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（新任者の論文）

Modeling of Sleep States and Estimation of Sleep Stages

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ABSTRACT：The judgment standards of R-K method include ambiguities and are thus compensated by subjective interpretations of sleep stage scorers. This paper presents a novel method to compensate uncertainties in judgments by the subjective interpretations by the sleep model estimation approach and by describing the judgments in probabilistic terms. A full-order Luenberger observer based on the two sleep models with no body movement and with body movement was designed. Sleep stages judged by three different scorers were re-judged by the observer. The two sleep models were stochastically estimated from bio-signals from 15 subjects and the re-judged scores by the observer were evaluated by the data from 5 subjects. The average values of kappa statistics, which show the degree of agreement, were 0.85, 0.89 and 0.81, respectively, for the original sleep stages. Because the new method provides probabilities on how surely the sleep belongs to each sleep stage, we were able to determine the most, second most and third most probable sleep stage. The kappa statistics between the most probable sleep stages were improved to 0.91, 0.92 and 0.85, respectively. Those of sleep stages determined from the most and second most probable were 0.94, 0.96 and 0.90 and those from the most, second most and third most probable were 0.95, 0.97 and 0.92. The sleep stages estimated by the observer are expressed by probabilistic manner which are more reasonable tin expression than those given by deterministic manner. The expression could compensate the uncertainties in each judgments and thus were more accurate than the direct judgments.

Keywords：sleep stage, R-K method, sleep stage transition probability matrix, sleep stage state variable equation

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1．Introduction

Sleep plays a vital role in recovery from mental and physical fatigue [1, 2]. Its importance is reflected in Japan's national health improvement projects involving sleep [3] and many organizations are researching non-invasive techniques for measuring sleep conditions.

Sleep is categorized into six different stages using the R-K method, in which a nominal scale is applied to brain waves, eye movement and myoelectricity of the submental muscles [4] at time intervals divided independently for all-night sleep. The stages are AWAKE, REM-Sleep and Non-REM-sleep 1, 2, 3 and 4. In using the R-K method, however, some of the rules include ambiguities and the scorers must subjectively interpret what happens during the sleep from the bio-signals above. As a result, different scorers might judge different sleep stages for the same data. A method called kappa statistics is used to evaluate the reliability of judgments [5].

We propose that having another reference, a sleep transition model that shows the all-night sleeping trend characteristics and applying it to compensate the judgments given by scorers, would improve the reliability of judgment. There have been various reports on using a sleep model [6, 7], but our model and method are different in that we use a new sleep transition model and apply a full-order Luenberger observer to the model. Here, we cite the sleep stage transition equation estimated from clinical data and use it as a state variable equation for designing a full-order Luenberger observer. The measurements used for the observer are the temporal changes in sleep stages judged by a scorer or automatic sleep stage estimator. The state variables estimated by the observer are probabilities of how surely the sleep can be categorized into each sleep stage. Here, we describe how to build the sleep stage transition probability matrix, sleep stage transition equation and optimal observer.

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2. Objective

This paper is aimed at describing a novel scheme to compensate uncertainties of sleep stage judged by sleep medical specialists. The uncertainties are due to the ambiguities of the standards of the R-K method and fluctuations of sleep characteristics in the judgment time interval. In spite of such the uncertainties, the conventional expression of the sleep stage was deterministic, which is not reasonable. Here we present a method to express the sleep stage by probabilities on how surely the sleep belongs to each sleep stage. Further, we present a novel method to compensate the fluctuations in judgments by comparing the judged sleep state with the normal sleep transition model. The state of sleep and/or awake when body movement occurs and the state of sleep when no body movement occurs are different, and so we prepare two different transition models. An approach based on the state estimation theory is newly introduced to realize the algorithm for the compensation. Here we describe a new methodology of scoring the sleep stages based on probabilistic terms instead of scoring in a deterministic manner to compensate uncertainties in judgments. The validity of the method is examined using only young subjects as examples.

3. Method

3. 1 Formulation process

First, in building the sleep stage transition model, numbers are assigned to the sleep stages as follows: 1 for WAKE, 2 for REM, 3 for Non-REM1, 4 for Non-REM2, 5 for Non-REM3 and 6 for Non-REM4. The number is nominal and is used instead of the sleep category in mathematical representations.

