**Unobtrusive assessment of neonatal sleep state based on heart rate variability retrieved from electrocardiography used for regular patient monitoring**.

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**Running Title:**

Automated preterm infant sleep state separation

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**Abstract**

As an approach of unobtrusive assessment of neonatal sleep state we aimed at an automated sleep state coding based only on heart rate variability obtained from electrocardiography used for regular patient monitoring. We analyzed active and quiet sleep states of preterm infants between 30 and 37 weeks postmenstrual age. To determine the sleep states we used a nonlinear kernel support vector machine for sleep state separation based on known heart rate variability features. We used unweighted and weighted misclassification penalties for the imbalanced distribution between sleep states. The validation was performed with leave-one-out-cross-validation based on the annotations of three independent observers. We analyzed the classifier performance with receiver operating curves leading to a maximum mean value for the area under the curve of 0.87. Using this sleep state separation methods, we show that automated active and quiet sleep state separation based on heart rate variability in preterm infants is feasible.

**Keywords:**

Active sleep, quiet sleep, heart rate variability, support vector machine, automated, separation

# **List of abbreviations**

AS Active sleep

AUC Area under the curve

CFS Correlation based feature selection

ECG Electrocardiogram

EEG Electroencephalogram

FSMC Minority class based feature selection

GA Gestational age

HR Heart rate

HRV Heart rate variability

LDA Linear Discriminant Analysis

LOOCV Leave one out cross validation

NREM Non rapid eye movement (sleep)

PMA Postmenstrual age

PSG Polysomnography

QS Quiet sleep

REM Rapid eye movement (sleep)

ROC Receiver Operating Characteristic

SVM Support vector machine

# **Introduction**

Newborn infants show two distinct sleep states defined as active sleep (AS) and quiet sleep (QS) [1]. In full-term infants AS is traditionally associated with rapid eye movements (REM), increased variability in cardiorespiratory rates, low muscle tone, and body movements in combination with specific continuous patterns of the electroencephalography (EEG). In contrast, QS is associated with absence of REM, decreased variability in respiratory rates and fewer body movements in combination with a discontinuous EEG pattern. Even in early preterm infants, rudimentary sleep states can be identified from 26 weeks postmenstrual age [2].

The important role of sleep states on brain development is only beginning to be understood. It has been shown that sleep cycles are necessary for normal sensory and cortical development of the fetus and newborn [3,4]. AS is important in providing the early stimulation and activity requirements of the growing brain. During AS several organizational events take place such as the topographic alignment of the somatosensory, auditory and the visual system and their connection to the cortex structures. [3,4]

The time spend in AS and QS has been shown to be associated with maturation [4–6]. The distribution changes from 80% AS and 18% QS at early gestational age (GA) to around 60% AS and 30% QS at term age (see **Figure 1**) [7]. The neonatal intensive care unit (NICU) environment has a profound detrimental effect on sleep pattern development. Significant differences are found in sleep behavior between fetuses and preterm infants at the same postmenstrual age. It has been shown that preterm infants spend less time in AS and more in QS compared to fetuses at comparable age [3,8,9] The difference can be related to the clinical condition of the preterm infant or to the interaction with the “hostile” NICU environment with a variety of noxious stimuli and painful procedures [9,10].

Therefore, investigation of sleep states in preterm infants provides the opportunity to gain more insight in preterm brain development and identify which factors support or disrupt preterm brain development. Currently, polysomnography (PSG) is considered to be the standard for sleep assessment. PSG employs audio and video recording of the infant as well as the typical recordings of respiration, heart rate (HR), electromyography, electro-oculography and EEG. However, the instrumentation required for these studies is only found in sleep laboratories and not in a typical NICU setting. Furthermore, PSG requires placement of multiple electrodes and sensors which are not tolerated by the skin of the vulnerable preterm infant.

