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Nightcap: A Home-Based Sleep Monitoring System

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Summary: In an attempt to offer a home-based adjunct to traditional sleep laboratory methods, we developed a system to monitor sleep, and to predict algorithmically non–rapid-eye-movement (NREM) and rapid-eye-movement (REM) sleep states, using eye and body motility as the only parameters. Eye movement was measured using a strain gauge transducer applied to the eyelid of subjects, while body movement was measured using a piezo-ceramic phono cartridge. Both transducers were mounted on a tennis headband, along with electronics that amplified, filtered, and digitized the signals. Digital pulse signals were input to a portable computer in minute-long epochs, and state-predicting algorithms were run based on this motility data. Four subjects were monitored in the sleep lab with both our headgear and standard polysomnography. Hand-scored sleep records were compared with those predicted by computer algorithms. Algorithm-predicted states agreed with hand-scored ones an average of 85.57% (SEM ± 1.7%). Mean values for sleep onset and REM latency were within 1.6 and 10.8 min of polysomnographic records, respectively. These results are encouraging, and suggest that this system could provide a comfortable, subject operable, and inexpensive method for the evaluation of sleep at home. **Key Words:** Automated sleep scoring—Home-based—Transducers—Algorithm.

Over the past 8 years this laboratory has sought a means to assess sleep stages in home settings. Ideally, such a device should be mountable and operable by the subject and impose minimum restrictions on the subject's freedom of movement or comfort. The device should also provide a means to assess sleep stages without a trained scorer or complicated data analysis.

Since Aserinsky and Kleitman's original report of regular periods of rapid-eye-movement (REM) during sleep (1), it has been clear that motility correlates with the brain states that constitute the human wake–sleep cycle (2,3). Using time lapse photography to study the body position of sleeping subjects, Hobson et al. (4) showed that most major body posture shifts came at predictable phases of the sleep cycle: immediately before and after a REM period. Aaronson et al. (5) subsequently generated a sleep-

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staging algorithm based on posture shifts alone, which detected wake and non–rapid-eye-movement (NREM), but was unable to detect REM reliably.

In related work, Kayed et al. (6) used submental electromyogram (EMG), eye movements (EMs), and limb movements to predict sleep onset, NREM, and REM periods very accurately (r = 0.98 against polysomnographically scored records). Although this method required a trained scorer, specialized polygraph equipment, and a submental EMG, it did suggest that scoring of sleep stages by way of EM and body movement (BM) transducers was possible.

In 1986, Helfand et al. (7) developed an algorithm to predict REM periods on the basis of EM alone. Limb transducers helped differentiate EMs associated with posture shifts from EMs in the absence of BM. The resulting algorithm predicted REM 90% in agreement with polysomnographic data.

The aforementioned reports are the basis for our concept of a two-channel movement detector whose data could be algorithmically analyzed to predict state. This article describes our technique of EM and BM monitoring, and reports results from our first tests of an algorithm based on these predictions.

MATERIALS AND METHODS

Sensors and electronic signal processing

Figure 1 shows a schematic drawing of the monitoring system electronics. The EM transducer (Fig. 1A) consisted of a semi-conductor strain gauge (Kulite Semi-

