

## **A plethysmography investigation comparing respiration rate before onset and after the end of central sleep apnoea episodes**

SAATCHI, Reza <<http://orcid.org/0000-0002-2266-0187>>, ABDUSSALAM, Ahmed, ELPHICK, Heather and KINGSHOTT, Ruth

Available from Sheffield Hallam University Research Archive (SHURA) at:

<https://shura.shu.ac.uk/32893/>

---

This document is the Accepted Version [AM]

### **Citation:**

SAATCHI, Reza, ABDUSSALAM, Ahmed, ELPHICK, Heather and KINGSHOTT, Ruth (2023). A plethysmography investigation comparing respiration rate before onset and after the end of central sleep apnoea episodes. In: 19th International Conference on condition monitoring and asset management (CM 2023). British Institute of Non-Destructive Testing (BINDT), 114-121. [Book Section]

---

### **Copyright and re-use policy**

See <http://shura.shu.ac.uk/information.html>

# **A plethysmography investigation comparing respiration rate before onset and after the end of central sleep apnoea episodes**

<sup>1</sup>Ahmed Abdussalam, <sup>1</sup>Reza Saatchi, <sup>2</sup>Heather Elphick, <sup>2</sup>Ruth N Kingshott

<sup>1</sup>Department of Engineering & Mathematics, Sheffield Hallam University, Howard Street, Sheffield, S1 1WB

<sup>2</sup>Sheffield Children's Hospital NHS Foundation Trust, Western Bank, Sheffield, S10 2TH.

## **Abstract**

The study explored possible changes in respiration rate immediately before onset and after end of central sleep apnoea (CSA) episodes using respiratory inductive plethysmography (RIP). RIP signals were recorded simultaneously from the chest and abdomen of 31 paediatric patients (mean age 7.12 years, standard deviation 4.40 years, 20 females, 11 males) attending a children's hospital for overnight sleep disorder monitoring. The patients were also monitored for electrocardiogram, electroencephalogram, electrooculogram, electromyograph, CO<sub>2</sub>, body position, SpO<sub>2</sub> and if they tolerated, their respiratory airflow using a thermistor (placed under the nose) and nasal prongs (placed in the nostrils).

An experienced clinical physiologist scored the recorded data by indicating the time point of each respiratory pause, its duration and type (i.e., apnoea or hypopnoea; central or obstructive). The RIP signals from the chest and abdomen were summed and converted to a respiration rate signal by determining the time points they crossed the time axis. Events were scored using standard paediatric sleep and breathing scoring rules. Statistical analysis indicated significant differences between the skewness and kurtosis of respiratory rate values immediately before the onset and after the end of CSA episodes, however the mean respiration rate did not change significantly. This indicates possible changes in the pattern of respiration rate immediately after the end of CSA episodes. It may be possible to use these results to predict the onset of a CSA episode, however to confirm the finding a larger study will be needed.

**Keywords:** central apnoea, sleep disorders, respiratory efforts, paediatrics.

## **1.0 Introduction**

Sleep apnoea is a disorder causing intermittent respiratory pauses or a significant reduction in respiratory airflow. Sleep related disorders are associated with stroke comorbidities, including obesity, hypertension, diabetes mellitus, ischemic heart disease, atrial fibrillation, and heart failure [1]. Sleep apnoea may be broadly categorised as obstructive sleep apnoea (OSA), central sleep apnoea (CSA) and a combination of OSA and CSA (Mixed) [2]. OSA is a common

disorder affecting an estimated 5% to 14% of adults [3] and 1-5% children [4]. In OSA, airflow to the lungs is restricted by an obstruction, typically because of collapsed soft tissue in the back of the throat and tongue. In CSA, the brain's mechanisms that control breathing do not function properly causing a respiratory effort failure (i.e., absence of chest movement) during its onset [5]. There are several manifestations of CSA with varying pathophysiology and the prevalence [6]. CSA is less common as compared with OSA. However, considerable overlap exists between the two conditions from the standpoint of pathogenesis and disease manifestations [6]. CSA can be divided into various subcategories, each having unique features and management issues.

