Noncontact Method for Sleep Stage Estimation

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***Abstract*—This paper describes a novel method to estimate sleep stage through noninvasive and unrestrained means. The Rechtschaffen and Kales (R-K) method is a standard to estimate sleep stage. However, it involves restraining the examinee and, thus, induces psychological stress. Furthermore, it requires specialists with a high degree of technical expertise and the use of an expensive polygraph. The sleep estimation method presented here is based on the noninvasive and unrestrained pneumatic biomeasurement method presented by the authors. Sleep stage transition in overnight sleep and the relationship between sleep stage and biosignals measured using the pneumatic method was analyzed and from the results, a mathematical model of sleep was created. Based on this model, a sleep stage estimator, including a sleep stage classifier and observer, was designed. The sleep state transition equation was the basis for the design of this observer, while the observed relationships were the basis for designing a classifier. Agreement of the estimated sleep stages with those obtained using the R-K method for the non-REM stage was 82.6%, for the REM stage was 38.3% and for Wake was 70.5%, including disagreement. However, the new method might ultimately result in better estimation of sleep stage due to the fact that it does not physically restrain the patient and does not induce psychological stress.**

***Index Terms*—Body movement, heartbeat, nominal scale, noninvasive biomeasurement, sleep stage.**

I. Introduction

A. Background of the Research

IN HUMAN adults, sleep occupies almost a third of each day, allowing the brain to recover from fatigue and thus maintaining health of both mind and body. Numerous people suffer from insomnia of varying degrees; some of them do not feel subjective symptoms, while others report serious symptoms. Insomnia due to apnea is one type that does not result in subjective symptoms. Furthermore, even in healthy individuals, sleep time tends to decrease due to increases in nocturnal activity [1]. Therefore, a simple, accurate and comfortable method for monitoring sleep states in daily life would provide important information for health care. At present, such a system does not exist.

Sleep stage is currently evaluated by medical specialists using polygraph data such as electroencephalogram (EEG), electrooculogram (EOG), and electromyogram (EMG) based on the Rechtschaffen and Kales (R-K) method [2]. However, this type of evaluation is subjective and the conclusions of one medical specialist using the R-K criteria may differ from those of another, which is one of several drawbacks described in the literature [3]. Furthermore, this method requires the use of physical restraints to hold the examinee, and can lead to psychological stress. This method is, therefore, difficult or impossible to apply in daily life. In addition, the use of restraints and the resultant stress can influence the results in healthy but nervous individuals who cannot sleep during measurement, thus yielding inaccurate sleep stage data.

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B. Research Achievements to Date

Several reports have suggested that heart rate and body movement are strongly related to sleep stage [4]–[6], [16]. Based on these suggestions, methods for estimating sleep stage based on heart rate measured using an electrostatic charge sensor set in the bed [7] and based on body movement measured noninvasively, via signals processed by an artificial neural network [8] have been presented. Methods for identifying Sleep/Wake based on wrist activity [9] as well as more general activity-based Sleep/Wake identification [10] have also been presented. These methods attempted to directly relate sleep stage and biosignals. Therefore, when applied to a different examinee, or to the same examinee under different physical conditions, estimates can include systematic errors. In order to prevent such errors, it is necessary to consider the relationships between sleep stage and biosignals measured under more specific investigational conditions.

The authors previously presented the fundamental idea of the pneumatic method [11]–[14] and have presented a practical system [15], which noninvasively measures heartbeat, respiration, snoring, and body movement of an unrestrained examinee in bed. A thin air-filled cushion tightly packed with urethane sponge is laid between the bed and mattress (regardless of mattress type). All human movements act on the air in the cushion through the mattress, and the air pressure within the cushion changes synchronously with these movements. These changes in air pressure are detected by a supersensitive pressure sensor and filtered in order to discriminate between the four types of biosignals. The method and system presented in this paper is based on the pneumatic method. Because the pneumatic method is noninvasive and unrestrained, sleep stage may be estimated in daily life.

Heartbeat, respiration, snoring, and body movement data measured using the pneumatic method are all related to sleep. Among these, we primarily use the heart rate signal, and secondarily use body movements to compensate the sleep stages estimated from the heart rate data. The estimation algorithm based only on heart rate can be applied to the heart rate data measured by different heartbeat sensors and measurement methods.

II. Sleep Stage Estimation and Description of Problems

A. Sleep Stage Estimation

Fig. 1 shows the biosignals obtained from a sleeping individual and the estimated sleep stage. A normal individual sleeping overnight experiences the Wake stage, the REM sleep stage and the first, second, third, and fourth non-REM stages. In each of these stages, his heart rate changes; he breathes, and may roll over several times, or begin snoring; and he may experience apnea, which is a temporary cessation of breathing. Sleep stage may remain in the same stage for a length of time, or change from one stage to another. These transitions are mainly stochastic processes.

In Fig. 1, the upper figure shows biosignals measured by the pneumatic method. The method noninvasively measures heartbeat, respiration, snoring, and body movement in an unrestrained individual. In the figure, the change in heart rate and body movements per minute are shown. The lower figure shows the sleep stage as determined by the R-K method using biosignals measured by a polygraph. For determination of sleep stages, EEG, EMG, and EOG data are required. The Wake stage, REM stage and four non-REM stages are logically differentiated by occurrences of α-wave, δ-wave, spindle and K-complex wave on EEG, detection of REM on EOG and occurrences of voltage on EMG. To measure these data, electrodes must be firmly stuck to the scalp, jaw and eyelid, which can lead to substantial physical and psychological stress.

B. Nominal, Variables, and Constants

For the sleep data shown in Fig. 1, we define the nominal scale numeral for each sleep stage and define the constants and variables to be cited in this paper as below.

⟨Nominal scale numeral of the sleep stage categories⟩

6: Wake stage;
5: REM sleep stage;
4: Non-REM first stage;
3: Non-REM second stage;
2: Non-REM third stage;
1: Non-REM fourth stage.

⟨Relating to time⟩

t: time;
T: total sleep time in one night;
$\tau(=t/T)$: normalized time;
t_{R_i}: time at which ith REM sleep occurs, i $= 1, 2, \ldots, \mathrm{m}$.

⟨Relating to heart rate⟩

$h(t)$: heart rate;
$h_c(t)$: circadian heart rate (low-frequency range);
$h_u(t)$: ultradian heart rate (middle frequency range);
$h_r(t)$: heart rate in high-frequency range;
$n_h(t)$: undefined fluctuation (noise) in heart rate with zero mean;
g_{hc}: gradient of change in circadian heart rate;
h_a: average overnight heart rate.

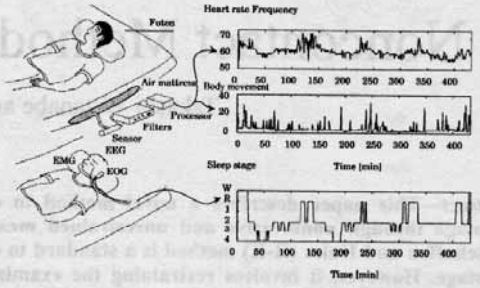

Fig. 1. Sleeping conditions and measurement of data for sleep stage estimation.

⟨Relating to transition of sleep stage⟩

$s(t)$: transition of sleep stage throughout the night;
$s_l(t)$: transition of sleep stage in low-frequency range;
$s_m(t)$: transition of sleep stage in middle frequency range;
$n_s(t)$: undefined fluctuation (noise) in sleep stage with zero mean;
s_a: average overnight value of sleep stage;
g_{sc}: gradient of change in sleep stage in low-frequency range;
$\hat{\cdot}$: symbol denoting estimates.

⟨Relating to body movement⟩

$M(t)$: body movement;
$M'(t)$: normalized body movement;
M_0: average value of the body movement $M(\mathrm{t})$ during Wake stage in bed;
$M_{\max}$: average value of the first-fifth maximum value of $M(t)$;
I_{wr}: index to discriminate Wake and REM stages.