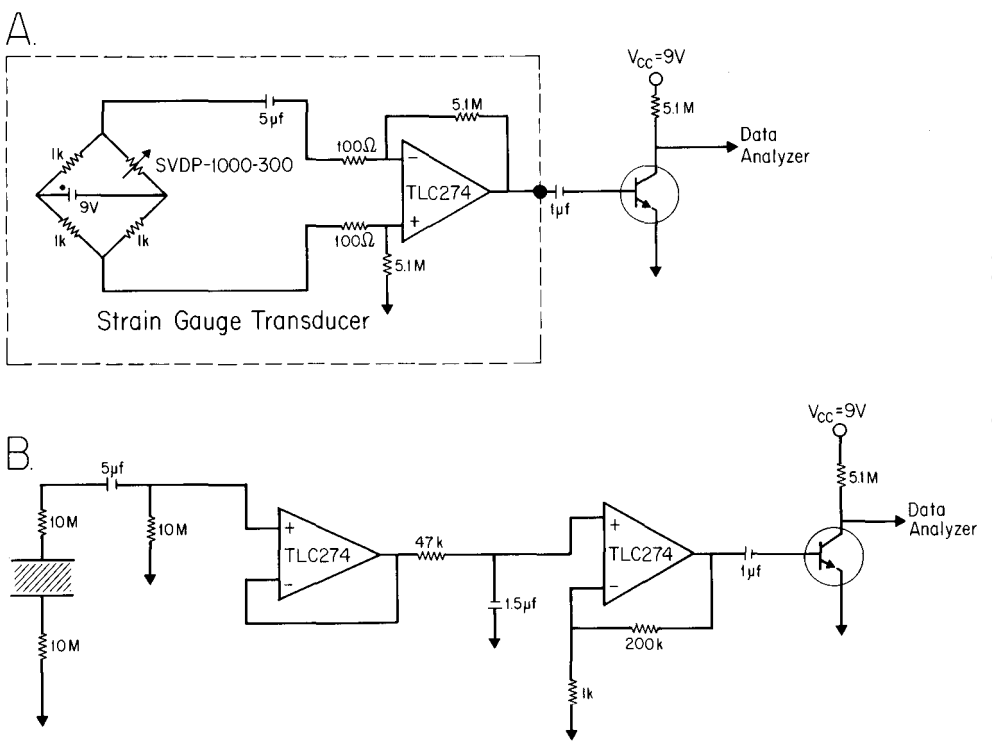

FIG. 1. Schematic drawing of transducers and electronics used in the Nightcap headgear. The eye movement transducer (A), and the body movement transducer (B).

Conductor, SVDP-1000-300, Kulite Semiconductor Products, Inc., Leonia, NJ) attached to the eyelid with a 1" × 0.25" piece of surgical tape. The transducer measured 7 mm × 3 mm and weighed 1 g—small enough to allow the subjects to open their eyes while wearing it. The gauge served as one arm of a wheatstone bridge circuit, and the bridge output signal was capacitively coupled to a differential amplifier (8,9).

The bridge circuit output fed into a differential amplifier (Tandy TLC274 Quad OP-AMP) with a gain of 10,000. The amplifier output signal was filtered and input to a transistor (Motorola 2N222A) that operated as a digital trigger, since any input signal >0.3 V caused the output voltage to switch from 4.5 to 0 V, signaling that an EM had occurred.

Since our previous investigations had suggested that major postural shifts during sleep involved all parts of the body (4,5), we hypothesized that head movement would reliably detect such activity. A 2-cm, 4-g piezo-ceramic phonograph cartridge (EVG, Inc. E/V 26D) was mounted on a printed circuit board containing the device electronics with the phonograph needle tip touching the surface of the board. Since the needle tip was not secured to the board, it acted as a vibration sensor when a head movement occurred, vibrating against the board and generating a voltage proportional to the size of the movement (10). The output signal was filtered to eliminate frequencies >5 Hz, and amplified to provide signals in the 1–2 V range for large posture shifts. Signals were then input to a transistor configured identically to that for EMs. When a signal >0.3 V was applied to the base, a pulse signal was generated.

All electronic components were mounted on a 5 cm × 4 cm printed circuit (PC) board. A 9-V transistor battery powered the electronics. The board, its components, and the battery were mounted at the apex of headgear that consisted of two tennis headbands sewn together (Fig. 2A). A wire was run through the headband to interface with the EM transducer. The total weight of the system was 500 g.

