A Pilot Study on Predicting Daytime Behavior & Sleep Quality in Children With ASD

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***Abstract*—Sleep problems are a common concern for parents and caregivers in children with autism spectrum disorder (ASD). One of the main challenges in sleep studies with these individuals is the difficulty in monitoring sleep quality without sensors and wires attached to the subject's body. Additionally, there is limited knowledge of how their sleep quality is related to their daytime behaviors. In this study, we evaluate an unobtrusive and inexpensive smart bed system for in-home, long-term sleep quality monitoring using ballistocardiogram (BCG) signals. By extracting different sleep quality indicators using BCG signals, we build bi-directional predictive models for daytime behaviors and nighttime sleep quality using two classifiers as support vector machine (SVM) and artificial neural network (ANN). For all daytime behaviors of interest, we achieve more than 78% average accuracy using previous nights sleep quality. Additionally, night time sleep qualities are predicted with more than 78% average accuracy using previous day and night features.**

I. Introduction

Autism spectrum disorder (ASD) refers to a wide range of conditions characterized by difficulty in social skills, repetitive behaviors, speech and nonverbal communication [1]. According to Centers for Disease Control, about 1 in 59 children are diagnosed with ASD, affecting 1% of the global population. The range of thinking, learning, and intellectual abilities of these children can be from gifted to severely challenged. Thus, some may need lots of help in their daily activities and some may need less.

Several factors can affect the development of autism which are mostly accompanied by seizures or sleep disorders, mental health challenges such as depression and anxiety, as well as challenging behaviors such as self injury, tantrums and aggression. Among all, sleep problems are one of the main concerns for caregivers and parents of these individuals [2], [3]. Specifically, in more than 50-80% of this population, reduced sleep time and sleep efficiency, frequent night awakenings, and increased bedtime resistance have been reported [4]. Moreover, previous studies indicate that poor sleep quality can have negative impacts on child's behaviors [5]. However, the link between sleep problems and daytime behaviors in children with ASD are not well understood since there is a major problem in assessing sleep quality objectively for a long term studies.

Generally, there are two measures to assess sleep quality in children with disabilities, subjective and objective methods. Subjective measures generally include parent-report questionnaires, Japanese Sleep Questionnaire for Preschoolers (JSQ-P), Child Behavior Checklist (CBCL), or completion of a sleep diary record [6], [7]. However, using subjective measurements is highly dependent on individual's recall. In contrast, objective measures of sleep rely less on information from parents or caregivers, and instead directly measure aspects of sleep through different technologies. Some of the most common objective approaches used to assess sleep in children with ASD include polysomnography (PSG) [8] and actigraphy [9], [10]. However, both technologies require on-body sensors or wearable devices which is not possible for individuals with ASD for a long term study and it may impact their comfort level and further sleep quality. An unmet need remains for a low-cost and unobtrusive technology to quantitatively measure sleep quality of disabled children. We have developed a bed-based system previously validated for measuring sleep quality [11], [12]. This smart bed system provides BCG data as a promising, unobtrusive and inexpensive methodology to monitor sleep. The recording of the recoil responses of body to the heart's micro-movements is known as BCG. In contrast to other cardiac monitoring technologies such as ECG and PSG, BCG signals can be recorded without any electrodes or sensors attached to the body. Also, compared to conventional actigraphy, which uses ankle or wrist-worn sensors, the bed-based BCG system allows actigraphy monitoring without requiring the subject to wear any sensors. Using this smart bed system, we aim to uncover the links between sleep quality and daytime behaviors in children with ASD.

A. Related Work

Previous studies on finding the links between behaviors and sleep problems in children with ASD are mixed. In some studies, sleep problems (such as reduced sleep efficiency and increased night awakenings) were found to have a negative impact on the rate of daytime behaviors (such as aggression and self-injurious behaviors) [13], [14] using subjective questionnaires and actigraphy to measure sleep quality. Lambert et al. [7] studied sleep problems and daytime functioning in both TD and ASD children based on one-night PSG and questionnaire-based sleep quality measurements and interestingly, assessment with PSG found sleep issues even in ASD children who did not report sleep complaints from sleep habit questionnaires. Goldman et al. [15] reported that there was an association between poor sleepers and behavioral problems using Children's Sleep Habits Questionnaire but the directionality of this relationship could not be determined. Cohen et al. [16] investigated sleep patterns predictive models of daytime behaviors in individuals with low-functioning autism using manually measured sleep pattern for more than 20,000 nights of sleep. Since the study uses a caregiver to collect measurements related to sleep quality, it is difficult to scale this approach beyond clinical settings. Therefore, an unobtrusive and autonomous sleep quality monitoring system is needed. Thus, although the association between sleep and behavior has been investigated in children and adults with ASD [7], [13], [17], there still exists limitations to get unobtrusive sleep data from these individuals for a long term home monitoring environment.