⟨Probability distributions of heart rates at each sleep stage⟩

m_i: normalized average value of heart rate in sleep stage i(i $= 1, \ldots, 6$);
σ_i: variance the heart rate with sleep stage i(i $= 1, \ldots, 6$);
k: normalized sleep stage continuously estimated;
N: total frequency number of histograms;
$H_{is}(k)$: frequency of histogram for class $k(k = 1, \ldots, N)$;
S_h: Summation of $H_{is}(h)$ for all k;
$h_{is}(k)$: normalized histogram $(k = 1, \ldots, N)$

⟨Sleep stage transition equation and observer⟩

$x_k(t)$: probability that the sleep is in k stage;
$\boldsymbol{x}(t)$: state variables vector of $\{x_k(t)\}$ of 6×1 dimension;
$\boldsymbol{A}$: sleep stage transition matrix of 6×6 dimensions;
$\boldsymbol{y}(t)$: vector of assigned sleep stage by classifier, which corresponds to $\boldsymbol{x}(\mathrm{t})$;
$\boldsymbol{C}$: output matrix of sleep stage transition equation given by 6×6 dimensional unit matrix
$\boldsymbol{T}$: diagonal transformation matrix for $\boldsymbol{A}$ with 6×6 dimensions;
λ_i: eigen values of matrix $\boldsymbol{A}(\mathrm{i} = 1, \ldots, 6)$;
μ_i: eigen values of full order observer $(\mathrm{i} = 1, \ldots, 6)$;

C. Assumptions and Problems

For the sleep in Fig. 1, we make the following assumptions:

A1) The examinee experiences the Wake stage, the REM sleep stage and the four Non-REM stages during overnight sleep.

A2) The transition from one stage to another follows a single Markov process [17] and the heart rate frequencies in each stage are normally distributed.

A3) Sleep stages 1 to 6 are given by six different categories that correspond to numbers on a linear scale based on the relationship between sleep stage and heart rate.

Assumption A1) comes from the limitation that the sleep data to be analyzed were obtained from examinees without any sleep disorders. If data for sleep disorders are available, analysis can be more general and the sleep model for any individual can be built by extending the model for a normal sleeper. Assumption A2) is cited to simplify the mathematical model for sleep. It is unknown exactly how sleep stage changes, but the single Markov process is widely used as an approximation [17]. Assumption A3) itself is restrictive because the numerals used in a nominal scale correspond to categories rather than quantity. However, as will be shown, the numbers used for sleep stage are correlated with heart rate, and partially explain the actual situation. The final results will be discussed by removing this assumption and, thus, assumption A3) is provisional in order to lead into the final results.

Under the assumptions above, we also consider the following problems.

P1) Analyze sleep itself separately from sleep stage based on the R-K method in order to develop a sleep stage transition equation using data obtained in clinical trials.

P2) Elucidate the relationship between changes in sleep stage and heart rate and body movement in overnight sleep.

P3) Develop a noninvasive and unrestrained sleep stage estimation method using biosignals measured by the pneumatic method.

P4) Prove the validity of the method experimentally.

III. Sleep Data Acquisition

A. Experimental Systems

In order to analyze sleep itself and to determine useful relationships between sleep stage and biosignals measured using the pneumatic method, we acquired data from clinical trials. Fig. 2 shows the experimental system. All of the required biosignals were measured using a digital multi-purpose polygraph (EE2514; NEC medical systems). Sleep stage was evaluated by the international 10/20 method [5] and, thus, EEG at points C4-A1, C3-A2 of the head, eye movement and EMG at the jaw were measured. Electrocardiogram was measured using the I-induction correction method [5]. Sampling interval of the data acquisitions was 0.01 s.

Sleep stage was automatically evaluated via the computer program "Sleep Sign version1.05" (Kissey Comtech) based on the R-K method and EEG, EMG and eye movement data. The program "Sleep Sign" is an automatic sleep classifier, but the classifications obtained from this program and those from several sleep specialists showed good agreement. Sampling interval of evaluation was 1 min. Results given by the computer were checked and corrected if an obvious error was noted by an expert. The final output signal from the system is shown in Fig. 1 (lower figure).

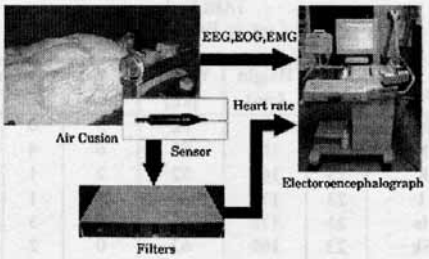

Fig. 2. Experimental system used to acquire sleep data.

We simultaneously measured heartbeat, respiration, snoring, and body movement by the pneumatic method. Between the bed and mattress, a thin air-filled cushion (thickness, 5 mm; size, 450 mm × 90 mm) was placed. When the examinee is in bed, forces due to movements such as the heartbeat, respiration, snoring, and body movement act on the air in the cushion through the mattress. The air pressure in the cushion then changes synchronously with these movements. The pressure due to slight human movement is around 0.2 Pa–1.5 Pa, which corresponds to forces of 0.05 N to 0.38 N. The changes in pressure were measured by a supersensitive pressure sensor with a high-pass filter characteristic with a gain of 5.7 mV/Pa at frequency 0.2 Hz and 18 mV/Pa at frequency range higher than 1 Hz. The frequencies and manner in which pressure occurs due to the movements described above are different and are, thus, discriminated by filters with the AGC function and envelope detection circuits. The bandwidth of the filter for respiration was 0.1–0.5 Hz, that for heartbeat was 5–10 Hz, and that for snoring was 100–500 Hz. The body movement signal was detected by the AGC signal for heartbeat. Heartbeat and respiration frequencies were calculated every minute. The fast Fourier tarnsform (FFT) algorithm was employed to estimate heartbeat and respiration frequencies (rates) for acquired data with a sampling interval of 0.1 s. The number of data points was 512 and, thus, the measurement interval was 51.2 s. Frequencies with a maximum peak correspond to the fundamental component or harmonics of heartbeat and respiration. The final output signal from the pneumatic system is shown in Fig. 1 (upper figure).

B. Examinees

Table I shows a list of the 8 examinees and the number of clinical trials. The number of initial trials to obtain the data required for the mathematical sleep estimator and classifier models was 15 and the number of trials to obtain test data to evaluate the method and system was 12. Therefore, the total number of test trials was 27. Examinee M in Table I exhibits a normal sleep pattern, whereas examinee N exhibits a slightly irregular pattern in the sense that the examinee moves very frequently in overnight

TABLE I
LIST OF EXAMINEES

Examinee	Age	Height [cm]	Weight [kg]	Number of trials		
				Initial	Test	Total
M	23	177	82	5	0	5
N	24	168	85	6	4	10
K	23	168	52	2	1	3
I	23	172	60	1	1	2
Is	23	171	63	0	3	3
Sk	23	169	62	0	2	2
Og	23	170	63	0	1	1
S	23	168	63	1	0	1
Subtotal and total				15	12	27

sleep. Three additional normal examinees K, I, S were employed in order to obtain the initial data. Selections of these examinees, despite a greater number of trials using examinees M and N, cover a variety of sleep patterns. Some of the test data were acquired from the same examinees used in the initial trials, but the data were sampled on different days. Two other examinees participated in several trials, but could not psychologically tolerate the electrodes attached to the head, jaw and eyelids for the R-K method. They (M, N, K, I, Is, Sk, Og, S) were all adult men and were not examined for sleep disorders by a medical doctor, but complained of no subjective symptoms. All examinees were university students and their daily life patterns varied greatly, as follows.

M) Lives alone and regularly goes to sleep around 2 a.m., waking up around at 9 a.m.

N) Lives with his family and goes to sleep around 2 a.m., waking up around noon. Sometimes feels tired during the day.

K) Lives alone and goes to sleep around 3 a.m., waking up around 1 p.m. Sleeps as much as he wants.

I) Lives alone. Often goes to sleep about 3 a.m. and wakes up about 10 a.m., but sleeping times are not always regular.

Is) Lives alone. Regularly goes to sleep around 1 a.m. and wakes up at 8.30 a.m.

Sk) Lives with his family and regularly goes to sleep around 1 a.m., waking up at 8 a.m.

Og) Lives with his family. Usually goes to sleep around 1 a.m. and wakes up at 7.30 a.m., but this is not always the case.

S) Lives alone. Goes to sleep around 4 a.m. and wakes up in the afternoon.

For the clinical tests, examinees went to bed around 11.30 p.m. All parameters were measured until the examinee woke up the next morning.