The EM and BM counts were input to a portable computer (Laser 128; Video Technologies) through a digital interface card (Microport 32, Micro Systems Research). A

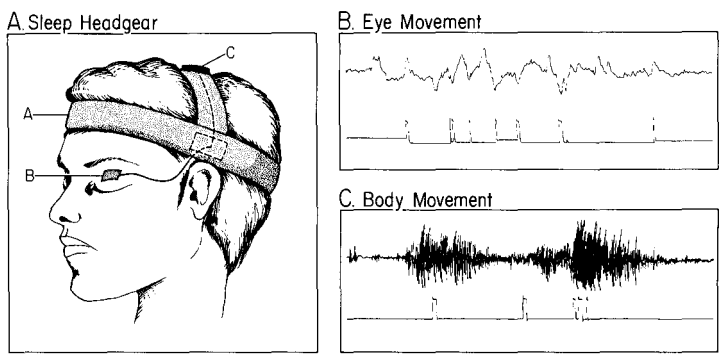

FIG. 2. A: Artist's rendering of the Nightcap monitor. A = headband, B = eye movement transducer, and C = body movement transducer and all other device electronics. The broken line represents a wire running from the main electronics board to the eye movement sensor. B: Comparison of EOG and headgear-recorded eye movement counts. C: Comparison of EMG and headgear-recorded body movement counts. In (B) and (C) each square hash mark on the lower tracing corresponds to one movement count. Correlation of EOG with eye transducer counts is low on an event-by-event basis, but the density of these counts across states is well correlated with density of EOGs. The same is true for EEG movement artifact and body movement counts. Chart speed for both tracings is 6 mm/s.

data acquisition program stored the number of EM and BM counts that occurred every minute in computer memory, and transferred these data to disk for subsequent analysis.

Experimental design

Three of four healthy medical students studied (ages 23–25, two men and two women) slept in the sleep laboratory for four consecutive nights (one subject three nights only). Electroencephalogram (EEG) (C3/A2-O2/A1-C4/A2-O2/A2), electro-oculogram (EOG) (ROC/A1-LOC/A1), and submental EMG were recorded on a Grass Model 8-10 polygraph, while data was collected simultaneously from the Nightcap headgear worn by the subjects. Output signals from the headgear transducers were fed into the polygraph. Each movement count produced a square wave pulse on the polygraph record, allowing us to compare EEG/EOG/EMG and headgear data on an event-by-event basis (e.g., EOG vs. EM counts, posture shifts vs. BM counts) (Fig. 2B). Behavioral observations were also recorded.

Before each sleep session, eye transducers were calibrated by asking the subject to look to the left, right, upper, and lower visual fields. Some EOG-measured EMs were not detected by the strain gauge because too little eyelid distortion occurred to activate the digital trigger. In exchange, many eyelid blinks not measured by the EOG were counted. Thus, while typically 80–90% of these "well-defined" calibration EMs were detected, a criterion of 60% was established as the level above which the sensor was considered to be a useful measure of oculomotor activity. Body movement transducers were calibrated by asking the subject to roll 90° to the left and right from a supine position, and testing that such large movements generated at least one movement count for each posture shift.

Eleven of the 15 sleep records were analyzed. Technical problems with the headgear rendered the data incomplete for the remaining four nights. Sleep records were manually scored in 1-min bins according to standard criteria (11) and spot-checked for consistency by a second scorer. The sleep stages were then input to the computer.

Algorithm design

The algorithm program scored each minute as an EM minute or a BM minute, by comparing minute counts with a predetermined threshold level. Any minute with EM counts greater than threshold was scored as an EM minute, and any minute with BM counts greater than threshold was scored a BM minute. Threshold values for EM and BM minutes were determined by testing the first night's count data for each subject until the highest agreement between algorithm and manual scoring was found. When both an EM and BM minute occurred simultaneously, the epoch was regarded as a BM minute.

Previous investigations (5,7) suggested a general structure for the stage-scoring algorithm, and iterative testing of EM and BM minute data from two nights (S1N1, S2N2) served as a training set to establish thresholds that yielded an algorithm that best agreed with manual scoring (85.75% overall). These thresholds were then applied to the remainder data. Some retesting of these thresholds with other nights of data confirmed that the thresholds established by the training subset were consistently reliable.

