Automated Quiet Sleep Detection for Premature Newborns Based on Video and ECG Analysis

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Abstract

A newborn is preterm if birth occurred before a gestational age of 37 weeks. He has several immature functions, which implies a specific monitoring and, among others, the analysis of its sleep. Here we make a focus on Quiet Sleep (QS), whose increasing is primordial with age, and characterized by an absence of motion and a regular cardio-respiratory rhythm. A method to automatically detect QS is proposed, on the basis of a video analysis (detection of motion), supplemented by the estimation of ECG and respiration "qualities". This approach combines feature extraction and machine learning methods. It was validated on a set of 15 newborns and 25 eight-hours recordings manually annotated. Best results were obtained by combining non-motion intervals and ECG quality, but showing also an overestimation of QS (Se=88%, Sp=49%). However, regarding extracted features, we observed similar trends between manual and automated QS, with an increasing of average duration of QS intervals and percentage of time in QS with age, also approaching values of the full-term newborns. Finally, computation of QS on a larger set of 45 recordings confirmed the interest of the approach for maturation evaluation purposes.

1. Introduction

A newborn is preterm if birth occurred before a gestational age (GA) of 37 weeks. He has several immature functions, which implies a specific monitoring and, among others, the analysis of its sleep, a major contributor to the development of the neonatal brain [1].

By newborn, sleep stages are said "behavioral" and their annotation, performed by observing the baby, is subjective and time-consuming. Necessity to automatize this procedure is obvious. In [2], we showed that video and audio could be useful to have a pre-estimation but limitations had been found to separate Quiet Sleep and Active Sleep, both being characterized by an absence of motion and a regular cardio-respiratory rhythm.

As a consequence, the analysis of ECG and respiration seem to be interesting to improve results. Here we make a focus on Quiet Sleep (QS), whose increasing is primordial with increasing Post-Menstrual Age (PMA). Previously, we set a study to annotate QS periods from recordings of videos and vital physiological signals (i.e. ECG and respiration) during maturation of preterm infants, where we demonstrated the correlation between PMA and temporal organization of QS [3].

In this paper, a method to automatically detect QS is proposed, on the basis on video analysis (detection of motion), supplemented with the processing of ECG and respiration signals (detection of "quality").

2. Materials and Methods

2.1. Protocol and Database

Data acquisition was performed in the scope of the Digi-NewB project [4] in six French hospitals. It was based on the recording of videos with infrared cameras and electrophysiological signals. Newborns were recorded several times (from birth to discharge) and were either placed in incubator or in open bed, depending on their age (see [5] for a more detailed description). Each recording session lasted eight hours. Video streams were recorded at 25 frames per second with MPEG-4 encoding. ECG and respiration sampling frequencies were equal to 500 and 62.5Hz respectively.

For this study, a rigorous examination of clinical records was made by clinicians in order to identify a subset of newborns without pathological development. In total, 23 newborns were selected. We focused on three dates (when available): during the 1st week after birth (Day1), 10 days after (Day2) and near discharge around 38 weeks PMA (Day3), which led to a total of 45 recordings (360 hours).

2.2. Manual annotations

To evaluate the method, a subset of 25 recordings belonging to 15 newborns of the database was manually an-

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notated. Data of Day1 and Day3 were considered. QS annotation was performed using a specific annotation tool allowing visualization of videos, ECG, RR and respiration signals. QS was established over periods of at least 20 seconds epochs. Startles and sighs were considered as part of QS phases during the annotation. More details can be found in [3].

2.3. Method

Automated QS detection method is based on the analysis of three different signals i) motion, ii) ECG and iii) respiration (Figure 1).