Recent advances in technology allow to collect a variety of physiological data in the clinical setting and to process and analyze these in an automated fashion. Various methods have been explored to develop sleep state separation techniques that require only a subset of standard PSG measures. [11–13]. Automated sleep staging (or sleep state classification) based on e.g. heart rate variability (HRV) is already successfully implemented in adults [14–17]. For preterm infants, automated sleep scoring is still in the exploration phase while the development of stable EEG based algorithms is recently emerging.   
Several groups are working on this topic from as early as 1987 (see **Table 1**). The first research was introduced in the same year by Harper et al. [18] and Haddad et al. [19]. Harper et al. used cardiorespiratory signals with a discriminant analysis on 25 term infants over a period of 6 month to separate AS, QS and wake. They created different models depending on age and achieved an overall agreement with the manual observations of 84.8 %. The model used for the first week after birth gained even a slightly higher overall agreement of 85.6%. Haddad et al. [19] exceeded the results of Harper et al. classifying only AS from QS based on respiratory variability with an accuracy of 99% on detecting AS and of 93% on detecting QS using Kolmogorov Smirnov distances. These good results might be explainable with the age of the subjects with around 44 to 56 weeks GA. Sleep state separation becomes easier with increasing maturation as each sleep state becomes more pronounced and can be separated more clearly. This was also found by Sadeh et al. [20] who separated AS, QS and wake only using actigraphy. They created several movement-based features which were analyzed with an linear discriminant analysis (LDA) for 41 term infants with age ranging from birth (term) to 1 year of age. The classification accuracy increased over the curse of development from 88.9% to 97.2% for sleep and wake distinction. Nason et al. [21] confirmed this in 2001 when they used wavelet analysis in combination with LDA and antedependence models (AM) to separate sleep and wake on one subject over a duration of 4 month. Performance increased over age from 75-90% with an LDA and 90-96% with AM.

In 2004, the group around Lewicke and Schuckers used the CHIME study for sleep staging in term infants based on HRV. Lewicke et al. [22] first compared the use of HRV against actigraphy for sleep staging with a learning vector quantization (LVQ) neural network. They reported that the use of HRV resulted in a correct detection of sleep in 89.5% and wake in 56.5%. The use of accelerometer measurements led to 92.3% for sleep and 42.4% for wake detection. The lower agreement for wake could be explained with the use of accelerometer measurements which might not detect wake episodes with less or no movement. In addition, the generally lesser amount of data on wake episodes in term infants can reduce neural network performance as it is directly linked to the quantity of training data. In a second study [23], they applied two additional classification methods together with the LVQ on an extended data set of 190 early term infants. In that study, they used only HRV as input for the LVQ, Multilayer perceptron neural network and a support vector machine (SVM). With a huge amount of 57000 30s epoch for each training, test and validation set, they were able to increase the correct prediction for wake to 79.6%. The SVM created the highest scores with a detection accuracy of 90.2% for sleep and 78.8% for wake. This was the first time that such amount data was analyzed for automated sleep staging for early term infants. It could be postulate that this was the first stable sleep staging algorithm for early term infants.

The first analysis of automated preterm infant sleep using cardiorespiratory signals was completed in 2016. Similar to Haddad et al, Isler et al. [12] created a threshold-based algorithm where the threshold was derived from the normalized instantaneous breathing rate variance and respiration variability. By replicating the manual scoring process and tailoring the analysis specifically to the dataset they reached a 100% agreement with the observer annotations. The more general performance of their method ranges from 78% to 92% agreement with the observer annotations[24]

Latest results were presented in 2017 by Dereymaekerset et al. [25] and Koolen et al. [26] who both focused on the classification of preterm infant sleep states using EEG signals. Dereymaekerset et al. focused mainly on identifying QS, where they based their analysis on the heightened discontinuity of the EEG during QS. Using a cluster-based adaptive sleep staging method they achieved very high results from the “Receiver Operating Characteristic” (ROC) with an area under the curve (AUC) of 0.97 for detecting QS from other sleep states out of preterm infant data stream.