In the sleep stage transition, body movement plays the key functions [2, 8] as follows:

(F1) Non-REM1 sleep stage frequently occurs after REM, Non-REM3 and Non-REM4, triggered by a body movement.

(F2) The sleep stage frequently switches just after body movement when the stage is Non-REM3 or Non-REM4.

(F3) Body movement occurs just before and/or after REM.

(F4) AWAKE stage frequently occurs after a body movement.

Let $\boldsymbol{A}$ be the probability transition matrix. The element in matrix $\boldsymbol{A}$ can be determined statistically from clinical data. Body movement plays a key function in switching from one sleep stages to another as described above; here, we obtain two different probabilistic state transition matrices. One is when body movement is included and the other is when no body movement is included. Let $E_{j,i}$ be an event in which the sleep stage switches from i stage to j stage for i, j = 6, 5, 4, 3, 2, 1, let E_j be an event in which the sleep stage switches to j stage, let E_b and E_n be events in which body movement occurs and no body movement occurs, respectively, and let $P(E_{j,i})$, $P(E_j)$, and $P(E_b)$ be the probability of these events occurring, respectively.

The element $a_{7-j,\,7-i}$, which is the probability that sleep in i stage at k discrete time switches to j stage at k+1 discrete time, is given by conditional probability as follows:

$$a_{7-j,7-i} = \begin{cases} P(E_{j,i} \mid E_j, E_{\mathrm{b}}) & \text{(body movement occurs)} \\ P(E_{j,i} \mid E_j, E_{\mathrm{n}}) & \text{(no body movement occurs)} \end{cases} \qquad (1)$$

where $\sum_{i=1}^{6} a_{7-j,7-i} = 1$ must be satisfied.

3. 2 Sleep stage state variable equation

Here, we describe the sleep stage state variable equation. Let T_{ib} be the total time that the subject is in bed, let k (= 1, 2, 3, … T_{ib}) be a discrete time of every one minute with the sleep stage judged within that time, and let $x_6(k)$, $x_5(k)$, $x_4(k)$, $x_3(k)$, $x_2(k)$ and $x_1(k)$ be the probabilities of how surely the sleep stages belong to 6, 5, 4, 3, 2, and 1, respectively.

Furthermore, let the vector $\boldsymbol{x}(k)=[x_6(k), x_5(k), x_4(k), x_3(k), x_2(k), x_1(k)]^T$ be the state vector and the vector $\boldsymbol{y}(k)=[y_6(k), y_5(k), y_4(k), y_3(k), y_2(k), y_1(k)]^T$ be the sleep stage judged by a certain method such as the R-K method. $\boldsymbol{y}(k)$ is deterministically given corresponding to the judgment of sleep stage as follows:

$$
\boldsymbol{y}(k)=\begin{cases}
[1\ \ 0\ \ 0\ \ 0\ \ 0\ \ 0]^T & \text{(Wake)} \\
[0\ \ 1\ \ 0\ \ 0\ \ 0\ \ 0]^T & \text{(REM)} \\
[0\ \ 0\ \ 1\ \ 0\ \ 0\ \ 0]^T & \text{(Non-REM1)} \\
[0\ \ 0\ \ 0\ \ 1\ \ 0\ \ 0]^T & \text{(Non-REM2)} \\
[0\ \ 0\ \ 0\ \ 0\ \ 1\ \ 0]^T & \text{(Non-REM3)} \\
[0\ \ 0\ \ 0\ \ 0\ \ 0\ \ 1]^T \quad \textit{when} & \text{(Non-REM4)}
\end{cases}
$$

Then, the sleep stage state variable equation and measurement equation are given as follows:

$$\boldsymbol{x}(k+1)=\boldsymbol{A}\boldsymbol{x}(k) \qquad (2)$$

$$\boldsymbol{y}(k)=\boldsymbol{I}\boldsymbol{x}(k) \qquad (3)$$

$\boldsymbol{I}$ is an identity matrix with dimensions (6×6) in Eq. (3). The elements of state transition vector directly correspond to the sleep stage judgments (measurements). Thus, $\boldsymbol{y}(k)=\boldsymbol{x}(k)=\boldsymbol{I}\boldsymbol{x}(k)$. Just after bed-in and just before bed-out, the subject must be in the AWAKE stage; thus, $\boldsymbol{x}(0)=\boldsymbol{x}(T_{ib})=[1\ 0\ 0\ 0\ 0\ 0]^T$

Figure 1 shows a Shannon diagram of the sleep state transition equation and the coefficient $a_{7-j,\,7-i}$ is the (7-j, 7-i) element in matrix $\boldsymbol{A}$. The element $a_{7-j,\,7-i}$ has a different value for the body movement condition, as described in Eq. (1).

