philips PIIC iX, Data Warehouse Connect, Andover, MA) in routine patient monitoring. The waveform signals and video recordings were sampled at the following rates: 250Hz (ECG), 62.5Hz (CI), 125Hz (PPG), and 9fps (video).

For this study, the ethical committee of MMC provided a waiver (MMC N19.074). Informed consent was obtained from the infants' parents prior to that study.

B. Annotations

The video recordings were annotated by one of the authors, as described in a previous study on respiration monitoring [9]. The resulting labels were used as ground truth to evaluate motion detection performance.

The labels can be divided into three categories including infant activity, intervention and other [9]. Infant activity was annotated into gross-motor motion, fine-motor motion and still. Gross-motor motion involves torso or chest motion and fine-motor motion means motion only by head, hands, arms, fingers or even facial expressions. Intervention consists of parents and caregivers' interventions. Other is made up of someone (e.g. caregiver) in the background, infant out of bed, camera moving and incorrect camera position. It is worth mentioning that the labels are not exclusive, i.e. multiple labels can be true simultaneously. This study focused on three classes including *gross-motor motion, fine-motor motion* and *still*. All videos having one of these three labels were used in this study that focused on motion detection.

After excluding all segments for which motion could not be determined or waveform signals were not available (such as out of bed and part of parents and caregivers' interventions) 84% of the dataset remained, with 21.4% of the time labelled as *still*, 33.2% as *fine-motor* and 45.4% as *gross-motor motion*.

C. Data Preprocessing

We applied a second-order band-pass Butterworth filter with zero-phase shift correction on all raw physiological signals (ECG, PPG and CI). The cutoff frequencies of lower and upper bands were empirically set as 0.001 Hz and 0.40 Hz, respectively, to capture the low-frequency body motion information (i.e. motion artifacts) and suppress the breathing and heartbeat motion related signals.

D. Motion Measures

To estimate motion, two measures (i.e. CWT in the frequency domain and SII in the time domain) were extracted from the filtered signals. We used the characteristic that the cardiorespiratory signal waveforms are highly periodic and the disruptions caused by motion (i.e. motion artifacts) can be used to quantify motion. We implemented and optimized two measures.

The first measure is CWT [7], which was motivated by frequency differences between body motion and cardiorespiratory motion in a non-stationary time series. CWT was used to convert a time series to the time-frequency domain. CWT measures similarity between the signal and the wavelet function $\psi(t)$ for different scales and locations in the signal. It is defined as [10]

$$T(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\psi^{\star}(\frac{t-b}{a})dt, \tag{1}$$

Where x represents the signal, $\psi^{\star}$ is the complex conjugate of wavelet function ψ, a denotes scale and b is the location. The wavelet power spectrum (scalogram) is given by

$$P(a,b) = |T(a,b)|^2. \tag{2}$$

In our application, the CWT with a Morse wavelet function was implemented on filtered vital sign waveforms in such a way that it suppresses cardiorespiratory periodic motion. We set a fixed period threshold 1.5 s for heartbeat-related signals (ECG and PPG) and 0.4 s for respiration signal (CI). In addition to this, a window size of 6 seconds was utilized for all waveform signals with a moving step (sampling period) of 0.4 seconds. Only the middle 0.4 seconds range CWT scalogram of the window was extracted in order to reduce the edge effects produced by finite-length wavelet transform. Next, the 0.4-second scalogram was averaged along the temporal axis. When the period is greater than the corresponding threshold, the maximum value of the averaged scalogram was taken as the instantaneous motion measure to estimate the intensity of the motion.

The second measure is SII, which is a measure for signal instability based on kernel density estimation (KDE) [11]. KDE can be interpreted as a smoothed histogram and can be calculated by following equation:[8]

$$f(x) = \frac{1}{nh} \sum_{i=1}^{n} K(\frac{x-x_i}{h}), \tag{3}$$

where $f(x)$ is the KDE of a signal x, K is the kernel centered at point i and h is the bandwidth of the kernel. This bandwidth contains information on the instability of the signal and is extracted as the SII. n is the number of equidistance points in signal x. In this study, we set the number of points to be $n = 100$ using Gaussian kernel and we estimated the bandwidth using $1.06\sigma/n^{1/5}$ where σ is the standard deviation of the kernel, similar to our previous implementation [8]. Similar to CWT, the motion measure based on SII was also calculated using a 6-second moving window with a sampling period of 0.4 seconds.