IV. SLEEP ANALYSIS

A. Sleep Stage Transition Equation

Under assumptions A1) and A2), we consider problem P1). First, we consider a mathematical model of sleep. Overnight sleep passes from one sleep stage to another, which we define as $x_6(t), x_5(t), x_4(t), x_3(t), x_2(t), x_1(t)$, with the constraints

$$x_6(t) + x_5(t) + x_4(t) + x_3(t) + x_2(t) + x_1(t) = 1. \quad (1)$$

These are stochastic variables with values from 0 to 1 that correspond to the probability that sleep is in stage 6, 5, 4, 3, 2, or 1 at time t. The numerals 6 to 1 represent the nominal scale, as defined above. In addition, a_{ii} is the probability that sleep in stage i remains in the same stage at the next sampling and a_{ji} is the probability that sleep in stage j moves to stage i at the next sampling. Furthermore, the matrix $\boldsymbol{A}$ includes a_{ii} and a_{ji} as element (i, i) and element (j, i), respectively, and the vector $\boldsymbol{x}(t)$ includes $x_k(t)$ as element k of the vector. The stochastic behavior of sleep transition can then be described by the simultaneous difference equations

$$\boldsymbol{x}(t+1) = \boldsymbol{A}\boldsymbol{x}(t), \quad \boldsymbol{x}(0) = [1\,0\,0\,0\,0\,0]^{\mathrm{T}}. \quad (2)$$

The initial condition means that the examinee is initially in the Wake stage. Values of the elements in matrix $\boldsymbol{A}$ were estimated from the results of 15 initial trials above and are given as follows:

$$\boldsymbol{A} = \begin{bmatrix} 0.938 & 0.005 & 0.070 & 0.008 & 0.000 & 0.003 \\ 0.018 & 0.908 & 0.075 & 0.029 & 0.000 & 0.000 \\ 0.005 & 0.004 & 0.656 & 0.008 & 0.001 & 0.000 \\ 0.037 & 0.081 & 0.199 & 0.905 & 0.200 & 0.000 \\ 0.003 & 0.001 & 0.000 & 0.045 & 0.684 & 0.233 \\ 0.000 & 0.001 & 0.000 & 0.006 & 0.116 & 0.764 \end{bmatrix}. \quad (3)$$

Matrix $\boldsymbol{A}$ shows the average characteristics of sleep in 15 trials. If we divide all sleeping times into several intervals and obtain values of the elements for each interval, the matrices show slightly different characteristics depending on these intervals. The value of each element of matrix $\boldsymbol{A}$ is less sensitive to the overall characteristics of (2).

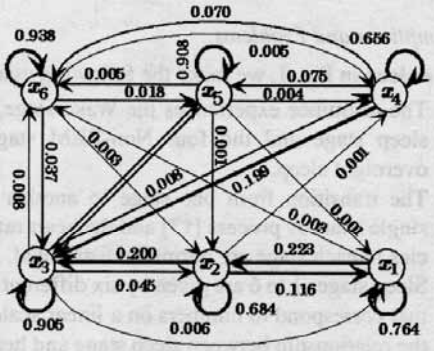

Fig. 3. Sleep stage transition diagram.

B. Shannon Diagram of the Sleep Transition

Fig. 3 shows a Shannon diagram of sleep stage transition given by (2). The steady-state solution $\boldsymbol{x}(\infty) = [x_6(\infty)x_5(\infty)x_4(\infty)x_3(\infty)x_2(\infty)x_1(\infty)]^{\mathrm{T}}$ of (2) is the

TABLE II
CLASSIFICATION OF HEART RATE AND SLEEP STAGE BY FREQUENCY

Frequency	Heart rate	Change in sleep stage
Low	Circadian rhythm	Gradual change in sleep stage throughout the night
Middle	Ultradian rhythm	Non-REM/REM oscillation
High	Random change in heart rate during REM sleep periods	-

average normalized length of each sleep stage and is obtained as

$$x_6(\infty) = 0.1, \quad x_5(\infty) = 0.15, \quad x_4(\infty) = 0.13$$
$$x_3(\infty) = 0.47, \quad x_2(\infty) = 0.09, \quad x_1(\infty) = 0.05. \quad (4)$$

The normalized average length of each sleep stage in individuals with no sleep disorders is reported [5] and these lengths were found to be almost the same as those obtained with steady-state values.

V. Relationships Between Sleep Stage and Change in Heart Rate and Body Movements

A. Biorhythms

Here, we consider problem P2). It has been reported that the changes in heart rate are measured as a part of a biological rhythm, such as circadian rhythms with a period of 25 hr, or ultradian rhythms with a period of 90 min, and as random changes, such as those occurring during REM sleep [5]. Table II shows the classification of rhythm frequencies.

Changes in heart rate and sleep stage are given by combining these changes in each frequency range for each rhythm [2], [5], as shown in Table II, and are expressed as

$$h(t) = h_c(t) + h_u(t) + h_r(t) + h_a + n_h(t) \quad (5)$$
$$s(t) = s_1(t) + s_m(t) + s_a + n_s(t). \quad (6)$$

Given that the changes in heart rate and sleep stage are given by (5) and (6), respectively, we first examined the relationship between $h(t)$ and $s(t)$. In the investigation to determine this relationship, we employed the normalized time τ, as defined above, because sleeping times of the examinees vary between individuals and between different trials in the same examinee.

B. Relationships in Low-Frequency Range Biorhythm

Here, we consider the relationship between changes $h_c(t)$ in heart rate in the circadian rhythm and sleep transition $s_1(t)$ in the low-frequency range.

Sleeping time is about eight hours per day and is in a part of the circadian rhythm period. Heart rate and sleep stage during this time can be approximated to change linearly. During sleep, sleep stage moves to stage 1 (Non-REM fourth) from stage 6 (Wake) in a short time and sleep gradually shallows from stage 1 to stage 6. From the provisional assumption A3), we can describe the gradual changes in sleep stage from stage 1 to stage 6 as a continuous value and, thus, changes in sleep stage and heart rate are given by linear functions. In the low-frequency range,

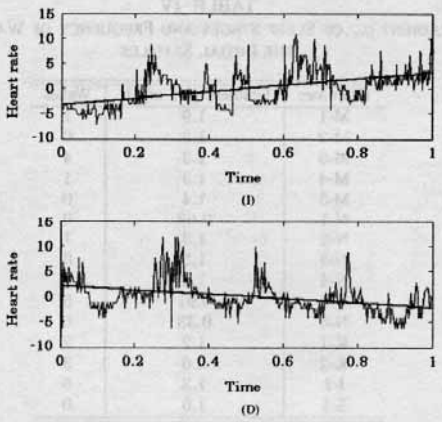

Fig. 4. Examples of average changes in heart rate. (I) Slight increase trend. (D) Slight decrease trend.

TABLE III
GRADIENT g_{hc} OF HEART RATES, AND I AND D CHARACTERISTICS OF HEART RATE IN THE 15 TRAINING SAMPLES

Examinee	Gradient [1/1 night]	Type
M-1	6.5	I
M-2	−4.2	D
M-3	0.15	I
M-4	6.8	I
M-5	−1.4	D
N-1	−19	D
N-2	−9.6	D
N-3	−8.6	D
N-4	−11	D
N-5	−15	D
N-6	−18	D
K-1	−7.1	D
K-2	−14	D
I-1	−20	D
S-1	−12	D

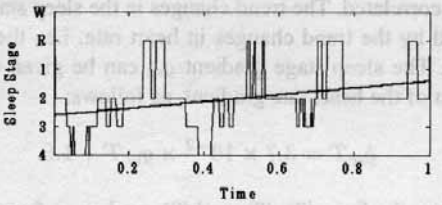

Fig. 5. Changes and trends in sleep stage throughout the night.

excluding the DC component, heart rate and sleep stage are described by

$$h_c(\tau) = g_{hc} T \cdot (\tau - 0.5) \quad (7)$$
$$s_1(\tau) = g_{sc} T \cdot (\tau - 0.5). \quad (8)$$

The gradient g_{hc} can be easily estimated using the least square method. Fig. 4 shows typical changes in heart rate in the low-frequency range and the estimated linear equations. Increasing (I) and/or decreasing (D) trend modes were observed. Fig. 4(I) shows an example of an increasing trend mode and Fig. 4(D) shows that of a decreasing trend mode. Table III shows a list of examinees and whether they exhibited I or D trend modes. Examinee M demonstrated an I trend. These gradients probably change according to physical conditions and are not presumable.