The algorithm (Fig. 3) worked as follows: At the beginning of each sleep record the subject was assumed to be awake, and each successive minute was scored as awake until the point at which no BM or EM minute occurred for ≥ 5 consecutive min. This point marked the transition from wake to sleep onset, and was scored as NREM. The

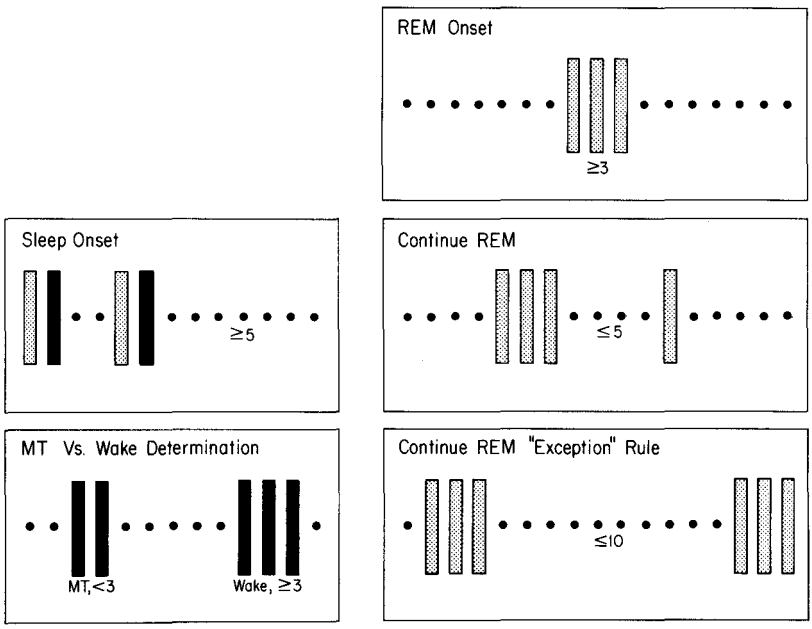

FIG. 3. Schematic representation of the two-channel sleep-stage–predicting algorithm. Solid vertical bars represent body movement minutes, stipled vertical bars represent eye movement minutes, and solid dots represent quiescent minutes. The numeric values listed are the optimal state predicting values found during data analysis.

algorithm scored NREM until any period of ≥3 consecutive EM min. This point marked the onset of REM. Once a REM period began, the algorithm scored REM until up to 5 consecutive min without an EM minute had elapsed. If >5 min elapsed, the 6th and succeeding minutes were scored NREM. The one exception to this rule was that if the time period between two consecutive REM onset periods was <10 min, the intervening period was scored REM as well.

Wake was scored at any time during the night if ≥3 consecutive BM min occurred. A period of <3 BM min was scored as movement time (MT), and the minute following the MT minute was evaluated on the basis of the state prior to it. On a minute-by-minute basis, algorithm-predicted sleep states were compared with those scored manually for agreement between the two methods. Time from wake to sleep onset, and from wake to the first REM period, were also compared. Reliability of the EM and BM transducers was evaluated.

RESULTS

Transducer sensitivities

Eye movement transducer. On an event-by-event basis, EOG and EM transducer count were only weakly correlated (r = 0.35). We then calculated the density of EM counts across states as the number of counts in a state divided by the total number of minutes spent in that state during a night. The mean density of EM counts in REM was 28.4 times as great as that in NREM (range, 12.9–93). This analysis suggests that the transducer apparatus was sufficiently sensitive to oculomotor activity to discriminate between REM and NREM, but not specific for EOG-related movement.

Body movement transducer. The BM detector proved to be sensitive to major posture shifts and less sensitive to smaller ones. On average, the BM detector failed to detect 15.6 episodes of movement (as measured by EMG artifact of duration >10-s) per night. Since sleep stages are scored in 1-min epochs, this shortcoming rarely (2.2% of all epochs) resulted in a failure to score state correctly. All major posture shifts included head movement, justifying our decision to mount the BM transducer directly on the headgear.