Koolen et al. used six features on a nonlinear SVM classifier, resulting in an AUC of 0.83 for preterm infants <32wk post menstrual age (PMA) and 0.87 for infants >32wk PMA.

We would state that the algorithms from Koolen et al and Dereymaekers et al. are the first stable classifiers for sleep staging for preterm infants (including early preterm infants).

A more complete overview on sleep state classification based on EEG is given in another article of this special issue by Anneleen Dereymaeker et al. “*Review of sleep-EEG in preterm and term neonates*” [enter final title].

As most population in the previous studies were based on term babies, in this publication we want to give an example of AS and QS classification based on HRV only for early preterm infants. This would be complementary to the studies by Koolen et al. and Dereymaekers et al. (focusing on EEG analysis) as well as the work by Isler et al. (focusing on respiratory analysis).

# **Material and methods**

## Population:

In this retrospective study we analyzed eight healthy and stable preterm infants born at a mean gestational age of 30 ± 2.6 weeks, who were studied at a mean postmenstrual age of 34 ± 2.8 weeks. The mean birth weight was 1646 ± 309 g. The infants were admitted to the neonatal department at Máxima Medical Center Veldhoven, the Netherlands. Ethical approval was given by the medical ethical committee of the hospital and written consent was given by the patient’s parents.

## Annotation:

Data were annotated by three independent observers for the following neonatal sleep states adhering the Prechtl system [27]: AS, QS, active and quiet wake, vocalization and body positions. The mean annotation time per infant was 334 ± 54 min with simultaneous video recording, ECG and thorax impedance. After removal of caretaking episodes, the recordings were divided into 30-s epochs and sleep states were assumed to be coded correctly if at least two annotators agreed. The total number of annotations were 4057 30-s epochs, of which 845 were discarded because of signal corruptions or disagreement between observers. Of the remaining 3212 annotated 30-s epochs, 283 had other sleep states than AS or QS. For the analysis a total of 2929 30-s epochs remained with AS (n=2617) or QS epochs (n=312). The Cohen’s kappa (κ) coefficient of agreement representing interrater variability ranged between 0.61-0.80 for AS (substantial) and between 0.41-0.60 for QS (moderate) [28].

## Data acquisition:

The ECG was recorded with three standard leads. The recording device was a Philips monitor (IntelliVue MX 800, Germany) using 250 Hz (*n*=2) and 500 Hz (*n*=6) sample frequency for the ECG. Sample frequencies of 250 Hz and higher are sufficient for linear HRV analysis [29]. From the ECG signal the R peaks were detected with an in-house developed algorithm [30]. As to date there are no validated preterm infant R peak detection algorithms, the in-house algorithm was chosen after an extensive manual comparison between several R peak detection algorithms and bio signal toolboxes as to date there are no validated preterm infant R peak detection algorithms. Subsequently, the R-R intervals were used for HRV feature analysis.

## HRV features:

We selected 20 HRV features combining 18 commonly used features in adult sleep analysis [14,16,31] with two preterm infant specific frequency domain features. The adult frequencies are mostly divided into very low frequency (VLF), low frequency (LF) and high frequency (HF). We refer to **Table 2** for details. To create the two additional premature frequency ranges we extended the HF feature to three HF features: HF, pHF1 and pHF2 with a standard adult frequency range from 0.15 to 0.4Hz for HF, and additional ranges of 0.45-0.7Hz for pHF1 and 0.7-1.5Hz for pHF2 [32] to accommodate the increased cardiorespiratory rates in preterm infants. A sliding window of different length (1; 2.5; 5 min) centered on each 30-s epoch was used to evaluate if different windowing gives additional information for separating sleep states in preterm infants.

R-peaks in ECG, needed for the HRV, appear inherently non-equidistant in time. To avoid introducing extra parameters in resampling the signal, the Lomb-Scargle algorithm for spectral analysis was applied [33].