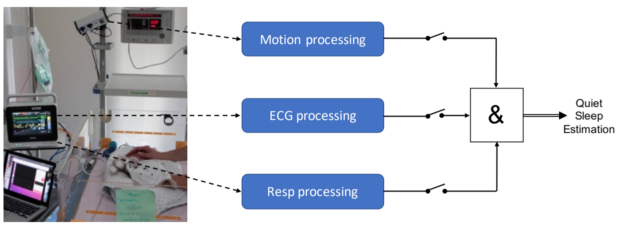

Figure 1. Workflow of the automated QS detection method

2.3.1. Motion processing

Motion processing from videos includes following steps: (i) motion estimation using difference inter-image method, (ii) detection of sole presence of the newborn using deep transfer learning and (iii) motion segmentation to retrieve motion and non-motion intervals using a Random Forest classifier. More details can be found in [6].

According to the manual annotation, we discarded motion intervals shorter than 5 seconds, in order to eliminate potential startles.

At the end, motion processing provides a series with 0 (motion) and 1 (non-motion) values.

2.3.2. ECG and respiration processing

Processing of ECG and respiration signals is based on the estimation of the "quality", initially developed during Digi-NewB project as an artefact rejection module [7]. Indeed, as QS requires regular heart and respiratory rates, we hypothesized that quality should be reliable with this definition.

Briefly, ECG and respiration signals were manually annotated on a subset of 11 subjects. In total, 880 ECG signal segments of 30 seconds and 1100 respiration signal segments of 10 seconds were used for training the classifiers. Four classification methods were compared using cross-validation: Random Forest (RF), Gradient Boosting Machine (GBM), Naïve Bayes (NB) and Logistic Regression (LR). For ECG and respiration, a RF and a NB classifier were respectively retained, with achieved accuracies of 85.8±10.6% and 85.5±5.9% respectively.

As for motion, ECG and respiration processing provides two series with 0 (bad quality) and 1 (good quality) values. Figure 2 shows the result of the ECG quality estimation on an excerpt of 5 minutes.

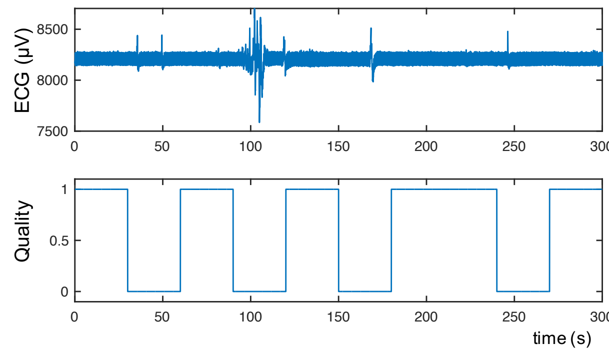

Figure 2. Example of ECG quality estimation.

2.3.3. Quiet sleep estimation

After motion processing, ECG and respiration, three binary series are available. To construct the QS estimation, all series were resampled to 25 Hz (as motion) and we applied a combination (logically "AND" function) between modalities (i) non-motion ("NoM") (ii) ECG quality and (iii) respiration quality.

In order to find which and how many modalities give the best performances, modalities were either considered one by one, two by two, or all three together (see Figure 1).

Furthermore, as in the annotation phase, a QS interval was defined as lasting at least 20 seconds, only automated QS intervals with a duration greater than 20 seconds were retained.

In the perspective of maturation analysis, QS can then be characterized by the two following features [3]:

1. Average duration of intervals (ADI) spent in QS;
2. Percentage of time spent in QS (%tQS).

3. Results

3.1. Evaluation of the QS detection method

In this section, manual and automated QS are compared (i) in order to identify the best combination of modalities and (ii) to evaluate the relevance of extracted features.

3.1.1. Best combination

Performances were evaluated by computing sensitivity (Se) and specificity (Sp) between manual and automated QS signals. Results are shown on Figure 3.