A few studies have explored prediction of sleep apnoea by analysing physiological data. An ability to predict upcoming apnoeic events in preterm infants could provide an opportunity to improve its management and thus decrease the long-term adverse consequences [7]. Wavelet decomposition of the nocturnal heart rate variability represented an efficient marker of OSA [8]. A model for predicting OSA using upper airway computerised tomography (CT) and deep learning has been evaluated in 219 patients with OSA and 81 controls [9]. The model enabled CT identification of patients with moderate to severe OSA.

This study examined possible changes in respiration rate immediately before and after the end CSA episodes using respiratory inductive plethysmography (RIP). RIP uses chest and abdominal bands to detect respiratory related chest movements. Typically, the signals from the chest and abdomen are recorded and summed to improve respiratory monitoring. Respiratory information from RIP can effectively reflect the respiratory airflow and correlates with the results from standard polysomnography sensors making the method reliable for respiratory event scoring [10]. Nasal prongs and thermistor-based methods of respiratory airflow measurement were not included in this study as some patients did not tolerate them or removed them during sleep.

In the following sections the methodology to record and analyse the RIP signals are explained and the results are discussed.

## **2.0 Methodology**

Ethics approval to recruit the patients was obtained from the National Health Service, United Kingdom. The recruits were 31 patient referrals to Sheffield Children's Hospital for sleep disorder monitoring. Their details are included in Table 1.

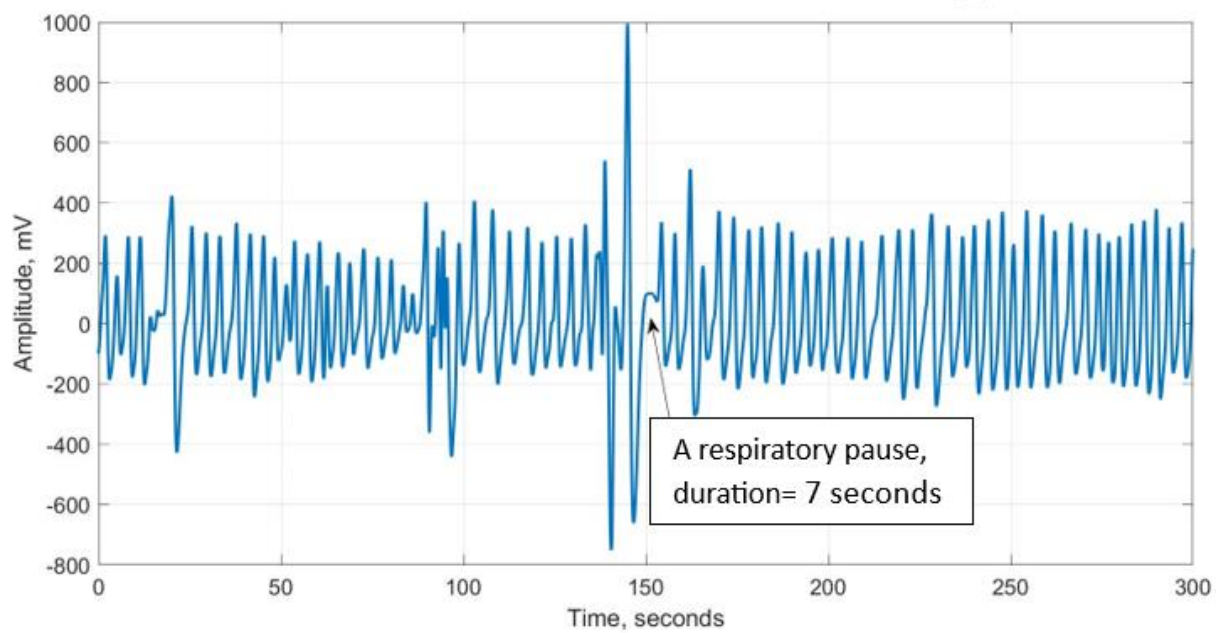
Data were recorded overnight at the hospital's sleep laboratory. SOMNOscreen device with two bands (one for chest and the other for abdomen) was used for RIP recording. Data capture rate was 32 samples per second. The two signals were added together for processing. An experienced clinical physiologist scored the status of the data by examining the electrocardiogram, electroencephalogram, electrooculogram, electromyograph, CO<sub>2</sub>, body position, SpO<sub>2</sub> and if the child tolerated, respiratory airflow using a thermistor (placed under the nose) and nasal prongs (placed in the nostrils). Events were scored using standard paediatric sleep and breathing scoring rules outlined by the American Academy of Sleep Medicine [11]. A CSA was scored, if there were two missed breaths and an associated 3% SpO<sub>2</sub> desaturation