## Feature selection:

Supervised learning for classification with a SVM needs a selection of normalized input features to avoid overfitting resulting in a decrease of performance. We implemented a linear and non-linear classification approach, including three feature selection methods (two filtering methods and a wrapper method) which were used to find the top feature subset separating AS from QS. First, the correlation based feature selection (CFS) was applied and second, because the classes are imbalanced, the minority based feature selection method (FSMC). For both filtering feature selection methods, a greedy forward search was used to find the optimal feature subset. The CFS is sorting the features by the highest correlation between feature and class as well as the lowest correlation in-between features [34]. The FSMC is determining the difference between feature values for majority and minority class. It sorts the features by the highest difference between the values for majority and minority class [35]. Third, a mixed wrapper method was implemented (**Figure 2**). Starting the wrapper, a brute force forward search was used where all possible subset combinations of all features (without repetition) were generated and for each subset sleep state separation performance was validated. With a search for highest performance the optimal subset was determined. Due to exponential increase of computation time per subset combination length (generation), subsets combinations of all features were limited to the seventh generation (137979 combinations/iterations in total). The remaining 10 generation of subset combinations were analyzed with a sequential forward search (best first), where only the next single best feature was added to the previous subset combination (105 iterations). The final subset with maximum performance was determined.

## Classifier:

After the feature selection and within the wrapper method, a SVM classifier, embedded in Python`s Scikit-learn library [36], was used to train and test on the dataset. SVM is a widely used classifier [37] which is searching for hyperplanes separating the different classes with a maximum margin under the condition that misclassifications are minimized. Thereby, misclassification is penalized with a constant C which is multiplied with the amount of misclassifications. A large C value will increase the misclassification penalty (decreasing the misclassification), leading to a decrease of the minimum margin around the hyperplane separating the classes and vice versa. If the C value is chosen to be large, the generalization of the SVM model can get weakened. For this study the C value was set to value 3.6 after a parameter search as a good balance between speed, accuracy and generalization.

As the data is unbalanced for AS and QS states the C value can additionally be multiplied with value pairs representing the distribution of a dataset to compensate for the class imbalance. In preterm infants the class distribution change over time and development, therefore, we clustered the participants into four different GA ranges and computed the class weight pair for each cluster not on the actual data distribution per cluster, but on the gross expected distribution known from literature [7] as seen in **Figure 1** . The subjects were ranked into the following clusters in GA: 31-32wk (n=2), 33-34wk (n=1), 35-36wk (n=2) and 37-39wk (n=3). This clustering should not be mistaken for an age clustering to create different feature/training sets which is not feasible due to the limited population size.

Within the wrapper feature selection method a nonlinear SVM classification was used. The SVM is optimal extendible for nonlinear tasks using the “kernalisation” or “kernel trick” where the training data are transformed into a higher dimensional feature space where the problem then becomes linear again [38]. The applied SVM used the radial basis function (RBF) kernel for non-linear approximation. The RBF kernel also uses a free parameter γ which determines the inverse influence of the support vectors. We used a γ value of 0.2.

A leave one out cross validation (LOOCV) was applied to attest the classifier performance. Cross validation methods separate the total data into different parts of which one is used to validate the classifier and the remaining parts to train. Nevertheless, for small datasets these methods can become biased as it is highly probable that training and testing sets are created from the same patients. To avoid a biased validation the LOOCV uses the patients itself as separation. All but one patient are chosen for training and the remaining patient for testing. For more detailed description we refer to the literature [37].

## Statistical analysis:

For continuous distributed data median and inter quartile range (IQR) were calculated. Data were analyzed with Matlab 2014b software program (MathWorks, Natick, Massachusetts, US). The performance of sleep state separation was calculated with the receiver operating curve (ROC) and corresponding area under the curve (AUC).