3. 3 Observer to estimate sleep stage appearance probability

Here, we consider an observer to estimate the probability of how surely the sleep belongs to each sleep stage based on the state variable equation. The observer is a state estimator for an object whose characteristics are given by an a priori mathematical model described as the state variable equations [9] Eq. (2) and Eq. (3). It estimates all state variables from measurements corrupted by noise. The state variable in Eq. (2) is the probability, thus we estimate the probability from the sleep judgments (measurements) which may include errors.

Let $\hat{\boldsymbol{x}}(k)$ be the estimate of $\boldsymbol{x}(k)$ and let $\boldsymbol{K}$ be the gain matrix of the observer so that all absolute eigenvalues of matrix $\boldsymbol{A}$-$\boldsymbol{KI}$ i.e., the characteristic roots of the observer are less than 1, then the following state variable equation is a full-order Luenberger observer for Eqs. (2) and (3):

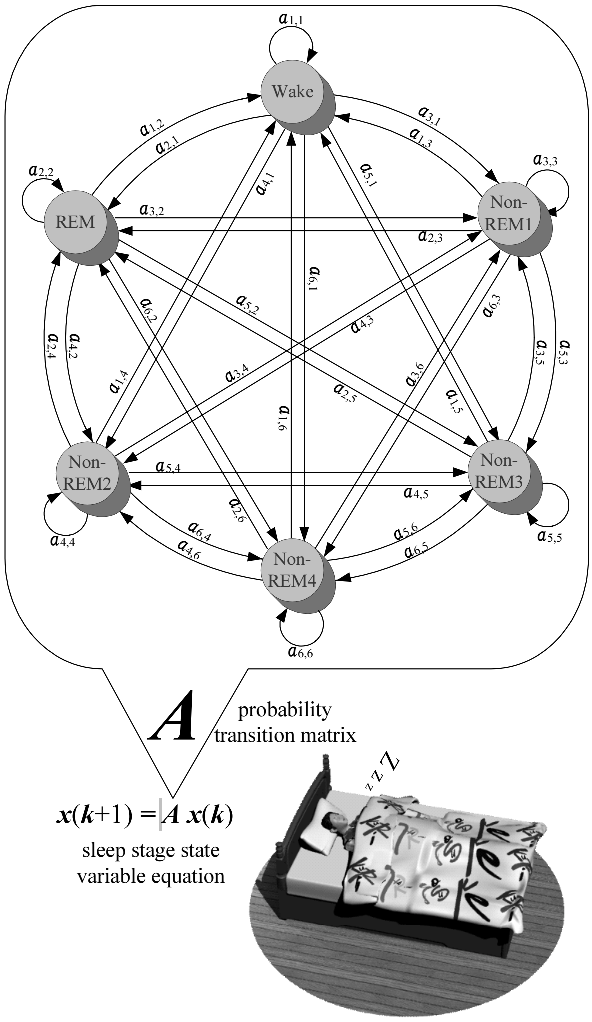


Fig. 1 Shannon diagram of sleep stage transition

$$\hat{\boldsymbol{x}}(k+1)=(\boldsymbol{A}-\boldsymbol{KI})\hat{\boldsymbol{x}}(k)+\boldsymbol{K}\boldsymbol{y}(k) \qquad (4)$$

If one of the absolute values of eigenvalues of matrix $\boldsymbol{A}$-$\boldsymbol{KI}$ is greater than 1, the observer equation Eq. (4) diverges, whereas if the absolute values of all eigenvalues are less than 1, it converges and $\hat{\boldsymbol{x}}(k)$ tends to $\boldsymbol{x}(k)$ from the theory of observer [9].

Eigenvalues λ_1- λ_6 of matrix $\boldsymbol{A}$-$\boldsymbol{KI}$ are optimally determined by genetic algorithm [10]. Genetic algorithms are one of the search techniques used in computing to find exact or approximate solutions to optimization and search problems. A degree of adaptation index shows the degree of how the process approaches the exact or approximate solutions. As an index, we selected the coincidence rate of the measurements $\boldsymbol{y}(k)$ and the most probable state in $\hat{\boldsymbol{x}}(k)$ estimated by the observer for the entire measurement time for the test subjects.