B. Contributions

The aim of this study is to develop and assess a methodology for assessing the link between longitudinal sleep quality in children with autism and daytime challenging behavior. In order to find sleep quality metrics, we are using our designed and validated sensor-laden bed with electromechanical film sensors (EMFis) which provide BCG signals as illustrated in Fig. 1 [11]. Since a child sleeps in a variety of positions throughout the night, making a single sensor system unwieldy. Thus, multi-film design choice was made and validate through a pilot study in [11]. Using these BCG data from bed, periods of motion/restlessness are identified and we use them as one of the main sleep quality features along with other metrics. We aim to develop predictive models to find the link between sleep quality and behaviors such as aggression, self injury, and total behaviors in classroom. Specifically, bi-direction inferencing is investigated: (1) predict daytime behaviors based on previous nights of sleep quality, (2) predicting sleep quality using daytime behaviors. We analyze over 200 nights of sleep BCG data from two subjects with low functioning autism. Two classifiers, SVM and ANN, are used to help build the predictive models for daytime behaviors. For daytime behaviors scenarios, we achieve more than 79%, 84%, and 78% average accuracy for predicting aggression (AGG), self-injury (SIB), and total behaviors in class (CL) behaviors respectively. Additionally, nighttime sleep qualities are predicted and our findings indicate 82%, 78%, and 81% average accuracy for restlessness (RST), total hours of sleep (THS), and sleep onset latency (SOL) respectively. The proposed methodology makes it possible to evaluate daytime and nighttime sleep quality by using unobtrusive bed system and corresponding extracted sleep features in children with ASD.

II. Method

A. Case Study

We conducted a longitudinal study for six months with two male individuals (Mean age =15.24 y/o, Mean weight =114 lbs) with severe and moderate intellectual disabilities (ID) at Heartspting residential school located in Wichita, Kansas. Two sensor-laden beds were placed in each child's room and the data were collected under KSU IRB protocol #7783. In total, we had more than 200 nights of data collected from these two children. Additionally, a low-resolutional thermal camera is used in each child's room in order to have information about motion artifacts, sleep and wake times, and diagnose system failures.

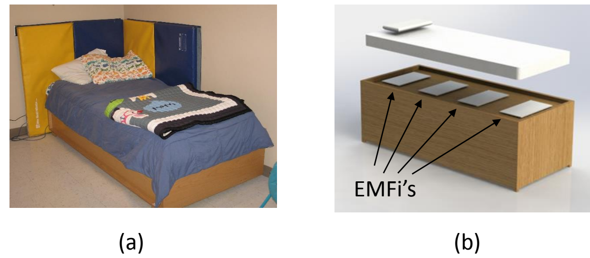

Figure 1: Smart bed system: (a) the whole bed system, (b) designed bed system with four film sensors (EMFi's) placed under the mattress.

B. Database Overview

The dataset used in this study includes two sets of data: (1) sleep quality measures, and (2) daytime behaviors. In the following sections, these two categories are presented in details.

1) Sleep Quality: Sleep quality measures are provided from a nighttime monitoring system as a multi-parameter bed sensor system [11]. The BCG data are collected with EMFi sensors using smart bed system for each subject. As the preprocessing step, each analog EMFi sensor output is conditioned with a charge amplifier, a second-order Sallen-Key lowpass filter, and a non-inverting gain stage. Low frequency content is removed via a Butterworth bandpass filter of order 6 (0.5-25 Hz). This filter is applied to each EMFi signals. After filtering, each BCG film signal is partitioned into short frames of equal length. Then, all BCG data are analyzed through our previously proposed motion detection method [18], [19] as in Fig. 2. Using motion artifacted BCG frames, we defined a surrogate sleep quality indicator as restlessness. RST is defined as any continued movements of subject longer than one minute. Other sleep features are computed from each night of sleep such as TST, defined as the length of the time spent sleeping; and SOL, defined as the length of time that it takes from wakefulness to sleep. These two features are measured based on observational data which were black and white images acquired through the thermal camera in each individual's room.