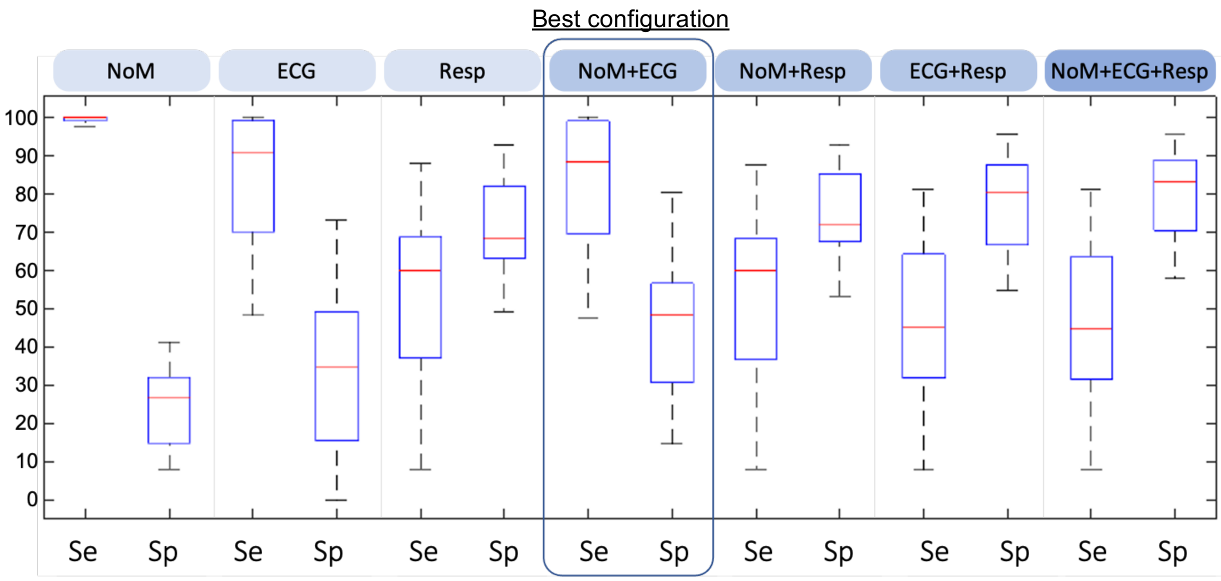

Figure 3. Performances (Se, Sp) of the QS detection method, with all combinations of the three modalities (non-motion, ECG and respiration). The best configuration is observed when the approach combines non-motion intervals (NoM) and ECG quality

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We can first observe that using only non-motion intervals ("NoM"), a very high Se was obtained (mean 99.5%, median 99.9%), meaning that all the QS intervals are included in non-motion intervals. However, Sp in this case was only around 26%, hence motivated the need to add another information to increase it. Finally, best configuration was obtained when associating motion and ECG quality ("NoM+ECG"). In this case, Se slightly decreased (mean 83.2%, median 88.5%) and Sp significantly increased (mean 49.0%, median 48.8%).

3.1.2. Feature comparison

In this section, features (ADI and %tQS) were computed from manual and automated QS series, for all the Day1 and Day3 recordings of three groups of newborns according to GA:

- Group 1: 5 very preterm (VP) ($28 \leq$ GA < 30);
- Group 2: 5 late preterm (LP) ($33 \leq$ GA < 37);
- Group 3: 5 healthy full-term (FT) (GA ≥ 39);

For group 3, only Day3 was available. Results are shown on Figure 4.

First, we can observe that trends are similar between manual and automated QS, with an increase of both features between Day1 and Day3 for groups 1 and 2. Additionally, values obtained for Day3 obtained by the preterm newborns (groups 1 and 2) are approaching values obtained by the full-term newborns (group 3). However, as seen before, values of %tQS are higher with automated

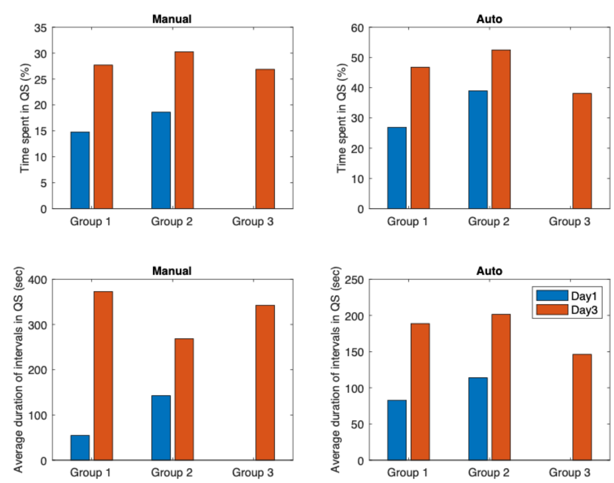

Figure 4. Time spent in QS (%) and average duration of intervals of QS (sec) between Day1 and Day3. Comparison between manual and automated QS.

method, confirming that the automated approach is tending to overestimate the quantity of QS. Besides, values of ADI are slightly lower with the automated approach.

