Conclusion: Sleep deprivation of a single animal within a group housed environment is possible using this system.
Support (If Any): This research was supported by NIH grant #1R43MH098595.

0281

THE EEG FINGERPRINT OF REM: ANALYSIS OF BRAIN RECURRENCE (ABR) ACCURATELY IDENTIFIES REM USING A SINGLE EEG LEAD

McCarty DE[1], Kim PY[1], Frilot C[2], Marino AA[1]
[1]Division of Sleep Medicine, LSU Health Sciences Center Shreveport, Shreveport, LA, USA, [2]School of Allied Health Professionals, LSU Health Sciences Center Shreveport, Shreveport, LA, USA

Introduction: Conventional electroencephalogram (EEG) analysis requires identification of features within the waveform, described in terms of morphology, frequency, amplitude, and location. Non-rapid eye movment (NREM) sleep stages (N1, N2, and N3) are defined solely by such features. Staging rapid eye movement (REM) sleep, however, requires incorporation of other physiologic parameters (electrooculogram, chin electromyelogram), due to visual similarities in EEG patterns found in N1, Wake, and REM. We previously developed an objective computer-based (CB) algorithm for characterizing recurrence of EEG patterns (analysis of brain recurrence (ABR)) and identified sleep depth markers that reliably separated NREM sleep stages, but could not disambiguate REM. The presence of tonic and phasic EEG activity in REM suggested that extended ABR variables capturing patterns of recurrence variability (*fragmentation)* would permit reliable detection of REM.
Methods: The cohort comprised 40 subjects (20 with, and 20 without obstructive sleep apnea (OSA)) who had undergone overnight PSG. EEG signals from a single lead (C3) were digitized and evaluated in a standard numerical computing environment. ABR markers for sleep depth and fragmentation were analyzed to place each 30-second epoch into one of three classes: wake after sleep onset, REM, or NREM. The primary outcome variable was percent REM sleep (%REM), defined as time in REM sleep divided by total sleep time (as determined by the algorithm), compared to %REM as determined by ground truth (expert staging).
Results: The CB-ABR algorithm identified mean %REM sleep in subjects with OSA as 17 ± 4%, statistically matching the results obtained by expert visual analysis staging of the PSG (17 ± 3%). In subjects without OSA, the CB-ABR algorithm showed similar precision, compared with ground truth (24 ± 6% vs. 23 ± 5%, respectively).
Conclusion: A CB-ABR algorithm allowed precise identification of REM sleep, disambiguated from wake and NREM sleep, using only a single EEG lead, in subjects with and without OSA.

0282

WIRELESS PATCH SENSOR FOR SCREENING OF SLEEP APNEA

Selvaraj N, Narasimhan R
Vital Connect Inc., Campbell, CA, USA

Introduction: Sleep Apnea Syndrome (SAS) is highly prevalent worldwide and severely affects quality of life. SAS screening with self-reported symptoms, upper-airway features, physical exam and questionnaires have been reported with reasonable sensitivity but poor specificity. Challenges with polysomnography (PSG) for SAS screening include high operating costs, inadequate availability and limited repeatability. We present a novel SAS screening tool using the Vital Connect HealthPatch™ sensor.
Methods: Volunteers (n = 53) of healthy and SAS patients were recruited for an overnight PSG. HealthPatch™ is an adhesive wireless sensor that can continuously measure ECG, actigraphy and many derived physiological metrics. Patch sensors were attached to the chest at three specified locations and orientations along with standard PSG. Each sensor was wirelessly connected to a smart phone via Bluetooth Low Energy and data were recorded. Per AASM guidelines, sleep technicians carried out sleep scoring on PSG data. Features were computed based on the overnight time-domain, frequency-domain, and nonlinear analyses of heart rate variability, ECG and accelerometry derived respiratory signals, posture, and movements. Support Vector Machine classifiers were trained on the feature set to detect moderate-to-severe apneic subjects (with apnea-hypopnea index ≥ 15). The classifiers were optimized using sequential backward feature selection with leave-one-out cross-validation.
Results: The performance (specificity, sensitivity) of the SAS screening algorithm was found to be (87.9%, 100%), (100%, 91.7%) and (96.2%, 100%) for the three patch locations, respectively. The accuracies (with 95% confidence intervals) were 91.5% (80.0-96.6%), 97.5% (87.2-99.6%) and 97.1% (85.5-99.5%) for the three patch locations, respectively. The results indicate that all the three chest locations can be used for accurate and effective SAS screening.
Conclusion: Overnight physiological monitoring with an unobtrusive patch sensor is an effective SAS screening tool. Such an inexpensive and disposable patch sensor can be very useful for widespread screening of SAS risk before the use of full PSG tests.

0283

FATIGUE DURING DEADLY FORCE DECISION-MAKING: MEASURING SKIN CONDUCTANCE IN SIMULATIONS

Winser MA[1], Hinson JM[2], James SM[1], Vila BJ[1], Whitney P[2], Van Dongen H[1]
[1]Sleep and Performance Research Center, Washington State University-Spokane, Spokane, WA, USA, [2]Department of Psychology, Washington State University, Pullman, WA, USA

Introduction: Sleep deprivation impairs risky decision-making. Skin conductance level (SCL) peaks in anticipation of risky decision outcomes and has been used as a measure of affective processes which may guide behavior. SCL may thus be a useful tool for investigating affective and cognitive processes underlying risky decision-making deficits due to sleep loss. We set out to measure SCL in deadly force decision-making (DFDM) in high-fidelity simulators developed for training police officers. However, SCL measurement within the simulators had not been previously attempted. This pilot study evaluated SCL during DFDM within the simulators, using different response devices and levels of interactivity.
Methods: 7 civilians (4 females) completed 16 DFDM scenarios in a high-fidelity simulator. During each of four 15-minute sessions, subjects were connected to skin conductance electrodes and then experienced 4 short scenarios simulating a police officer responding to a situation in which deadly force may or may not become appropriate. Subjects were asked to either actively interact with the characters on screen or passively observe the scenarios. The decision to use force was then indicated either by wielding an inert handgun or a trigger-style wireless computer mouse. Two minutes of rest separated each scenario, and 30 minutes of rest separated each session. Data were analyzed with repeated-measures ANOVA.
Results: Within scenarios, SCL steadily increased from baseline to a peak just before the deadly force decision point. Area under the curve (above the baseline floor) was used to quantify SCL responses. Use of the mouse showed greater SCL than use of the gun ($F_{1,6} = 6.4$, $P < 0.05$). Active viewing showed greater SCL than passive viewing ($F_{1,6} = 9.8$, $P < 0.05$).
Conclusion: In high-fidelity DFDM simulations involving civilian subjects, using a trigger-style wireless mouse rather than an inert gun and