# **Results**

In **Table 3** the median of all 20 HRV features for AS and QS are presented together with inter quartile range with 25 and 75 percentiles for comparability with the literature.

We used 1, 2.5 and 5 min windows to investigate effects of window length effects in preterm infant sleep staging. The combination of different window sized did not increase the classifier performance. In contrary, the analysis of only 30s epoch based HRV features lead to a lowered sleep staging performance of 0.71. Hence, we used the 5-min window length for sleep state separation and classifier methodology recommended by the Task Force [31].

To evaluate the linear approach of sleep state separation, we implemented the CFS and FSMC filter methodologies. The performance of the optimal subset was evaluated with a linear SVM classifier and resulted in a mean AUC of 0.32 ± 0.16 for CSF. The FSMC method could not identify any suitable features for a subset conformable with its selection rules. These results showed that sleep state separation with a linear kernel is not feasible for this set of features.

After exclusion of sleep state separation with a linear kernel we implemented a wrapper solution with a nonlinear kernel SVM. The optimal subset was obtained by training the SVM on seven preterm infants while one is left out for cross validation (**Figure 3 and Figure 4**). The performance analysis of sleep state separation was calculated with the ROC and AUC for each iteration of the wrapper and the following sequential forward search. The ROCs per patient and mean ROC of the chosen subset is shown in **Figure 3** with a mean AUC value of 0.85 ± 0.46.

As the sleep states were unbalanced we adapted the classifier parameter C with weighting factors pairs calculated from the expected distribution which grossly correspond with the four age cluster (see **Material and Methods**). Using the different class weights we achieved a better performance of the sleep staging with an AUC of up to 0.87± 0.42 (**Figure** 4). The optimal subset features resulted from the wrapper analysis for both classification types were BpE, NN20, SDNN, pNN20 and total power.

# **Discussion**

HR is an important physiological parameter for sleep monitoring in newborn infants, children and adults. In this study we explored the feasibility of sleep state separation by automated analysis of HRV features obtained from standard patient monitoring. A nonlinear kernel support vector machine for sleep state separation between AS and QS was used. The classifier performance with receiver operating curves resulted in a mean value for the AUC of 0.85 (**Figure** 3) and under consideration of sleep state distribution an AUC of 0.87 (**Figure** 4), indicating that HRV features are valuable for automated sleep state separation in preterm infants.

The early postnatal period for preterm infants is characterized by fluctuating periods of active sleep (AS) and quiet sleep (QS) states, with intermediate/undetermined sleep phases. These fluctuating states are associated with characteristic cardiorespiratory variability [6]. Although cardiorespiratory coupling is weak in very preterm infants, studies conducted in more mature infants show the presence of cardiorespiratory coupling [39]. In **Table 3** the different HRV values for AS and QS per feature are presented. Overall, the high IQR of the various HRV values may reflect an immature autonomic nervous regulation. Also, recovery to a stable state of autonomous control after any disturbance is reflected by a relative long time constant of approximately 10 minutes [40]. Our findings are comparable with other preterm infant HRV studies [41–43] and the time domain features shows less complexity in HR regulation during QS, reflected in lower median values and IQR. As the respiratory sinus arrhythmia in preterm infants is less dominant than in term babies [43], the median increase with AS in the time domain can probably be linked to the dominance of the sympathetic nervous system in preterm infants [31,44]. This might originate from the not fully developed adrenergic receptors in the sinus node [43]. It has been suggested that the limited cardiorespiratory coupling is stronger during QS than during AS [43]. This enhances the difference in median and IQR as more regular breathing patterns during QS reduce the signal complexity while the irregular breathing during AS does show only limited influence. The predominance of the sympathetic nervous system is associated with an increase in LF power [45], increasing the feature values for LF and LFnorm compared to HF and HFnorm. However, also vagal modulation of baroreflex response to blood pressure disturbances is important [46]. In addition, the baroreceptor reflex sensitivity increases during maturation [47] with reduced high frequency contribution to HRV in preterm infants. Like other studies the LF/HF ratio showed slightly higher values for QS, probably indicating a greater sympathetic or less vagal modulation [41]. In general, the spectral power values were decreased in QS compared to AS suggesting that the autonomic modulation is lower during QS [42]. This could be explained as the AS state is seen as the most basic state which is regulated by a network of several forebrain areas and the controlling brainstem [48] and therefore, earlier developed and more pronounced than the QS [49].