2) Daytime behavioral data: Daytime child wellness data are obtained from the school databases, which include demographic information (such as age, gender, level of severity in autism), medical information such as seizure frequency, medications (such as nights with and without medication), and more importantly child behaviors during day. Each child is assigned a paraeducator who manually records all the child's behaviors during day. Out of the total of 35 different behaviors, in this paper, we analyze the two most commonly exhibited behaviors: (a) AGG, defined as kicking, hitting, throwing objects at, or any

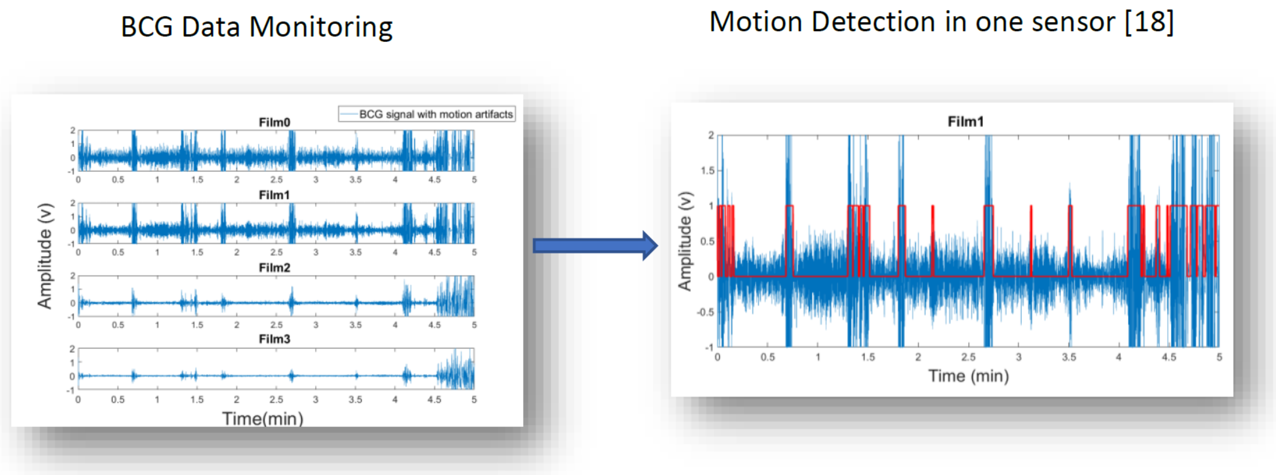

Figure 2: An example of BCG signals in four film sensors and the detected motions in one film sensor using our previously proposed motion detection algorithm [18].

other behavior that could cause injury to another person; and (b) SIB, defied as hurting or damaging one's own body. We analyze the presence or absence of each of these behaviors separately. The daytime behaviors were tracked and totals were generated for each day. Moreover, we measure all behaviors including aggression, property destruction, self-injury, tantrums, yelling, splints and mitts, and spitting on or at staffs, to arrive at an overall behavior score during class time. This cumulative metric is referred to as Total behaviors in class (CL) and is the third daytime feature of interest.

C. Classification Models

Our goal in this study is to build predictive models to find the relationship between daytime behavioral changes and nighttime sleep quality variations. All data including behaviors and sleep metrics are z-score normalized prior to training and testing procedure. First, we binary score the output parameter in each scenario for each subject separately, i.e. in daytime predictive scenario, the sleep parameters based on level of that sleep feature (average variation) , and in sleep quality ones, daytime behaviors based on presence or absence of that specific behavior. We repeat this classification procedure for each subject and each feature. In the first scenario, the inputs to the classifiers would be previous 4, 6, and 8 nights sleep qualities including RST, THS, and SOL which means for 4 previous nights $\sim$ 12 features, for 6 nights $\sim$ 18, and for 8 nights $\sim$ 24 features are extracted as sleep quality features. For the second scenario, only previous day behaviors are inputs to the classifier, i.e. $\sim$ 3 features in each model. As the classifier, in this study, we use two supervised machine learning algorithms namely SVM and ANN to help predict behavioral outcome based on sleep features and vice versa. All the samples in the dataset are over-sampled to enable balanced learning using

TABLE I
EVALUATION OF PREDICTIVE MODELS FOR AGG BEHAVIOR OVER 4-8 NIGHTS OF PRIOR SLEEP.

Classifier	Metric	4 Nights	6 Nights	8 Nights
SVM	$Accuracy(\%)$	79	81	80
	$F_1(\%)$	74	75	76
ANN	$Accuracy(\%)$	81	83	82
	$F_1(\%)$	76	76	76

both SVM and ANN. In order to compare classification models, we calculate a confusion matrix for each round of validation from which we drive the values for true positive (TP), false positive (FP), true negative (TN), and false negative (FN) cases. Then, we evaluate the performance of each approach by the following metrics: *Accuracy*, and F_1 *score*, which are commonly used for classification purposes and defined as:

$$Accuracy = \frac{\Sigma TP + \Sigma TN}{\Sigma(Total)}$$

$$F_1 = \frac{2TP}{(2TP + FP + FN)}$$

where TP is the number of correctly identified presence of a daytime behavior, TN is the number of correctly identified absence of a daytime behavior, and FP and FN are the numbers of mis-classification for each class, respectively. Since our work primarily relies on average values based on the subjects and different training and testing sets, we report the mean value for each model.