TABLE IV
GRADIENT g_{sc} OF SLEEP STAGES AND FREQUENCY OF WAKE IN THE INITIAL SAMPLES

Examinee	Gradient [1/1 night]	Wakes
M-1	1.9	1
M-2	1.2	0
M-3	2.3	4
M-4	1.3	1
M-5	1.4	0
N-1	0.68	0
N-2	1.3	1
N-3	1.5	0
N-4	1.1	0
N-5	0.91	5
N-6	0.38	0
K-1	1.2	2
K-2	0.6	3
I-1	1.3	0
S-1	1.6	0

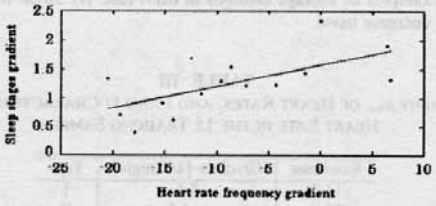

Fig. 6. Relationship between gradients for heart rate and sleep stage.

Fig. 5 shows a typical example of changes and trends in sleep stage. The gradients of the sleep stages were obtained by the algorithms as above. Table IV shows the gradient of sleep stage and the frequency of waking. The gradient of sleep stage transitions ranges from 0.38 to 2.3. Fig. 6 shows the relationship between heart rate gradients and sleep stage gradients. The correlation coefficient of these gradient data is 0.64 and, thus, the gradients of sleep stage gradient g_{sc} and the heart rate gradient g_{hc} are correlated. The trend changes in the sleep stages are influenced by the trend changes in heart rate, i.e., the circadian rhythm. The sleep stage gradient g_{sc} can be given as a linear function of the heart rate gradient, as follows:

$$\hat{g}_{sc}T = 3.7 \times 10^{-2} \times g_{hc}T + 1.6. \quad (9)$$

Consequently, from (7), (8), and (9), we have a formula for estimation of sleep stage in the low-frequency range

$$\hat{s}_1(\tau) = (3.7 \times 10^{-2} \times g_{hc}T + 1.6) \cdot (\tau - 0.5). \quad (10)$$

C. Relationships in Middle Frequency Range Biorhythm

Here, we consider the relationship between changes in sleep stage and heart rate in the middle frequency range both in the ultradian rhythm and in Non-REM/REM oscillation. In order to extract the heart rate and sleep stage components in the middle frequency range, an FFT-based nonrecursive digital band filter without phase shift was applied to both data. The period of Non-REM/REM oscillation is from 26 to 135 min [5], which is wide enough to include the ultradian rhythm. In the period (frequency) range of 26 min (6.41×10^{-4} Hz) to 135 min (1.23×10^{-4} Hz), the fundamental components of both data are always included. Thus, the cutoff for the long period (low-frequency) was fixed at 135 min, but the cutoff for the short period (high-frequency) was defined as the half of time between periods of peak heart rate. Fig. 7 shows the filtered data for heart rate and sleep stage in the middle frequency range.

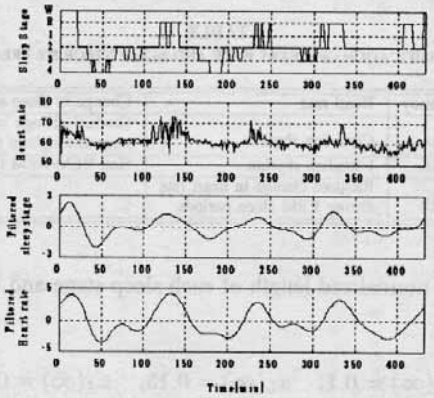

Fig. 7. Sleep stage, changes in heart rate, filtered sleep stage and filtered heart rate in middle (ultradian) frequency range for examinee M-2.

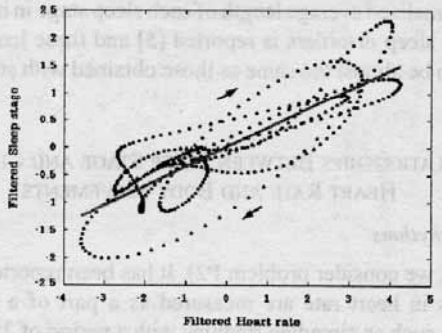

Fig. 8. Sleep stage versus heart rate in the middle (ultradian) frequency range. The correlation between these is 0.86.

In Fig. 7, the top row shows sleep stage data, the second shows heart rate data, the third shows the band-pass filtered sleep stage data and the bottom row shows the band-pass filtered heart rate data. Sleep stage and heart rate in the middle frequency range show similar trends. Fig. 8 shows the sleep stage versus heart rate in the middle frequency range. The correlation coefficient between these two data is 0.86 (very high). To find the relationship between sleep stage and heart rate, we cited assumption A3), which states that the nominal sleep stages 1 to 6 correspond to numbers of a linear scale with the same interval. This was initially an assumption, but the nominal sleep stage demonstrated a correlation with heart rate and, thus, these numbers may be able to provide quantitative information regarding biodata.

Careful observation of Fig. 8 reveals that there is a somewhat dynamic relationship between heart rate and sleep stage. Therefore, to determine a closer relationship between these, we estimated the dynamics of the relationship. The optimal relationship with regard to minimum error and stability was estimated by applying the least square method to the data from all training examinees. Estimated sleep stage based on heart rate data in the middle frequency is given by

$$\hat{s}_m(\tau) = 0.996\hat{s}_m(\tau - 1) + 0.255h_u(\tau) - 0.259h_u(\tau - 1). \quad (11)$$

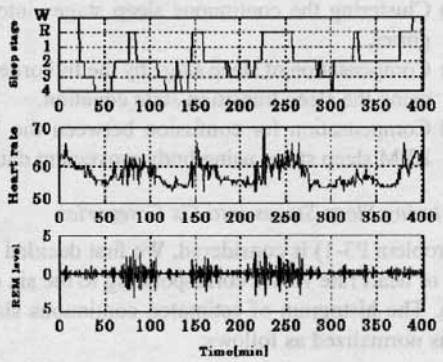

Fig. 9. High-pass filtered heart rate.

D. Relationships in High-Frequency Range Biorhythm

Changes in heart rate include high-frequency components when sleep is in the REM stage. To detect the REM sleeping time, a high-pass filter with a cutoff period of 3 min is applied to changes in heart rate.

The top row in Fig. 9 shows sleep stage, the second shows heart rate and the third shows the high-pass filtered heart rate data. In the time interval when the high-frequency component of heart rate $h_r(t)$ has a higher level, and heart rate in the ultradian rhythm $h_u(t)$ is at the high-frequency level, REM sleep and sometimes waking occurs.

Time t_{Ri}—when REM sleep occurs—can, therefore, be detected by

$$t_{Ri} = t \quad \text{when}[\{\text{maximum}(h_u(t))\} \text{ and } \{\text{maximum}(\text{envelope}(h_r(t)))\}]. \tag{12}$$

The envelope $h_r(t)$ is obtained by filtering absolute $h_r(t)$ values using a low-pass filter with a cutoff period of 20 min. The average $\hat{S}_a$ value (bias component) of the estimated sleep stage is determined by the fact that it is in the REM stage at time t_{Ri}, shown as follows:

$$\hat{s}_a = 5 - \sum_{i=1}^{m} \frac{\hat{s}_l(t_{Ri}) + \hat{s}_m(t_{Ri})}{M}. \tag{13}$$

E. Estimation of Sleep Stage From Change in Heart Rate

Each component in (6), i.e., $\hat{s}_1(t)$, $\hat{s}_m(t)$, and $\hat{s}_a$, is estimated from the overnight change in heart rate data using (10), (11), and (13), respectively. Consequently, estimating sleep stage exclusively from heart rate data is possible using

$$\hat{s}(\tau) = \hat{s}_1(\tau) + \hat{s}_m(\tau) + \hat{s}_a \tag{14a}$$

while the normalized continuous sleep stage is estimated from

$$k(\tau) = \frac{\hat{s}(\tau)}{\{\text{maximum}(\hat{s}) - \text{minimum}(\hat{s})\}}. \tag{14b}$$

Fig. 10 shows typical results of sleep stage analysis using the R-K method, and the estimated sleep stages using (14).