Algorithmic discrimination of sleep states

Table 1 summarizes the results of 11 nights of data analysis. Thresholds used to determine an EM and BM minute are listed for each subject. Any minute with eye or body counts greater than threshold was scored an EM or BM minute, respectively. This value did not change across nights for each subject. Sleep onset and REM onset (in minutes) are listed for records scored by both the EEG parameters, and the predictive algorithm (ALGO). Also listed are the total number of minutes spent in each sleep state, as determined by polysomnography and algorithm-scoring procedures, and the percentage of algorithm-predicted minute states that were identical to EEG scored states for each record.

State-predicting strength. Across all 11 nights the algorithm was in agreement with 85.6% of EEG-determined sleep states on a minute-by-minute basis. Excluding the first nights of sleep (3 of the 11) caused <2% difference in predictive accuracy, indicating that the headgear may be useful in estimating sleep even in restless sleepers. The distribution of the total number of minutes spent in each state (wake/MT, NREM, REM) correlated highly with EEG-determined values (r = 0.97).

Sleep onset and REM latency determination. The two-channel algorithm predicted sleep onset to within 10 min of EEG criteria in 10 of 11 nights. Interestingly, cessation of EM better predicted sleep onset than cessation of BM. This finding may only be

TABLE 1. *Summary of results*

				Latency measures				Duration measures						
		Threshold		Sleep onset (min)		REM onset (min)		Wake/MT (min)		NREM time (min)		REM time (min)		
Subject/night		EM	BM	EEG	ALGO	EEG	ALGO	EEG	ALGO	EEG	ALGO	EEG	ALGO	Percent agreement
1	2	0	5	7	8	67	66	38	35	293	262	99	133	82.71
	3	0	5	1	1	63	63	10	24	276	284	97	73	86.68
	4	0	5	1	2	75	75	40	29	300	268	82	125	85.07
2	1	1	2	6	26	150	211	14	79	270	252	112	65	74.49
	2	1	2	7	5	70	74	22	8	150	163	80	70	88.79
	3	1	2	3	10	97	101	20	39	283	253	91	100	80.96
3	1	2	4	26	27	99	78	40	45	239	212	72	94	85.47
	3	2	4	19	17	151	72	24	26	233	255	126	101	89.03
4	1	3	3	23	13	108	23	48	28	237	286	104	75	82.00
	3	3	3	2	1	62	61	6	13	233	230	124	120	95.04
	4	3	3	4	6	47	46	9	18	248	245	113	107	91.04
										(r = 0.97)[a]				
	$\bar{X}$			9.0	10.5	89.9	79.1	23.6	31.2	251.1	246.4	100	95.8	85.57
	SEM			2.8	2.8	10.6	14.5	4.6	5.8	12.5	10.6	5.4	7.1	1.7

EEG, electroencephalographic, manually scored states; ALGO, algorithm-predicted states; EM, eye movement; BM, body movement; MT, movement time

[a] Correlation derived from all 33 pairs of data.

characteristic of young, healthy sleepers. In more restless subjects BM may prove an equally good estimator of sleep onset.

Onset of the first REM period was predicted to within 4 min of EEG criterion in seven of 11 nights. REM onset averaged 89.9 (±10.6) min by EEG criterion, and 79.0 (±14.5) min by algorithm prediction. On four nights, REM onset predictions differed from EEG-scored latencies by >20 min. Three of these were first nights of sleep, in which first REM periods contained little EOG activity compared with the first REM periods of subsequent nights.

Overall system performance

Figure 4 shows a comparison of manually scored and algorithm-predicted hypnograms for the best and worst nights. Below each pair of hypnograms is a plot of EM and BM minutes, indicating the criteria used by the algorithm to score state. In the best case (Fig. 4A) the algorithm agreed with 95.04% of manually scored states. Sleep onset and REM onset were both predicted within 1 min of EEG-determined onset. In the worst case (Fig. 4B) the algorithm was 74.49% in agreement with polysomnographic data. Sleep onset was predicted 20 min later, and REM onset 61 min later than scored by polysomnography. Most cases fell in the middle of these extremes, as reflected by the 85.57% mean agreement value. In three out of four cases in which REM onset predictions grossly disagreed with EEG-scored latencies (S3N1, S3N3, S4N1), overall agreement percent was still high because proportionally few minutes of the total were taken up by the first REM period, and all remaining minutes were scored with high agreement.