Considering that CWT detects motion from the frequency perspective and SII is a motion indicator in the time domain, there could be a complementary effect in their combination. Motion measures calculated by both CWT and SII were normalized and summed as a combined motion measure for motion detection.

E. Combining Signals for Motion Detection

ECG and CI shared the same sensors on the infants chest but their underlying acquisition methods and functionalities were different. Additionally PPG sensors were clinically used in different positions such as arms and feet. Complementary information can be provided by combining these signals. Therefore the normalized motion measures from different signal modalities were added to detect motion.

F. Motion Detection Experiments and Metric

We categorized the motion data in three experiments for binary classification.

- *GrossMotorMotion-Others*: we merged the fine-motor motion into still to evaluate the ability to discriminate the gross-motor motion from others for different measures and waveform signals.
- *GrossMotorMotion-Still*: We removed fine-motor motion segments from the dataset in order to discriminate the gross-motor motion from still. It is supposed to have better performance since it is to evaluate the performance in a simple and ideal case.
- *FineMotorMotion-Still*: Additionally, we designed the last experiment to test if we can discriminate fine-motor motion from still.

For performance comparison of aforementioned measures (i.e., CWT, SII) and vital sign waveforms (i.e., ECG, PPG, CI), we evaluated the classification performance using a threshold-independent approach by directly calculating the area under the receiver operating curve (AUC) with motion measures. Each sample in the motion measure served as a threshold for classification. The threshold was not fixed, so that we can calculate AUC values with varying thresholds.

III. Results

Fig.1 illustrates an example of an annotated signal, the corresponding ECG signal of one hour from one infant and the two motion measures CWT and SII. It can be observed that the gross-motor motion and still were captured by both motion measures quite well. Fine motion however is not well reflected in the motion measures. Particularly noteworthy is that a few but not all of the fine-motor motion periods introduce disruption to ECG (e.g. fine-motor motion periods from 16:40 to 16:45 in Fig.1).

Table I shows the median(IQR) of the AUC for the 15 subjects corresponding to all three vital sign waveforms calculated by two measures and their combination in all three experiments. It is clear that CWT yields a better performance than SII, particularly to discriminate gross-motor motion from still with a medium(IQR) AUC of 0.92(0.87-0.95). Amongst all waveform signals, the best-performing signal for gross-motor motion detection is ECG. CI performs best when classifying fine-motor motion and still. The combined CWT+SII motion measures outperformed the single measure cases.

Table II shows performance for the combined waveform signals. The best performance in both Gross-motor-motion-others and Gross-motor-motion-still experiments comes from

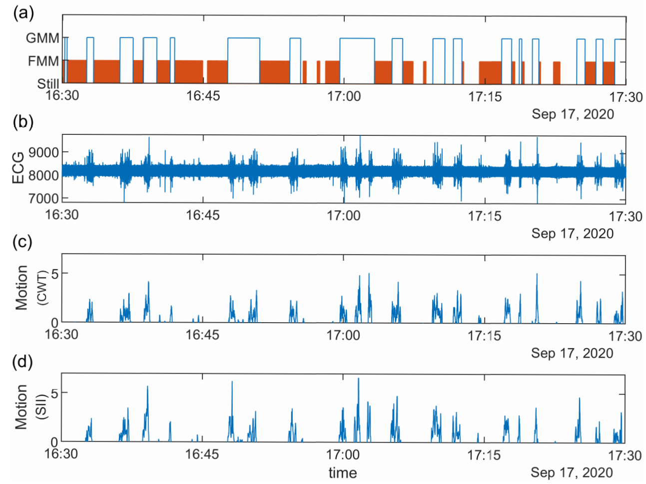

Fig. 1. (a) Annotations (GMM: Gross-motor motion involves torso or chest motion. FMM: Fine-motor motion means motion from head, hands, arms, fingers or face). (b) electrocardiogram (ECG). (c) Motion measure from CWT. (d) Motion measure from SII.