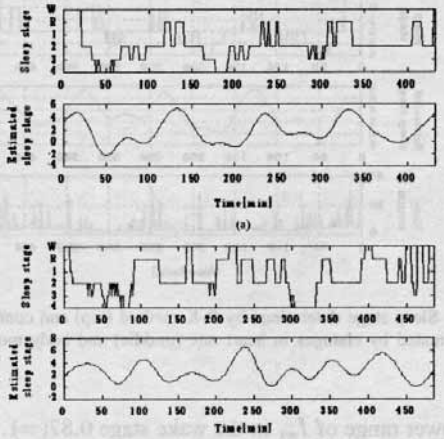

Fig. 10. Sleep stage determined by R-K method, and continuous sleep stage estimated using heart rate. (a) Examinee M-2. (b) Examinee N-5.

Fig. 10(a) shows a typical normal sleep pattern, while (b) shows irregular changes in sleep. Estimated stage is smooth and continuous but shows similar characteristics and oscillation as the conventionally determined sleep stage. The smoothness is because the estimation equation neglects undefined fluctuations in sleep stage $n_s(t)$.

F. Relationships Between Wake, REM Sleep, and Body Movement

Heart rate fluctuates greatly in REM sleep and in the Wake stage [5], [15], thus REM sleep or the Wake stage can easily be detected. However, discriminating REM sleep from wakefulness using only heart rate data is difficult. Therefore, other biosignal data is required. For this purpose, we employed body movement, as measured by the pneumatic method.

The signal level of body movement is very high when compared with that of heartbeats. The AGC control signal for each sampling interval is proportional to the body movement. In order to determine relationships between body movement and sleep stage, we calculated the average value $M(\tau)$ of body movement at each sleep stage and then calculated the normalized average value

$$M'(\tau) = \frac{M(\tau) - M_{\min}}{M_{\max} - M_{\min}}. \tag{15}$$

From the normalized average value $M'(\tau)$ and the average value M_0 of $M(\tau)$, we can define an index of body movement.

$$I_{wr}(\tau) = \frac{M'(\tau)}{M_0}. \tag{16}$$

From all the data obtained in the clinical trials, we obtained average indexes and standard deviations for each period of REM and wakefulness as follows:

$$\begin{aligned} \text{Wake stage} \quad & I_{wr} = 1.1 \pm 0.23 \\ \text{REM sleep stage} \quad & I_{wr} = 0.53 \pm 0.19. \end{aligned} \tag{17}$$

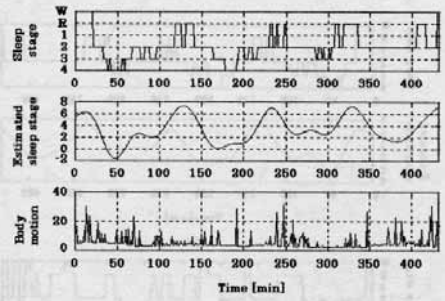

Fig. 11. Sleep stage determined by R-K method (top) and continuous sleep stage estimated by changes in heart rate (middle) and body movement data (bottom).

If the lower range of I_{wr} in the wake stage $0.87(=1.1–0.23)$ is used for this index, we can discriminate REM sleep from the Wake state as follows:

$$\begin{aligned} &\text{If } I_{\mathrm{wr}}(\tau) > 0.87, \text{sleep is in the Wake state.} \\ &\text{If } I_{\mathrm{wr}}(\tau) \leq 0.87, \text{sleep is in the REM state.} \end{aligned} \tag{18}$$

G. Sleep Analytical Results

In the above sections, we analyzed sleep itself, the relationships between sleep stage and heart rate, and the relationship between body movements in the Wake state and REM sleep for the data obtained in our clinical trials. Mathematical models can concisely express these results as follows:

1) Transition of sleep stage is given by the sleep state transition equations in (2) and (3).
2) Under the assumption A3), the relationship between sleep stage and heart rate is given by (14) along with (10), (11), and (13).
3) The relationship between the Wake and REM sleep states and body movement is given by (18).

VI. Development of a Sleep Stage Estimation Method

A. Problem Descriptions

Here, we consider the problem P3) and present a sleep stage estimation method based on the analytical results above. The continuous sleep stage in Fig. 10 estimated only by heart rate under assumption A3), is not always accepted by medical doctors. Most doctors are familiar with observing conventional sleep stages with six categories and most sleep indexes are defined by data obtained in these six stages. Furthermore, even though the sleep stage data in Fig. 10 shows a close relationship with the conventional sleep stage, some confusion between the Wake and REM sleep stages remains.

Our estimation method will fully use the analytical results above in order to provide more accurate sleep stage classification defined by the six categories.

Fig. 11 shows the sleep stages as determined by the R-K method (upper), those estimated by heart rate using (14) (middle) and body movement data (lower). The problem is how to clearly differentiate the upper sleep stages in Fig. 11 from the middle and lower biodata obtained by the pneumatic method. This problem is approached with regard to the following points.

P3-1) Clustering the continuous sleep stages into six categories.
P3-2) Compensation of sleep stage by the full order observer using the sleep transition state equation.
P3-3) Compensation for confusion between the Wake and REM sleep states using body movement data.

B. Clustering Sleep Stages Into Six Categories

Subproblem P3-1) is considered. We first decided on the six clusters of heart rate values corresponding to the six categories of sleep. The histogram of estimated continuous sleep stages $H_{\mathrm{is}}(k)$ is normalized as follows:

$$h_{\mathrm{is}}(k) = N \cdot \frac{H_{\mathrm{is}}(k)}{S_{\mathrm{h}}}. \tag{19}$$

From assumptions A1) and A2), the examinees experienced all sleep stages and heart rates corresponding to sleep stages are normally distributed. The normalized histogram in (19) is mathematically given by summation of the six normal distributed functions weighted by the average normalized length of each sleep stage $x_{\mathrm{i}}(\infty)$. The membership functions to cluster heart rates into the six categories are given by minimizing the following equation with respect to m_{i} and σ_{i}

$$\sum_{k=0}^{N} \left\{ h_{\mathrm{is}}(k) - \sum_{i=1}^{6} x_{\mathrm{i}}(\infty) \frac{1}{\sigma_i \sqrt{2\pi}} \times \exp\left(-\frac{(k-m_{\mathrm{i}})^2}{2\sigma_{\mathrm{i}}^2} \right) \right\}^2 \rightarrow \text{minimum}. \tag{20}$$

The coefficient $x_{\mathrm{i}}(\infty)$ are given in (4).

Minimization of (20) with respect to m_{i} and σ_{i} can be carried out using optimization algorithms. Here, we employed the Newton-Raphson method. Because minimization of (20) is nonlinear, the calculation may not converge if inappropriate initial values are used. As the initial values, we selected the normalized average values and standard deviations of the heart rate for each sleep stage, as follows:

$$\begin{aligned} m_6 &= 0.62 \pm 0.16, \quad (\sigma_6 = 0.15 \pm 0.08) \\ m_5 &= 0.65 \pm 0.10, \quad (\sigma_5 = 0.18 \pm 0.05) \\ m_4 &= 0.51 \pm 0.13, \quad (\sigma_4 = 0.13 \pm 0.10) \\ m_3 &= 0.44 \pm 0.08, \quad (\sigma_3 = 0.20 \pm 0.03) \\ m_2 &= 0.35 \pm 0.09, \quad (\sigma_2 = 0.17 \pm 0.06) \\ m_1 &= 0.33 \pm 0.14, \quad (\sigma_1 = 0.14 \pm 0.07) \end{aligned} \tag{21}$$

Furthermore, the search regions used in the Newton-Raphson method were restricted to the regions of standard deviation given by the symbol "±" in (21).

The exponential parts in the six normal functions correspond to the membership functions that show the degree of correlation of each heart rate with each sleep stage

$$y_i = \exp\left\{ -\frac{(k-m_i)^2}{2\sigma_i^2} \right\}, \quad i = 1, 2, \ldots, 6. \tag{22}$$

The value y_{i} ranging from 0 to 1 is the probability that continuous sleep stage k is associated with sleep stage i. For example, if $y_{\mathrm{i}} = 1$, continuous sleep stage k is correlated to sleep stage

i with a probability of 1. Thus, the continuous sleep stage $k(\tau)$ at each sampling interval is converted into six degrees of correlation to the six sleep stages. These degrees correspond to the state variables defined in (2).