## Features:

In general, the approach to automatically separate sleep states using a cardiorespiratory signal consists of a feature extraction approach (i.e. HRV features), followed by a classification step (i.e. SVM). The features we chose are derived from adult sleep analysis [50,51] as the main objective was to proof the feasibility of separating sleep states in preterm infants based on HRV. We also added two additional features with increased frequency ranges to accommodate the general higher cardiorespiratory rates in preterm infants. The new used frequency ranges for preterm infants (See **Table 1**) were proposed in 2008 by Indic et al. [32]. The new feature pHF1 consistently appeared in the top feature subsets (#2 onwards, AUC: 0.866) underlining the importance and influence on sleep state separation and also the assumption of Indic et al. that higher cardiorespiratory rates in preterm infants need adapted frequency ranges seems to be valid. This is not surprising as other groups already explained [6] and demonstrate [12,52] the benefit of respiration analysis for sleep staging.

In the top feature five feature subsets, which all resulted in comparable performance (AUC: 0.85-0.87), total power and SDNN were always present. pHF1, NN20, NN30 and pNN20 were present three out of five times. The time domain feature BpE appeared only in the top feature subset.

To further increase classification performance and stability, recently published novel term [53] or preterm infant HRV features [54] can be implemented in future research. In addition, the preterm infant desaturation features presented by Kommers et al. [55] can be used to eliminate episodes of tachycardia avoiding misinterpretation of autonomous activity due to, non-sleep-related, altered HRV. Also, instead of eliminating noise from the signal it could rather be used as additional information source supporting sleep state separation [56].

## Sleep states separation:

The nonlinear SVM kernel was chosen based on a good separation performance with a mean AUC of 0.85 to 0.87 (**Figure 3** and **Figure 4**). The SVM classifier was selected as it is robust against outliers, while showing high performance for single and multiclass classification problems [57]. Outliers have to be expected as the sleep state annotation is challenging by various covariates.   
The age clustering for compensating changing state distributions increased the performance. Nevertheless, while the performance improved for most subjects (4) some did not change (2) and one patient actually decreased. This could be interpreted as hitting the right cluster improves the classification while a false clustering can lead to a decrease of performance. In our opinion, only clustering on age is the reason for the possibility of a decrease in performance. Commonly, it is postulated that sleep state change over gestational age [7]. This is certainly correct, but age is only one indicator for neural development. The coupling between age and development (sleep state distribution) can change with neural miss-development. Therefore, we suggest that the correct clustering has to be determined and based not only on age but rather overall condition including weight and size and other biomarkers.

Nonetheless, also biomarkers which are not directly linked to neural development can give miss information and potentially create false sleep staging which consequently would lead to false results of development monitoring. Generally, it can be said that sleep state separation without additional background information should be aspired.