3.2. Application to maturation evaluation

In the context of maturation evaluation, we applied the computation of the automated QS and associated features on the whole database (23 newborns, 45 recordings, up to

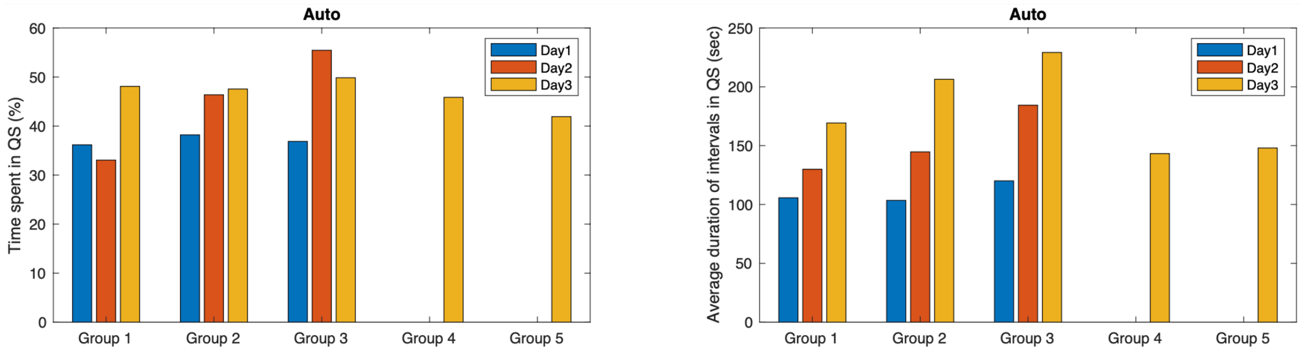

Figure 5. Time spent in QS (%) and average duration of intervals of QS (sec) computed from the automated QS. Newborns are split into 5 groups (depending on the prematurity severity) and three recording dates (Day1, Day2, Day3).

3 dates), divided into five groups according to GA:

- Group 1: 4 extreme preterm (EP) ($24 \leq GA < 28$);
- Group 2: 6 very preterm (VP) ($28 \leq GA < 32$);
- Group 3: 7 late preterm (LP) ($32 \leq GA < 37$);
- Group 4: 1 early term (ET) ($37 \leq GA < 39$);
- Group 5: 5 healthy full-term (FT) ($GA \geq 39$).

For groups 4 and 5, only Day3 was available.

Results are presented in Figure 5. We can observe that %tQS is always increasing between Day1 and Day3, but values of Day2 are not always between values of Day1 and Day3. However, values obtained for groups 4 and 5 are close to the values obtained in Day 3 for the three first groups. ADI shows a regular increasing from Day1, to Day2 and Day3. However, values obtained for groups 4 and 5 are poorly similar to the values obtained in Day3 for the three first groups.

4. Conclusion

In this paper, we have studied to feasibility of an automated QS estimation from motion, ECG and respiration in neonatal intensive care unit. Surprisingly, results showed that respiration degraded performances, but this may be due to strongly noisy signals using thoracic impedance.

These results are nevertheless encouraging since they show that the automated QS allows to identify dynamics in the features with increasing PMA, that are similar to the ones observed with the manual annotation. Hence, it can be used to compare populations or to observe the evolution of a subject with time.

Further perspectives will concern the processing of a larger database, with cleaner respiration signals. A fusion method using Machine Learning algorithms is currently under development and the estimation of all sleep stages of the newborn is targeted.

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