C. Compensation by the Full Order Observer Using the Sleep Transition Equation

Subproblem P3-2) is now considered. Small fluctuations in sleep stages are compensated for and adjusted using average sleep stage transition data. Sleep stage transition data is summarized using the sleep stage transition (2) and (3) (shown in Fig. 3 as the Shannon diagram). Sleep stages logically estimated above are continuously and finely adjusted. The full order observer was employed for fine adjustment. For the state variable equation given by (2), we used probability y_i calculated by (22) and compensated using the information in (18) for the six measurements. Thus, sleep transition can be described as follows:

$$\begin{aligned} \boldsymbol{x}(t+1) &= \boldsymbol{A}\boldsymbol{x}(t) \\ \boldsymbol{y}(t) &= \boldsymbol{I}\boldsymbol{x}(t). \end{aligned} \tag{23}$$

Let μ_i (i $= 1, 2, \ldots 6$) be the characteristic roots of the observer and let the λ_i(i $= 1, 2, \ldots, 6$) be the characteristic roots of (2) (the eigen values of the matrix $\boldsymbol{A}$), and let

$$\boldsymbol{K} = \boldsymbol{T}\begin{bmatrix} \lambda_6 - \mu_6 & & \boldsymbol{0} \\ & \lambda_5 - \mu_5 & \\ & & \ddots \\ \boldsymbol{0} & & \lambda_1 - \mu_1 \end{bmatrix}\boldsymbol{T}^{-1}. \tag{24}$$

Then the full order observer to compensate for small fluctuations is given by the following:

$$\hat{\boldsymbol{x}}(k+1) = (\boldsymbol{A} - \boldsymbol{K}) \cdot \hat{\boldsymbol{x}}(k) + \boldsymbol{K} \cdot \boldsymbol{y}(t). \tag{25}$$

D. Compensation for Confusion of Wake and REM Stages

Subproblem P3-3) is now considered. From heart rate data only, the Wake and REM stages were sometimes difficult to differentiate. However, body movement data discriminates between these stages, based on (18). The Wake and REM stages are, thus, confirmed using body movement data.

E. Sleep Stage Estimation Algorithm

The sleep stage estimation algorithm is summarized as follows.

- Step 1) Obtain the continuous sleep stage from (14) and body movement data using (16).
- Step 2) Obtain the histogram of heart rate from (19) and obtain m_i and σ_i by minimizing (20).
- Step 3) Obtain the membership function from (22) and cluster heart rates into the six categories.
- Step 4) Compensate for small fluctuations using (25) based on sleep stage transition data.
- Step 5) Compensate for the Wake and REM stages using body movement data from (18).

In the above algorithm, steps 4) and 5) should be exchanged when both heart rate and body movement are measured. Steps 3) and 5) are logical judgments at each sampling point. Step 4) is a continuous filtering stage based on the average data of overnight sleep. Processing in Step 4) should, therefore, be applied to the results of steps 3) and 5) obtained in incremental times. Here, we selected these steps because in many investigations, only heart rate is measured. Steps 1)–4) can be used in such cases and Step 5 may be applied when body movement data is available. In the algorithm, Wake and REM are discriminated by body movements in the final step, in which body movement data is primarily used to identify the Wake and REM stages.

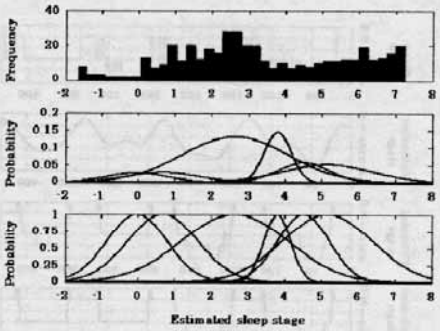

Fig. 12. Histogram of sleep depth, six decomposed normal distribution histogram fitted curves and membership functions to classify continuous sleep depth to one of six categories.

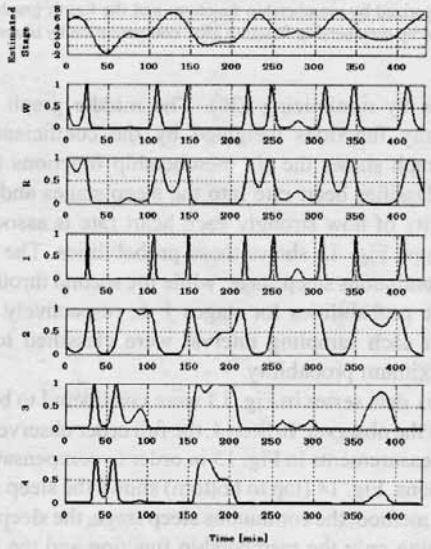

Fig. 13. Continuous sleep stage estimated using heart rate data and probability of association with discrete sleep stage.

F. Examples of Sleep Stage Clustering

Using the above algorithm, we will now estimate sleep stage in one sample case. Continuous sleep stage and body movement data are given in Fig. 11. In the following steps, the data shown in Fig. 11 will be used to provide an example of how this algorithm can be applied. In Step 2, the histogram of the continuous sleep stage must be obtained. The upper graph in Fig. 12 shows this histogram, and was estimated by summation of the six normal distributed probability density

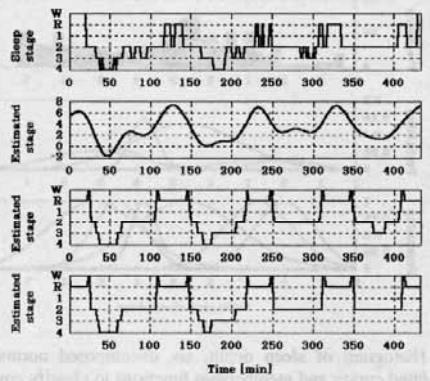

Fig. 14. Sleep stages. The first graph shows the sleep stages obtained by R-K method; The second graph shows continuous stage; the thired graph shows stage categorized by membership function; and the fourth graph shows stage categorized by membership function after compensation by observer.

functions by minimizing (20). The middle graph shows the six density functions weighted by the coefficients and the lower graph shows the six membership functions for Step 3, which classifies heart rate into the sleep stages and shows the probability of how strongly each heart rate is associated with sleep stage. Fig. 13 shows these probabilities. The upper part shows continuous sleep stage, while the second through seventh show the probabilities for stages 1–6, respectively. The sleep stages at each sampling interval were classified to the stage with maximum probability.

The six data series in Fig. 13 were considered to be measurements of the observer. In Step 4, the full order observer is applied to the measurements in Fig. 13 in order to compensate for small fluctuations. Fig. 14 (top to bottom) shows the sleep stage using the R-K method, the continuous sleep stage, the sleep stage classified using only the membership function and the sleep stage classified and compensated for by the observer from the first graph. The compensated stage by the observer is almost the same as that determined using the membership classifier, but between 360 and 400 min, a fluctuation is clearly eliminated. However, some confusion between the Wake and REM sleep stages remained.

In Step 5, the Wake and REM stages are clearly discriminated. Fig. 15 shows the final results processed using all five steps in the algorithm. Fig. 15(a) shows the final results for data set M-2 cited in the example of the initial trials. Fig. 15(b) shows a different test example; one of the most difficult cases because sleep transition was irregular and different from normal patterns. Fig. 15(c) shows another example Is-1; one showing a normal sleeping pattern.

The estimated sleep stage and the stages determined using the R-K method show subjectively similar results. We then investigated the accuracy of the sleep indexes obtained using the sleep stages estimated above.

VII. Evaluation of Estimated Sleep Stages

Here, we consider problem P4). We will prove the validity of the sleep stage estimation method by comparing estimates with the stages determined using the standard R-K method.

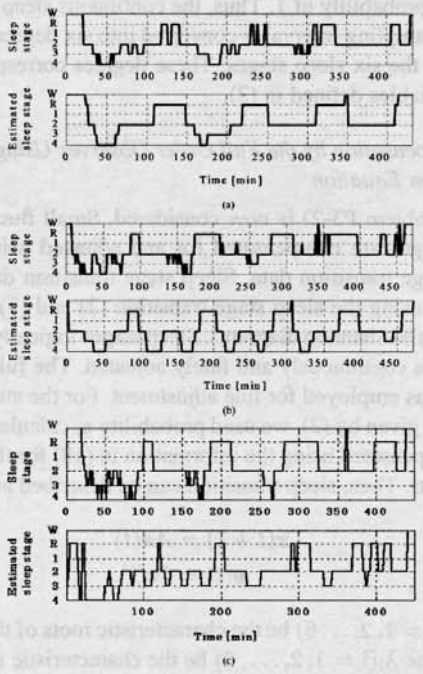

Fig. 15. Final sleep stage estimation using body movement data. (a) Examinee M-2. (b) Examinee N-10. (c) Examinee Is-1.