Headgear comfort and convenience

Subjects reported no serious discomfort with the headgear, and found it easy to self-apply. One subject reported a slight irritation from the eye transducer leads, but no subject felt the headgear disturbed their sleep.

DISCUSSION

Hardware problems and refinements

The EM transducer detected oculomotor activity, but this activity did not always correlate with EOG potentials. This is because the transducer responds not only to horizontal and vertical eyeball movement, but also to eyelid twitches and blinks. Since the density of all these movements is increased in wake and REM, compared with NREM, the transducer works well to help discriminate state.

The direct mounting of the BM transducer on the headgear provided a compact means to measure large posture shifts. The inability of the BM transducer to detect smaller BMs created a scoring problem in two instances in which the subject awoke but did not make a large posture shift. In these instances (twice in 11 nights), the EM detector counted EM, while the BM detector was silent, so REM was erroneously scored. Increasing BM transducer sensitivity should help eliminate this problem.

While we are encouraged by our results, we believe that the technology present in commercially available wrist actigraphs and piezo-film transducers can be used to produce even more reliable and comfortable activity monitors. For example, replacing the strain gauge with a polyvinylidine difluoride (PVDF) piezo-electric film transducer

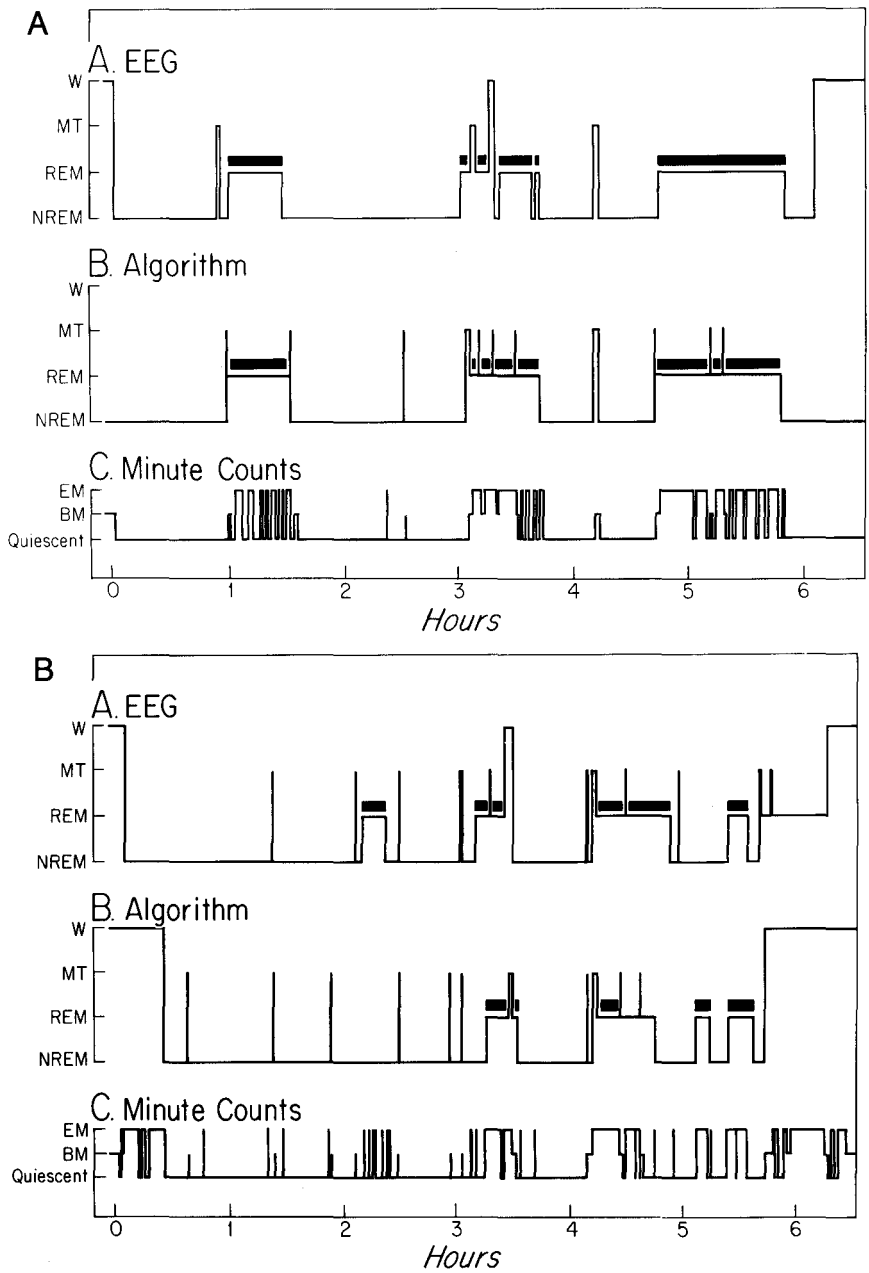

FIG. 4. Hypnograms comparing hand-scored and algorithm-predicted sleep states for both the best (95% agreement) (A) and worst (75% agreement) (B) cases analyzed. In both cases, A is the EEG-scored hypnogram, while B is the computer-predicted hypnogram. C shows each minute's movement score (EM = eye movement, BM = body movement) and thus displays the criteria used by the algorithm to predict state.

(Kynar Piezo Film, Pennwalt Co., King of Prussia, PA) should result in a more comfortable and accurate means to detect EM. Success with on-board memory (12) and wireless telemetry units (13) in wrist actigraphs suggests that such modifications are also possible for the Nightcap system.

EM and BM minute threshold variability