or an arousal. This resulted in an analysis that indicated when a respiratory pause occurred, its duration and the type of sleep apnoea.

Figure 1 shows a typical summed RIP signal.

**Table 1. Details of the participants included in the study.**

Details	Values
Number of participants	31
Average age	7.12 years
Standard deviation of age	4.40 years
Minimum age	0.28 years
Maximum age	14.68 years
Sex	20 Females, 11 Males



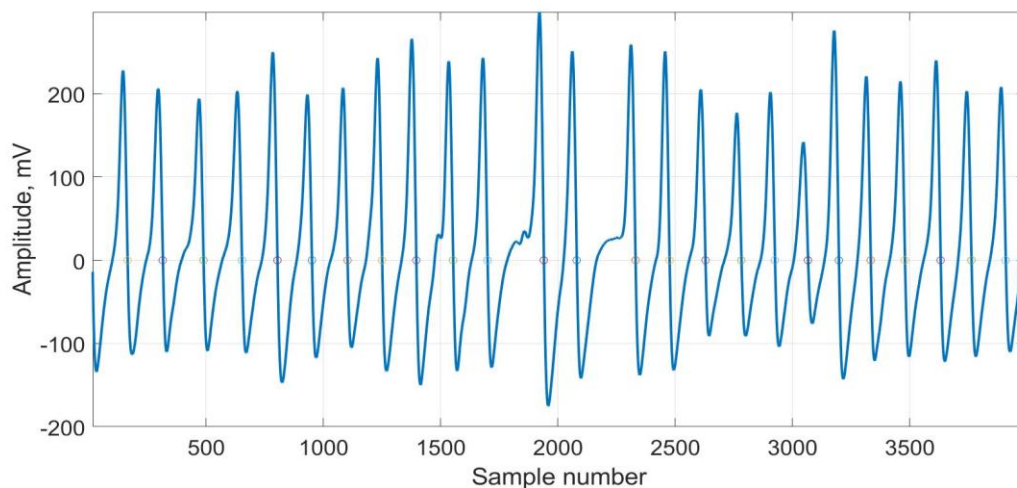
**Figure 1. A typical summed RIP signal.**

The steps undertaken to process the summed RIP signals are shown in Figure 2.

1	<ul style="list-style-type: none"> <li>• Extract respiration rate (RR) values from the summed RIP signal</li> <li>• RR measurement method: zero crossing detection</li> </ul>
2	<ul style="list-style-type: none"> <li>• Determine statistical measures of respiration rates</li> <li>• Statistical measures: Mean, standard deviation, skewness, kurtosis, interquartile range</li> </ul>
3	<ul style="list-style-type: none"> <li>• Analyse statistical measures</li> <li>• Analysis: Kolmogorov-Smirnov test (to examine distribution), ttest (test of mean difference) and Wilcoxon rank sum test (test of median difference)</li> </ul>