A. Direct Comparisons

The six sleep stages classified using the R-K method and those estimated by the proposed method were directly compared. Sleep is frequently categorized into three stages (Wakefulness, REM and Non-REM) by integrating the stages with nominal values 4, 3, 2, 1 into one Non-REM stage. Further, we directly compare sleep in the three categories. Table V shows the percentage of agreements at each sampling time. The results based on test data are listed in Table V(a) and those based on initial data are listed in Table V(b) for comparison. The first column (ALL) shows the agreement percentage over all six categories. Among the 12 test data sets, the best agreement was 57.6% and the worst agreement was 26.1%, while the average agreement was 42.8%. The result for initial data was 44.0%, which differs only slightly from the test data. The second column (Non-REM) shows the agreement for Non-REM sleep. The best agreement for the test data was 95.8%, and the average agreement was 82.6%. The result for initial data was 83.6%, which again is only slightly different. The third column (Wake) shows the agreement for the Wake stage. Among the 12 test trials, there were cases of 100% agreement. The average rate was for the test data 70.5% and the standard deviation was 35.8%. The result for initial data was 44.0%, which is lower than the results for test data. The forth column (REM) shows the agreement for the REM sleep stage. The average agreement for the test data was 38.3% with a standard deviation of 20.3%. The result for initial data was 47.5%. The agreement for the Wake and REM stages include fluctuations that are due to difficulties in differentiating between the Wake and REM sleep stages. Furthermore, the wake times in these experiments were short.

TABLE V
AGREEMENT OF SLEEP STAGE ESTIMATION BETWEEN PROPOSED METHOD AND R-K METHOD. (a) FOR THE TEST DATA. (b) FOR THE INITIAL DATA

Samples No.	Agreement [%]			
	ALL	Non-REM	Wake	REM
N-7	40.0	89.4	100.0	41.7
N-8	33.6	70.1	100.0	40.5
N-9	26.1	81.3	5.9	0.0
N-10	48.3	83.6	50.3	80.6
I-2	37.2	53.7	88.6	20.5
K-3	38.7	81.1	100.0	31.7
Is-1	56.0	92.9	92.3	55.1
Is-2	43.4	83.3	100.0	57.6
Is-3	53.9	84.7	20.3	32.4
Sk-1	35.9	86.7	60.0	27.5
Sk-2	43.3	88.4	28.6	43.7
Og-1	57.6	95.8	100.0	28.4
Mean	42.8	82.6	70.5	38.3
S. D.	9.6	11.2	35.8	20.3

(a)

Samples No.	Agreement [%]			
	ALL	Non-REM	Wake	REM
N-1	34.6	88.0	28.6	44.0
N-2	43.1	85.9	20.9	51.9
N-3	52.7	84.7	9.1	82.1
N-4	52.5	84.8	16.7	72.7
N-5	33.3	69.5	38.5	60.6
N-6	44.8	82.4	25.0	70.2
M-1	43.3	86.1	100.0	37.1
M-2	60.4	97.4	50.0	44.3
M-3	50.7	92.5	43.1	33.8
M-4	34.8	96.4	17.1	34.9
M-5	62.2	90.6	100.0	66.7
I-1	27.0	57.0	32.7	0.0
K-1	32.8	71.8	62.5	47.4
K-2	40.4	63.4	92.5	30.0
S-1	46.9	93.3	22.2	37.0
Mean	44.0	83.6	44.0	47.5
S. D.	10.4	12.5	31.0	20.8

(b)

B. Comparisons Between Sleep Indexes

Sleep indexes to evaluate the sleep quality and the skills of the sleep analyst are as follows.

1) sleep latency (SL);
2) bed out latency (BOL);
3) sleep period time (SPT);
4) total sleep time (TST);
5) sleep effective index (SEI);
6) proportion of sleep stages (PSS).

Detail definitions of the indexes are summarized in the Appendix.

Table VI(a) shows the disagreements in the test data in the above indexes for the estimates of sleep stage using the proposed method and the sleep stages determined by the standard method. Table VI(b) shows the disagreements in the initial data for comparison. Among the indexes, SL and BOL included large differences. This is due to the time interval of SL and BOL being very short. The maximum difference in the trials is just several minutes when it is converted into time. The average difference in SPT in the test data was 2.9% with a standard deviation of 2.1%. These are relatively small. The estimated sleep period times are accurate and consistent. The total sleep time TST is defined by subtracting SL and BOL from the total measurement time. The total measurement times were relatively long. Thus, the relative differences in the TST are small. Furthermore, the SEI is the percentage of TST for the total measurement time and percentage differences are same with those of TST. The average difference by the test trials was 8.4% with a standard deviation of 11.8%. The SEI is frequently used to evaluate sleep quality and, thus, the fact that the index can be accurately estimated by the proposed method demonstrates the effectiveness of this method for estimating sleep quality.

Disagreements in the PSS, total times in each sleep stage as a percentage of total sleep time are shown in the right column of Table VI. From Wake to Non-REM sleep stage 4, differences (standard deviations) by the test trials were 6.7% (7.6%), 9.4% (6.0%), 1.4% (1.8%), 7.4% (8.0%), 6.5% (3.8%), and 7.7% (6.7%), respectively. These are all within 10% and are relatively small. The PSS is also an important index for evaluating sleep itself. The differences in average differences in the test and initial data are minimal.

C. General Comments on Differences in Estimated Stage and Sleep Indexes

From the results above, the proposed sleep stage estimation method included large differences in estimating sleep transition in short time intervals such as for the SL and BOL. However, sleep indexes such as SPT, TST, SEI, and PSS, which are defined by sleep stages over the whole night, are estimated accurately with disagreements of less than 10%. Evaluation of the accuracy might be different depending upon application. Based on the above results, this method is not effective for classifying sleep stages in a short period but is effective in classifying sleep stages over the whole night. The R-K method, which is the international standard, requires electrodes to be stuck to the scalp, eyelids and jaw. This leads to substantial physical and psychological stress in examinees, which certainly influences sleep. The question of how accurately sleep stages can be estimated using data measured under such stress is not known. On the other hand, the proposed sleep stage estimation method described here includes overall different classifications of 10% or less and is based on biodata that is collected through noninvasive and unrestrained means. The reduction in stress induction is more conducive to accurate measurement of biodata and can compensate for disagreement rates of 10%. By being less invasive and less stressful than the R-K method, our method's sleep stage estimations may be more representative of the patient's actual sleep behavior. The existence of the terminology, such as "first night effect," in the application of polygraph-based approaches indicates that these approaches strongly influence sleep itself, whereas the proposed pneumatic method does not.

The proposed method is sufficiently accurate to screen sleeping at a patient's home.

VIII. DISCUSSION

A. Limitations and Generalization

The examinees selected to determine the parameters in the sleep estimation algorithm were all young adult males. Thus, the algorithm in this paper is considered most applicable to such individuals. However the proposed sleep estimation algorithm is composed of 1) sleep trend estimation by heart rate data in the

TABLE VI
DISAGREEMENT IN SLEEP INDICES AND OVERALL DIFFERENT CLASSIFICATION OF SLEEP STAGE [%]. (a) FOR THE TEST DATA. (b) FOR THE INITIAL DATA

Samples No.	SL	BOL	SPT	TST	SEI	PSS					
						6	5	4	3	2	1
N-7	75.0	0.0	1.4	1.4	1.4	1.3	15.8	1.1	16.3	7.1	10.0
N-8	77.8	66.7	1.9	4.7	4.7	4.4	3.6	0.2	4.2	5.7	2.5
N-9	71.4	75.0	1.7	5.2	5.2	5.1	22.3	5.7	0.4	1.9	21.5
N-10	75.0	91.7	3.8	4.5	4.5	4.2	6.6	2.3	6.4	8.7	10.8
I-2	45.5	94.1	2.3	43.7	43.7	27.8	4.1	0.2	13.4	7.8	2.7
K-3	93.8	90.0	7.9	12.4	12.4	11.0	12.3	1.5	5.2	9.5	2.8
Is-1	8.3	87.5	1.3	3.2	3.2	3.0	3.4	0.2	0.9	11.8	12.4
Is-2	90.5	50.0	4.8	5.5	5.5	5.2	4.3	0.0	1.1	8.2	10.2
Is-3	69.2	37.5	5.4	13.6	13.6	13	10.4	0.7	6.3	11.1	2.8
Sk-1	84.6	100.0	2.2	2.2	2.2	2.1	13.5	0.5	27.7	1.2	15.6
Sk-2	0.0	85.7	1.2	3.4	3.4	3.2	4.4	0.0	2.8	3.0	1.4
Og-1	60.0	12.5	0.9	0.9	0.9	0.9	11.5	4.3	4.5	1.5	0.2
Mean	62.6	94.0	2.9	8.4	8.4	6.7	9.4	1.4	7.4	6.5	7.7
S. D.	30.2	94.2	2.1	11.8	11.8	7.6	6.0	1.8	8.0	3.8	6.7