The EM and BM thresholds (unlike the fixed thresholds of the sleep-staging algorithm) were variable across subjects, ranging from 0 to 3 for EM and from 2 to 5 for BM min, but for each subject the threshold values that gave the highest agreement with manual scoring for the first night resulted in the highest agreement values for all subsequent nights. This indicates that while subject-to-subject variability of movement in sleep is great, within-subject variability is tolerably small. The optimal values for these thresholds can be predicted by plotting a histogram of EM and BM counts recorded in the first night. The most frequently recorded count determines the threshold level for future nights of scoring.

Sleep onset and REM latency determination

The determination of sleep onset is an important data point in the investigation of sleep disorders such as insomnia. The results of our study are encouraging in that regard. At present, wrist actigraphs are estimated to predict sleep onset to within 15 min of true sleep onset (Dan Redmond, personal communication). The headgear algorithm was substantially more accurate, predicting sleep onset within 1.5 min of EEG-determined onset.

Differentiation of REM from episodic arousal proved to be less accurate. Since the algorithm required at least 3 consecutive EM min to score REM onset, any period of REM <3 min was systematically scored incorrectly. Since headgear data can be collected inexpensively, and with minimal discomfort to the subject, these problems can be mitigated by collecting data on each subject for many (more than 5) nights and adding the results to produce an "average" sleep profile for each subject. This approach should minimize the influence of any single night's data.

Future prospects

More data is needed to determine the full efficacy and limitations of this device. We plan to test the headgear on more healthy sleepers, as well as on patients with endogenous depression (14,15) and central sleep apnea (16). Other clinical populations (17) should be tested as well to determine its widespread applicability. We anticipate the need for modifications of the current configuration in studies of narcolepsy (where sleep onset REM periods would escape detection) and nocturnal myoclonus (where limb movement would be missed). While it is impossible for the headgear to replace the wealth of EEG data collected in the sleep lab, it is likely that such a device will prove useful as a screening device for detecting sleep disorders such as endogenous depression, and a useful research tool for the field investigation of many aspects of normal human sleep physiology that have proved costly or unwieldy with polygraphic methods.

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