4. Results

In order to estimate a normal sleep stage transition equation, we employed 10 normal sleep subjects, average age 22.2 years old, and we conducted clinical tests over a period of 20 nights. Figure 2 shows the sleep conditions.

We obtained informed consent from each subject. Sleep stage was evaluated by the international 10/20 method [8] and so EEG at points C4-A1 and C3-A2 of the head, eye movement and EMG at submental muscles were measured. Electrocardiograms were measured using the I-induction correction method [8]. The sampling interval of the data acquisitions was 0.01 s. For the measurements we employed a polygraph (SANEI FIT 2500). To follow the R-K procedure, we let scorers judge two times for every one minute i.e., every 30 s, and let them make a final single judgment from two judgments for every minute. Body movements can be detected by EMG artifacts occurring in the measurements of brain wave and eye movements. The body movements can be classified into small body movements which continue for less than 0.5 s, and large body movements which continue for more than 0.5s [8]. We detected body movements using this detection procedure. The method was verified by comparison with the pneumatic body movement detection method [11]. Sleep stages were judged by three different scorers.

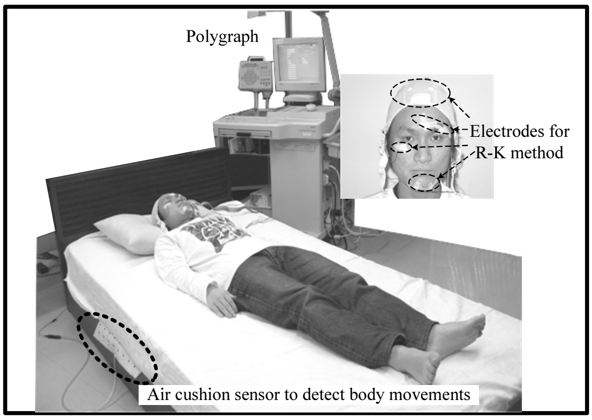


Fig. 2 Measurement system

4.1 Estimation of sleep stage transition equation

First, we estimated the transition matrix $\boldsymbol{A}$. Data from the 20 nights was randomly divided into two groups: G1 consisting of 15 nights' data, and G2 consisting of the remaining 5 nights' data. The G1 data was used to estimate the transition matrices and the G2 data was used to evaluate the models. The occurrence of body movement was detected from artifacts in the brainwave measurements. The transition matrix was calculated from the stages judged by Scorer 1 using the R-K method. Transition matrices when body movement occurred and when no body movement occurred were obtained as follows:

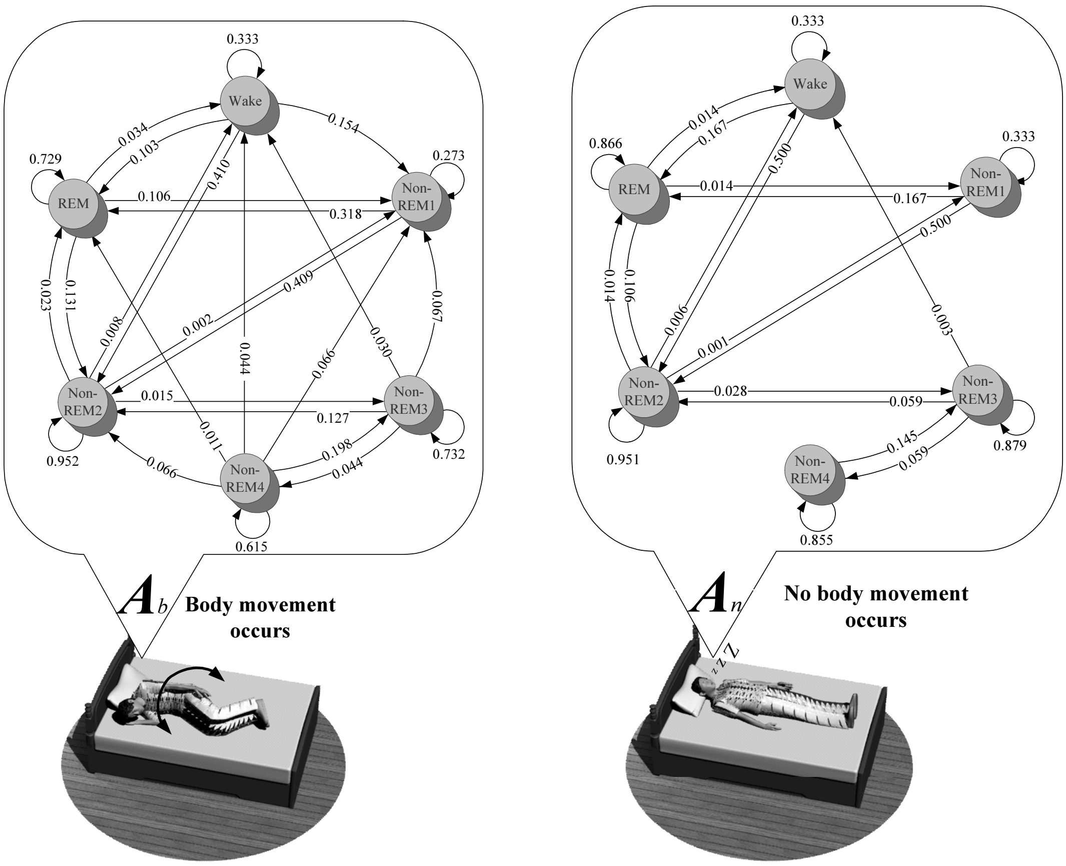
When body movement occurred:

$$\boldsymbol{A}_{\mathrm{b}} = \begin{bmatrix} 0.333 & 0.034 & 0.000 & 0.008 & 0.030 & 0.044 \\ 0.103 & 0.729 & 0.318 & 0.023 & 0.000 & 0.011 \\ 0.154 & 0.106 & 0.273 & 0.002 & 0.067 & 0.066 \\ 0.410 & 0.131 & 0.409 & 0.952 & 0.127 & 0.066 \\ 0.000 & 0.000 & 0.000 & 0.015 & 0.732 & 0.198 \\ 0.000 & 0.000 & 0.000 & 0.000 & 0.044 & 0.615 \end{bmatrix} \tag{5}$$

When no body movement occurred:

$$\boldsymbol{A}_{\mathrm{n}} = \begin{bmatrix} 0.333 & 0.014 & 0.000 & 0.006 & 0.003 & 0.000 \\ 0.167 & 0.866 & 0.167 & 0.014 & 0.000 & 0.000 \\ 0.000 & 0.014 & 0.333 & 0.001 & 0.000 & 0.000 \\ 0.500 & 0.106 & 0.500 & 0.951 & 0.059 & 0.000 \\ 0.000 & 0.000 & 0.000 & 0.028 & 0.879 & 0.145 \\ 0.000 & 0.000 & 0.000 & 0.000 & 0.059 & 0.855 \end{bmatrix} \tag{6}$$

Figure 3 shows the Shannon diagram of the sleep transition equation.



(a) **Body movement occurs** **(b) No body movement occurs**

Fig. 3 Shannon diagram of the matrix *A*

When no body movement occurred, the probability of transition was zero for "WAKE→Non-REM1", "Non-REM3→Non-REM1",
"Non-REM4→AWAKE", "Non-REM4→REM",
"Non-REM4→Non-REM1"and
"Non-REM4→Non-REM2".
When body movement occurred, the probability increased and thus sleep stage transition occurred frequently. Especially, the probability of switching from Non-REM4 to a shallower stage is high. Here, we analyze whether the Shannon diagram in Figure 3 or the transition matrices in Eqs. (5) and (6) satisfy the sleep feature (F1) – (F4) in conjunction with body movement as described in Section 3. Table 1 shows the value of elements $a_{3,2}$, $a_{3,5}$, $a_{3,6}$ in $\boldsymbol{A}_b$ and $\boldsymbol{A}_n$.

Table 1 Body movement (F1)

Matrix element	Transition matrix	
	$\boldsymbol{A}_b$	$\boldsymbol{A}_n$
$a_{3,2}$ (REM→Non-REM1)	0.106	0.014
$a_{3,5}$ (Non-REM3→NonREM1)	0.067	0.000
$a_{3,6}$ (Non-REM4→Non-REM1)	0.066	0.000

The elements in Eq. (5) when body movement occurred are greater than those in Eq. (6) when no body movement occurred, with a 5% significance level. Thus, (F1) "Non-REM1 sleep stage frequently occurs after REM, Non-REM3 and Non-REM4, triggered by body movement" is shown. Table 2 shows the values of elements $a_{5,5}$, $a_{6,6}$.