TABLE I

Motion Detection Performance in AUC from Single Signal Modality Using CWT and SII. Results are Presented in Median(IQR)

AUC		Gross-motor Motion-Others	Gross-motor Motion-Still	Fine-motor Motion-Still
CWT	ECG	0.88(0.82-0.91)	0.92(0.87-0.95)	0.64(0.57-0.71)
	PPG	0.83(0.81-0.86)	0.91(0.85-0.93)	0.64(0.60-0.68)
	CI	0.84(0.81-0.87)	0.91(0.87-0.93)	0.67(0.63-0.7)
SII	ECG	0.86(0.81-0.89)	0.90(0.84-0.93)	0.65(0.57-0.7)
	PPG	0.82(0.81-0.86)	0.89(0.86-0.92)	0.64(0.59-0.66)
	CI	0.81(0.78-0.83)	0.87(0.85-0.90)	0.63(0.60-0.68)
CWT+ SII	ECG	**0.89(0.83-0.92)**	**0.92(0.86-0.96)**	0.67(0.58-0.73)
	PPG	0.83(0.81-0.89)	0.91(0.86-0.94)	0.65(0.62-0.68)
	CI	0.87(0.83-0.90)	0.92(0.89-0.94)	**0.70(0.65-0.72)**

the full signal combination (ECG+PPG+CI). It reaches median(IQR) AUC of 0.90(0.86-0.93) and 0.95(0.91-0.96) respectively. Best-performing signal combination to detect fine-motor motion from still, with a median(IQR) AUC of 0.71(0.65-0.73), is the combination of PPG and CI, while using both CWT and SII.

IV. Discussion

Our study shows that the vital sign signals are disrupted in most gross-motor motion periods and that both motion measures manage to capture the gross-motor motion presence in all available vital sign signals. However, there is limited performance in detecting fine-motor motion for both measures.

We observed that the CWT outperforms SII in all motion detection experiments, meaning that the lower-frequency power introduced by motion is more informative than the regularity and amplitude change of the signal. For gross-motor-motion detection, ECG is the best performing signal followed by CI and next comes PPG. This is in line with our previous study, where the variation in SII was much larger

TABLE II
MOTION DETECTION PERFORMANCE IN AUC BY COMBINING SIGNAL MODALITIES. RESULTS ARE PRESENTED IN MEDIAN(IQR)

AUC		Gross-motor Motion-Others	Gross-motor Motion-Still	Fine-motor Motion-Still
ECG+ PPG	CWT	0.89(0.84-0.90)	0.93(0.88-0.95)	0.65(0.62-0.72)
	SII	0.87(0.83-0.89)	0.92(0.87-0.94)	0.64(0.61-0.69)
	CWT+SII	0.90(0.85-0.92)	0.94(0.88-0.96)	0.66(0.63-0.72)
ECG+ CI	CWT	0.88(0.83-0.91)	0.93(0.87-0.94)	0.68(0.62-0.71)
	SII	0.85(0.81-0.88)	0.90(0.86-0.93)	0.66(0.60-0.70)
	CWT+SII	0.90(0.85-0.93)	0.94(0.89-0.95)	0.70(0.63-0.74)
PPG+ CI	CWT	0.86(0.83-0.90)	0.94(0.88-0.95)	0.68(0.63-0.71)
	SII	0.86(0.82-0.88)	0.92(0.88-0.93)	0.67(0.64-0.70)
	CWT+SII	0.90(0.85-0.92)	0.95(0.91-0.96)	**0.71(0.65-0.73)**
ECG+ PPG+ CI	CWT	0.89(0.84-0.91)	0.94(0.90-0.96)	0.67(0.63-0.72)
	SII	0.86(0.84-0.90)	0.93(0.88-0.94)	0.67(0.63-0.71)
	CWT+SII	**0.90(0.86-0.93)**	**0.95(0.91-0.96)**	0.69(0.65-0.74)

when applied on the PPG compared to application to ECG [8]. Unlike ECG and CI, which are placed on the infant's chest, PPG is typically placed on one of the feet of the infant, it might be more prone to noise due to poor contact with the skin. Zuzarte et al [7] applied CWT to PPG signals and they found that motion patterns changed with maturation, however they did not apply filter to suppress cardiorespiratory motion signal and did not use the ECG and CI as additional signals. In our study, we evaluated performance using video acquisition, and the measured performance may be influenced by the limited camera view that may have impact on the accuracy of the annotations. We found that fine-motor-motion detection based on PPG-signal detection performed worse than CI-based detection, even though the collected raw CI signals suffered from signal truncation in some periods leading to poorer signal quality compared with ECG. Combining PPG and CI gave best performance on fine-motor-motion detection, suggesting that it is useful to combine available signals in motion detection studies.