(a)

Samples No.	SL	BOL	SPT	TST	SEI	PSS					
						6	5	4	3	2	1
N-1	33.3	83.3	1.6	0.3	0.3	0.3	4.9	0.5	13.1	10.0	17.9
N-2	83.3	25.0	1.9	25.7	25.7	23.6	14.9	0.4	3.1	6.4	1.2
N-3	75.0	90.9	3.1	0.8	0.8	0.8	8.1	0.4	0.2	2.1	5.5
N-4	66.7	80.0	1.6	4.0	4.0	3.7	4.3	0.8	7.3	5.7	7.3
N-5	75.0	87.5	2.8	10.3	10.3	9.1	11.3	0.4	1.2	3.3	17.9
N-6	300.0	80.0	1.3	1.3	1.1	1.0	9.7	1.9	15.9	2.9	2.5
M-1	80.0	96.2	8.3	9.6	9.6	8.8	17.3	1.2	4.6	11.8	6.7
M-2	14.3	375.0	4.6	5.6	5.4	5.1	12.5	0.0	11.9	6.2	0.5
M-3	90.9	20.0	2.4	1.9	1.9	1.6	17.1	1.3	13.5	13.5	6.9
M-4	41.7	80.0	1.8	4.3	4.3	4.1	27.5	5.9	26.9	3.5	4.7
M-5	72.7	91.7	7.3	7.3	7.3	6.7	3.0	2.2	2.5	13.9	12.9
I-1	27.0	0.0	2.3	6.7	6.7	4.8	4.1	0.0	3.0	3.9	1.5
K-1	59.1	45.5	3.5	19.0	19.0	15.1	8.3	0.7	1.3	12.5	12.4
K-2	50.5	80.0	10.8	16.9	16.9	11.8	10.9	1.4	9.1	2.1	10.2
S-1	250.0	85.7	0.9	1.7	1.7	1.6	9.9	4.4	18.5	7.4	3.9
Mean	88.0	88.1	3.6	7.7	7.6	6.5	10.9	1.4	8.8	7.0	7.5
S. D.	79.7	84.9	2.9	7.5	7.5	6.4	6.4	1.7	7.7	4.3	5.7

(b)

Normal sale numeral in PSS corresponds to the following stage, 6:Wake, 5:REM, 4:Non-REM1, 3:Non-REM2, 2:Non-REM3, 1:Non-REM1

low-frequency range, given by (9) and (10), 2) rhythm estimation by heart rate data in the middle frequency range, given by (11), 3) estimation of REM interval, 4) compensation or correction of sleep estimated by heart rate using body movement data, given by (17) or (18), 5) compensation of sleep stage probability by the observer based on the sleep transition equation, and 6) classification of sleep stage by the self-learning membership function. This structure of the sleep classifier is general. Only 6 parameters, in (9), (10), (11), and (18), depend on the sleep characteristics of the examinee. The coefficients in A matrix are less sensitive to sleep stage. The observer based on the matrix plays the minor role of simple smoothing. The parameters in (21) give the ranges to restrict the parameters in learning by the Newton-Raphson method. These are not essential. Based on the same structure, the proper sleep classifier for different classes of examinee can be realized by tuning these six parameters using data measured in a variety of subject samples. Some of these parameters may be obtained by converting previously reported data. In assumption A1), we cited that the examinee experiences the five sleep stages and Wake. The number of sleep categories is also one parameter. Thus, if sample data for a class of examinees with less than five categories are available, the sleep classifier for this class of sleepers is realizable by tuning the above parameters.

B. Comparisons With the Conventional Methods

Here we compare the proposed method with conventional methods other than the R-K method. A previous study [3] attempted to clarify the relationship between heart rate and sleep stage. However, the data given in that study is qualitative and is not applicable to classification of sleep stage. Another report [6] describes the relationship between gross body movement and sleep stage. However, the variances in body movement reported in the paper are too large to estimate sleep stage. Another method [7] based on a static charge sensitive bed is noninvasive, but it classifies sleep stage into two categories "active" and "quiet." An approach [8] via an artificial neural network, which determines sleep stage from body movement as measured by an infrared sensor, classifies three stages including Wake. The results were not compared and evaluated. A method [16] using cardiorespiratory data classifies infant sleep into three stages. This method used the ECG and is, thus, invasive. However, the data for infants reported in that study may be used to tune the parameters in the present sleep classifier for application to infants.

In comparison with the studies cited above, the proposed sleep estimation algorithm has the advantage of classifying sleep into six stages, and the structure of the classifier is explicit

and, thus, if data from a certain class of patients are given, the estimation algorithm can easily be applied to that class of examinees.

IX. Conclusion

This paper describes a novel estimation method for classifying sleep into six categories. This method uses heart rate and body movement data measured noninvasively by the pneumatic method for sleep stage estimation rather than using a polygraph, which can lead to physical and psychological stress.

In order to develop this estimation method and to evaluate the method, we carried out clinical trials over 27 nights to obtain sleep data and to compare data obtained noninvasively to that collected by conventional methods.

Analyzes of sleep itself and the relationships between biosignals and sleep revealed the following.

1) Overnight sleep behavior was mathematically modeled using a sleep stage transition equation in the form of state variable equation.

2) Under the assumption that sleep stage, classified into six nominal stages, is linearly proportional to sleep depth, sleep stage (depth) is given by linear functions of heart rate. Experimental results show a good correlation between heart rate in the middle frequency range and sleep stage (depth), indicating that this assumption is confirmed by actual quantitative data.

3) In the relationship described above, Wake and REM sleep stages are sometimes confused. To discriminate between these, body movement data, measured by the same pneumatic sensor, was effectively used.

While developing the estimation method, we determined the following.

4) Sleep with given heart rate and body movement levels can be categorized into one of six stages. An automatic sleep clustering method is presented.

5) Sleep indexes obtained from the estimated stage data using the proposed method is not always accurate with short-term sleep indexes, such as SLL and BOL, but are accurate in for overall sleep events. Therefore, SPT, TST, SEI, and PSS were estimated with disagreements of less than 10%.

The proposed method is effective to overcome disagreements, particularly when we consider the stress of the examinees and the cost of measurements using the conventional R-K method. The present method is effective for screening patients before precise investigation using a polygraph in the hospital. The proposed sleep estimation algorithm still includes disagreements. However, the pneumatic method is able to measure heartbeat, respiration, body movement, snoring, and coughing, all of which are strongly related to sleep. Full use of these biomeasurements will yield more accurate sleep stage estimates. Furthermore, the pneumatic measurement method is not only applicable to sleep medicine but also to various medical fields, including ventilatory analysis, which is our future research theme.

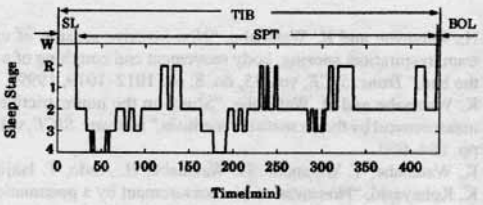

Fig. 16. A pattern of sleep stage transition in overnight and sleep indexes.

Appendix I
Sleep Indexes

Fig. 16 shows a typical pattern of sleep stage transition in overnight sleep. The sleep indexes are defined on the pattern as follows.

- *Time In Bed (TIB):* the total time when a person is in bed;
- *Sleep Latency (SL):* the time from awake to sleep in bed;
- *Bed Out Latency (BOL):* the time from awake to getting out of the bed;
- *Sleep Period Time (SPT):* total sleep period given by SPT = TIB−SL−BOL;
- *Total Sleep Time (TST):* total sleep time given by TST = TIB − total awaking times;
- *Sleep Effective Index (SEI):* percentage of TST for TIB given by SEI = 100 (TST/TIB);
- *Proportion of Sleep Stages (PSS):* percentage of total sleep time of each stage for TIB.

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