III. RESULTS AND DISCUSSION

In this study, two predictive models are introduced based on two hypotheses. First, we develop models to predict behaviors using previous nights of sleep quality

TABLE II
EVALUATION OF PREDICTIVE MODELS FOR SIB BEHAVIOR OVER 4-8 NIGHTS OF PRIOR SLEEP.

Classifier	Metric	4 Nights	6 Nights	8 Nights
SVM	$Accuracy(\%)$	87	86	84
	$F_1(\%)$	76	75	75
ANN	$Accuracy(\%)$	88	88	85
	$F_1(\%)$	77	78	78

TABLE III
EVALUATION OF PREDICTIVE MODELS FOR CL BEHAVIOR OVER 4-8 NIGHTS OF PRIOR SLEEP.

Classifier	Metric	4 Nights	6 Nights	8 Nights
SVM	$Accuracy(\%)$	78	80	82
	$F_1(\%)$	76	79	79
ANN	$Accuracy(\%)$	79	82	84
	$F_1(\%)$	77	76	79

for all three daytime behaviors as AGG, SIB, and CL. Second, we investigate the reverse problem which is the studying of how sleep quality can be predicted from day activities and previous nights sleep qualities. In the following subsections, two models are discussed along with their prediction results.

A. Nighttime to Daytime

We first investigate how prior sleep can predict the occurrence of a given daytime behavior for the following day. The goal here is to predict the presence or absence of a given behavior including AGG, SIB, and CL using sleep feature of previous nights. After careful analysis for each subject across duration of prior sleep, we notice that 4, 6 and 8 prior nights of sleep information have higher accuracies of predicting behaviors. The average accuracy and F1 score using both SVM and ANN classifiers are reported for all models across the subjects as in Tables I, II, and III. Our findings in this study show a significant predictive relationship with high average accuracy of 83%, 88%, and 84% for AGG, SIB , and CL, respectively. Using F1 score, we evaluate the classifier's performance for the predictive models. Based on F1 values, ANN outperforms SVM for almost all scenarios with slight variations. However, from complexity and parameter tuning aspects, SVM needs less time compared to ANN to be trained.

TABLE IV
EVALUATION OF PREDICTIVE MODELS FOR SLEEP QUALITIES: RESTLESSNESS, TOTAL HOURS OF SLEEP, AND SLEEP ONSET LATENCY USING PREVIOUS DAY AND NIGHT FEATURES.

Classifier	Metric	RST	THS	SOL
SVM	$Accuracy(\%)$	82	78	81
	$F_1(\%)$	79	75	77
ANN	$Accuracy(\%)$	83	81	85
	$F_1(\%)$	79	76	79

B. Daytime to Nighttime

In the second hypothesis, we analyze the predictive models for nighttime sleep quality variations. We analyze the level of restlessness, sleep onset latency, and total hours of sleep for each subject, thus we need to group the data in two classes for each sleep feature based on the average variation. We study the classification performance for sleep quality based on daytime behaviors as input features for a timescale of 1-6 previous days. The accuracy has higher and more acceptable values for scenarios using only the previous days' behaviors as input features. Based on our findings, the reported performances for more than 2 previous days in this case are low and we can conclude that in these subjects, sleep quality is mostly predictable based on only previous days' behavioral data.

Next, we investigate whether using both daytime and night-time features as input features offers better performance. In our model, we use both daytime behaviors and night-time sleep quality as input features to predict level of sleep quality (which can be below average or above the average for each subject) for the following night. Again, we average the evaluation metrics across subjects to get a single overall score to evaluate the system. The results are illustrated in Table IV. For all three sleep quality metrics, ANN outperforms SVM in terms of accuracy.

While we achieve high overall performances through both SVM and ANN for both hypotheses, the exact relationship between sleep quality and daytime behaviors in individuals with ASD varies by subject and can't be generalized. However, the takeaway message from our study is that our smart bed enables a simple way to collect sleep quality measurements and help clinicians and paraeducators predict subject's behaviors based on these measurements.

IV. CONCLUSIONS

In this study, we investigate the link between sleep quality and daytime behaviors in children with ASD using an unobtrusive methodology to measure sleep quality from a long-term home monitoring system. Using day activities and extracted nighttime sleep features, we build predictive models with two classifiers as SVM and ANN. The reported accuracies indicate that the usefulness of our designed bed system and how well sleep measurements can help improve predicting following daytime behaviors and nighttime sleep quality in children with ASD.

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