It is not surprising to see the poorer performance in fine-motor-motion detection, because the positions of the sensors are not always sensitive to fine-motor motion from face, head or arms. Improvement of fine-motor motion detection should be sought in incorporating other promising video and audio processing technologies [9][12][13] or using motion sensitive mattresses [8][14] in future work.

The performance improvement introduced by combined measures also can be seen clearly in both tables. This indicates that motion information acquired from frequency domain and time domain has a complementary effect on motion detection. Besides, the best performance provided by full signal combination in gross-motor motion detection demonstrates that sensors with different functionalities and placing positions can also provide complementary information for motion detection. Generally, all waveforms perform well for gross-motor motion detection, and the signal with best signal quality can be chosen in clinical application, though – when available- using a combination of signals would be preferred for gross-motor-motion detection. The users can flexibly choose the approximate threshold to determine the specificity and sensitivity based on the applications.

V. CONCLUSIONS

This study compared body motion detection performance for CWT and SII using multiple vital sign waveforms and evaluated the performance based on video annotations as ground truth. Regarding gross-motor motion detection, our findings suggest that using the combined CWT+SII measure outperformed the cases of using a single measure when all vital signs are available. The combined measure also worked better than the single measure when less sensing modalities are involved, showing that it is more resilient when some of the signal sources become less reliable or disconnected when detecting the body motion of preterm infants. Our study demonstrates the feasibility of gross-motor motion detection based on clinically-available vital signs.

ACKNOWLEDGMENT

This research was performed within the framework of e/MTIC.

REFERENCES

[1] P. Ashorn et al., "The Lancet Small Vulnerable Newborn Series: science for a healthy start," Lancet, vol. 396, no. 10253, pp. 743–745, 2020
[2] M. Kudawla, S. Dutta, and A. Narang, "Validation of a clinical score for the diagnosis of late onset neonatal septicemia in babies weighing 1000-2500g," J. Trop. Pediatr., vol. 54, no. 1, pp. 66–69, 2008.
[3] E. H. Verstraete, K. Blot, L. Mahieu, D. Vogelaers, and S. Blot, "Prediction models for neonatal health care-associated sepsis: A meta-analysis," Pediatrics, vol. 135, no. 4, pp. e1002–e1014, 2015.
[4] L. Cabrera-Quiros et al., "Prediction of Late-Onset Sepsis in Preterm Infants Using Monitoring Signals and Machine Learning," Crit. Care Explor., vol. 3, no. 1, p. e0302, 2021.
[5] I. Zuzarte, D. Paydarfar, and D. Sternad, "Effect of spontaneous movement on respiration in preterm infants," Exp. Physiol., pp. 1–36, 2021.
[6] I. Zuzarte, A. H. Gee, D. Sternad, and D. Paydarfar, "Automated movement detection reveals features of maturation in preterm infants," in Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS, Jul. 2020, vol. 2020-July, pp. 600–603.
[7] 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.
[8] R. Joshi et al., "A ballistographic approach for continuous and non-obtrusive monitoring of movement in neonates," IEEE J. Transl. Eng. Heal. Med., vol. 6, no. September, pp. 1–10, 2018.
[9] I. Lorato et al., "Towards continuous camera-based respiration monitoring in infants," Sensors, vol. 21, no. 7, pp. 1–18, 2021.
[10] P. Fonseca, R. M. Aarts, X. Long, J. Rolink, and S. Leonhardt, "Estimating actigraphy from motion artifacts in ECG and respiratory effort signals," Physiol. Meas., vol. 37, no. 1, pp. 67–82, 2015.
[11] A. Georgieva, S. J. Payne, M. Moulden, and C. W. G. Redman, "Computerized fetal heart rate analysis in labor: Detection of intervals with un-assignable baseline," Physiol. Meas., vol. 32, no. 10, pp. 1549–1560, 2011.
[12] 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.
[13] S. Cabon, F. Porée, A. Simon, O. Rosec, P. Pladys, and G. Carrault, "Video and audio processing in paediatrics: A review," Physiol. Meas., vol. 40, no. 2, 2019.
[14] 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.