## Unobtrusive HRV measurement:

In this study adhesive ECG electrodes were used as part of standard care and patient monitoring. Recently, there have been innovative developments in obtaining unobtrusively cardiac signal measurements from which HRV can be derived [7]. In general, the unobtrusive HRV measurements can be classified as contact and non-contact methods. The contact methods include a variety of options, including a neonatal jacket embedded with smart textile electrodes for ECG measurements [58], a neonatal snuggle embedded with reflectance photoplethmography based on near infra-red spectroscopy technology for pulse oxygenation monitoring [59], and intelligent bed sheet embedded with polyvinylidenefluoride or electromechanical film sensors for ballistocardiography measurements [60]. These contact ECG sensors are suitable for sleeping scenario by integrating into a bed sheet or a mattress. The non-contact methods include HRV extracted from thermal imaging, video analysis, Doppler effect, and capacitively coupled ECG [7,61–63]. The imaging and Doppler methods could be embedded into a neonatal incubator for non-contact measurements. For example, the sensory neonatal jacket and snuggle provide natural platform for seamlessly embedding sensors for unobtrusive measurements. A major limitation of most unobtrusive methods are the sensitivity to motion artifacts deteriorating the signal quality. In general, the type of unobtrusive HRV method depend on various factors, such as the neonatal sleep monitoring scenario, the environments of incubator inside NICU, the reliability of measurements and the suitability for long term sleep monitoring.

## Methodological limitations:

The small sample size of analyzed preterm newborns is the main limitation of our study.

This study also only included AS and QS states. However, AS and QS are the dominant states in the early weeks after preterm birth and other states are less well defined in preterm infants.

As we necessarily had to discard certain epochs of disagreement in the annotation, we biased the classification in favor of good epochs. Nonetheless, we want to point out that in this study we meant to showcase that the majority classes AS and QS, which are most important for development monitoring, can be separated based on the rather unobtrusive HRV measure alone. Future studies will have to attend the integrated problems of sleep staging.

To increase the performance of sleep state separation, several demographic variables such as gestational and postnatal age could be taken into consideration as these variables influence the HRV [64]. Note that the methodology of gestational age clustering in this study was used only for consideration of the sleep state distribution, not for age determined feature creation and training sets. In our case age clustering for different classification was not feasible due to the small dataset. Clustering the data would have further decreased the training data. Finally, this study used mainly the (adult) recommendations from the Task Force as there is no consensus in neonates and preterm infants. The European and North American Task Force was formed in an attempt to set standards for future studies of HRV [31]. While important recommendations were made for the length of recordings and the required spectral indices, the conclusions were based on adult studies only. As the neonatal heart and breathing rate differs from adults the recommendations of the Task Force may not be applicable in preterm infants. However, until recommendations for neonatal standardized analytical methods are made, many fetal and neonatal studies uses the recommendations of the Task Force [65,66]. We followed this approach by using mainly the adult recommendations from the Task Force. Nevertheless, to account for the increased cardiorespiratory rates in preterm infants we used two additional frequency domain features, pHF1 and pHF2 [32].

**Future Recommendations**  
For a stable performance based only on HRV and over a wide range in the preterm infant population, additional data is needed. For possible clinical application and a more holistic view on preterm infant sleep, classification between all states should be considered.

For future work we also suggest to increase the stability by using the uncertainty of the observer annotations, especially for transition states which are often difficult to manually observe. As earlier groups showed the good performance of respiratory analysis for sleep staging we highly recommend to use cardio and respiratory features in combination to achieve higher or more stable performance.  
Also, if enough data is at hand we suggest clustering by age in combination with developmental biomarkers.  
Finally, as the R peak detection is essential for correct classification with HRV, we suggest to investigate and validate R peak detection algorithms specifically for preterm infants. To our knowledge, no validated algorithm of that kind exists to date.

# **Conclusion**

This study shows that using a nonlinear SVM classifier approach for HRV features provides good results for preterm infant sleep state analyses of AS and QS. While our findings cannot yet be seen as robust due to the limited trial population, the classifier performance can compete with the literature [23,26,52]. Merging the different vital sign approaches e.g. respiration [12] and activity [67] with HRV will most likely lead to a robust, unobtrusive automated methodology for continuous preterm infant sleep monitoring.

# **Key Guidelines**

* Automated sleep state analysis is not included in clinical practice to date.
* Sleep state analysis is infrequently used for neural development assessment.
* Sleep state analysis is not used for scheduling caretaking around preterm infants.

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