**Figure 2. Steps to process summed RIP signal.**

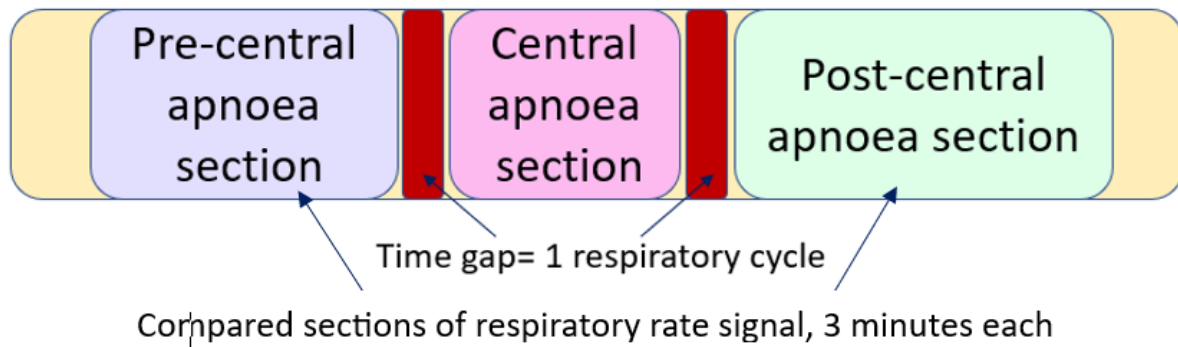
The summed RIP signals were processed by a zero-crossing algorithm that determined the time the signal's falling edge crossed the horizontal time axis as shown in Figure 3. The detected zero-crossing points are shown as black circles on the time axis.



**Figure 3. Zero crossing detection of RIP signal**

The time interval between two successive zero-crossings indicated the duration of a respiratory cycle in seconds ( $T_R$ ). Respiration rate in breaths per minute was calculated by  $60/T_R$ . The value of respiration rate was determined for each respiratory cycle. This process converted the summed RIP signal to a respiration rate signal.

To determine the effect of CSA onset on respiration rate, a 3-minute section of respiration rate signal prior to the onset of CSA and a 3-minute section following the end of CSA episode were compared (Figure 4). Longer intervals would have caused an overlap in measurements associated with two successive CSA episodes in some patients. A respiratory cycle just prior to CSA and a cycle immediately after it were avoided as this part of the signal in some patients was distorted (abnormal breathing).



**Figure 4 Respiratory rate signal sections used in the analysis.**

For each onset of CSA, the respiration rates associated pre-CSA section and post-CSA section were represented by their means, standard deviation, skewness, kurtosis, and interquartile range. For each patient, the overall statistical measures were determined by averaging these measures across all onsets of CSA.

Kolmogorov-Smirnov test was used to establish whether the differences between the statistical variables pre- and post-CSA sections across all patients were from a normal distribution. If the differences were from a normal distribution (95% confidence level), t-test was used to determine whether the mean differences were significant otherwise Wilcoxon rank sum test was used to determine whether the median differences were significant.

### 3. Results and discussion

Table 2 shows the average of statistical measure across all patients.

**Table 2. Respiration rate values of statistical measures averaged across all patients.**

Variable	Pre-CSA section	Post-CSA section	Percentage change
Mean (bpm)	20.73	21.00	1.30
Standard deviation (bpm)	9.13	7.33	-19.72
Skewness	1.17	0.80	-31.62
Kurtosis	5.41	4.12	-23.85
Interquartile range (bpm)	6.94	7.61	9.65

Following the end of CSA episodes, mean respiration rate increased by 1.3%, standard deviation decreased by 19.72%, skewness decreased by 31.62%, kurtosis decreased by 23.85% and interquartile range increased by 9.65%.

**Table 3 shows the outcome of distribution tests using Kolmogorov-Smirnov test and statistical tests of significance.**

<b>Variable</b>	<b>Distribution</b>	<b>T-test</b>	<b>Wilcoxon Rank Sum</b>
Mean	Normal distribution	Not significant	-
Standard deviation	Not normal distribution	-	Not significant
<b>Skewness</b>	<b>Not normal distribution</b>	-	<b>Significant (p= 0.046)</b>
<b>Kurtosis</b>	<b>Not normal distribution</b>	-	<b>Significant (p= 0.000)</b>
Interquartile range	Not normal distribution	-	Not significant

Only the mean variable was from a normal distribution. Statistical significance tests indicated that differences comparing pre- and post-CSA sections for the skewness and kurtosis were statistically significant but for the remaining variables, the changes were not statistically significant. The finding may indicate changes in the pattern of respiration rate after the end of CSA episodes. Follow on studies will examine whether the changes could be used to predict CSA onset. If CSA onset could be predicted, then there may be a possibility to devise a mechanism to avoid it (e.g., an electronic device to alert the patient). This study was on paediatrics however it should be extended to adults. This study was on a small number of patients and so a larger study would be needed to confirm findings.

## **4.0 Conclusion**

The study showed that skewness and kurtosis of respiration rate changed significantly when comparing pre- and post- central sleep apnoea sections. These measures had negative values. Skewness is a measure of asymmetry in the data as compared to the normal distribution. Kurtosis is a measure of the combined weight of a distribution's tails relative to its centre. This was a pilot study using a small number of patients. The study needs to be repeated with a larger number of patients to confirm the findings.

## **References**

1. P Siarnik, M Jurík, K Klobučníková, B Kollar, M Pirosova, M Malík, P Turcani, M Sýkora, 'Sleep apnea prediction in acute ischemic stroke (SLAPS score): a derivation study', Sleep Medicine, 2021, Vol 77, pp 23-28, 2021.

2. M Shokouejinejad, C Fernandez, E Carroll, F Wang, J Levin, S Rusk, N Glattard, A Mulchrone, X Zhang, A Xie, M Teodorescu, J Dempsey, J Webster, 'Sleep apnea: a review of diagnostic sensors, algorithms, and therapies'. *Physiological Measurement*, Vol 38, R204–R252, 2017.
3. C Mencar, C Gallo, M, Mantero, P Tarsia, G E Carpagnano, M P F Barbaro, D Lacedonia, 'Application of machine learning to predict obstructive sleep apnea syndrome severity', *Health Informatics Journal*, Vol 26, No 1, pp 298–317, 2020.
4. C L Marcus, L J Brooks, K A Draper, D Gozal, A C Halbower, J Jones, M S Schechter, S D Ward, S H Sheldon, R N Shiffman, C Lehmann, K Spruyt, 'Diagnosis and management of childhood obstructive sleep apnea syndrome, American Academy of Pediatrics. *Pediatrics.*, Vol 130, No 3:e714-55, 2012, DOI: 10.1542/peds.2012-1672
5. S Ghirardo, A Amaddeo, L Griffon, S Khirani, B Fauroux, 'Central apnea and periodic breathing in children with underlying conditions', *Journal of Sleep Research*, 30:e13388, pp 1-12, 2021, <https://doi.org/10.1111/jsr.13388>.
6. D J Eckert, A S Jordan, P Merchia, A Malhotra, 'Central Sleep Apnea: pathophysiology and treatment', *Chest*, Vol 131, No 2, pp 595–607, 2007.
7. K Lim, H Jiang, A P Marshall, B Salmon, T J Gale, P A Dargaville, 'Predicting apnoeic events in preterm infants', *Frontiers in Pediatrics*, Vol 8, No 570, pp 1-7, 2020.
8. F Roche, V Pichot, E Sforza, I Court-Fortune, D Duverney, F Costes, M Garet, J-C Barthelemy, 'Predicting sleep apnoea syndrome from heart period: a time-frequency wavelet analysis', *Eur Respir J.*, Vol 2, pp 937–942, 2003.
9. Z Zhang, Y Feng, Y Li, L Zhao, X Wang, D Han, D. 'Prediction of obstructive sleep apnea using deep learning in 3D craniofacial reconstruction', *Journal of Thoracic Disease*, Vol 15, No 1, pp 90-100, 2023.
10. D-Y Park, T Kim, J J Lee, J H Ha, H J Kim, V'alidity analysis of respiratory events of polysomnography using a plethysmography chest and abdominal belt'. *Sleep and Breathing*, Vol 24, pp 127–134, 2020.
11. Berry, R B, Albertario, C L, Harding, S M, Lloyd, R M, Plante D T, Quan, S F, Troester, M M Vaughn, B V, 'for the American Academy of Sleep Medicine. The AASM manual for the scoring of sleep and associated events: rules, terminology and technical specifications', Version 2.6. Darien, IL: American Academy of Sleep Medicine, 2020.