Table 2 Body movement (F2)

Matrix element	Transition matrix	
	$\boldsymbol{A}_b$	$\boldsymbol{A}_n$
$a_{5,5}$ (Non-REM3→Non-REM3)	0.732	0.879
$a_{6,6}$ (Non-REM4→Non-REM4)	0.615	0.855

These are the probabilities of maintaining the same sleep stage. Those in Eq. (5) are less than those in Eq. (6), with a 5% significance level. Thus, (F2) "Sleep stage transition frequently switches just after body movement when the stage is Non-REM3 or Non-REM4" is shown.

Table 3 shows the values of elements $a_{2,1}$– $a_{2,6}$, except $a_{2,2}$, and $a_{1,2}$– $a_{6,2}$.

Table 3　Body movement (F3)

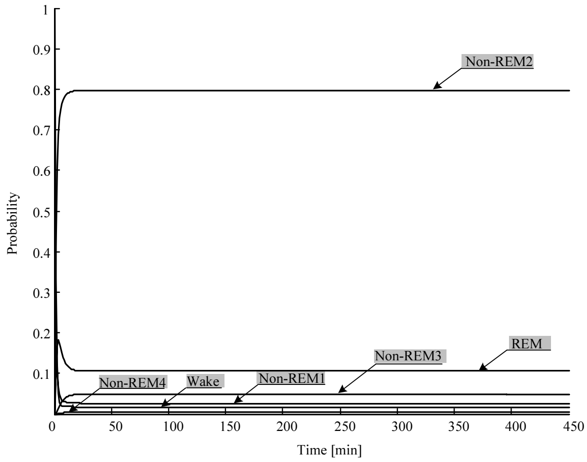
Matrix element	Transition matrix	
	$\boldsymbol{A}_b$	$\boldsymbol{A}_n$
$a_{2,1}$ (Wake →REM)	0.103	0.167
$a_{2,3}$ (Non-REM1→REM)	0.318	0.167
$a_{2,4}$ (Non-R2→REM)	0.023	0.014
$a_{2,5}$ (Non-R3→REM)	0.000	0.000
$a_{2,6}$ (Non-R4→REM)	0.011	0.000
$a_{1,2}$ (REM →Wake)	0.034	0.014
$a_{3,2}$ (REM→Non-REM1)	0.106	0.014
$a_{4,2}$ (REM→Non-REM2)	0.131	0.106
$a_{5,2}$ (REM→Non-REM3)	0.000	0.000
$a_{6,2}$ (REM→Non-REM4)	0.000	0.000

The elements $a_{2,3}$, $a_{2,4}$ in Eq. (5) are greater than those in Eq. (6), with a 5% significance level. This means that just after body movement in Non-REM1 and Non-REM2 sleep, there is a tendency to switch to REM. The elements $a_{1,2}$, $a_{3,2}$, $a_{4,2}$ in Eq. (5) are greater than those in Eq. (6), with a 5% significance level. This means that just after body movement in REM sleep, there is a tendency to switch to Non-REM1 or Non-REM2. Thus, (F3) "Body movement occurs just before and/or after REM" is shown. Table 4 shows the values of elements $a_{1,2}$, $a_{1,5}$, $a_{1,6}$.

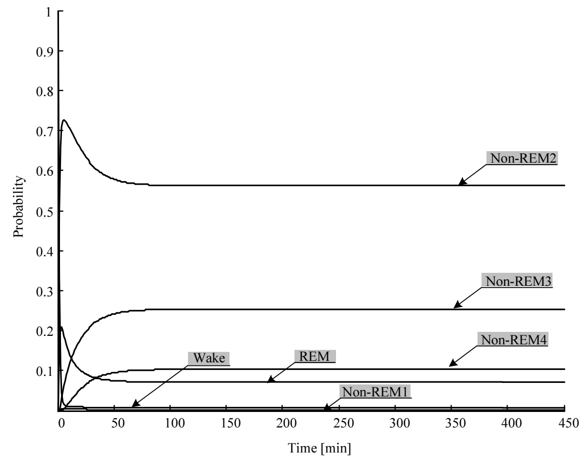
Table 4　Body movement (F4)

Matrix element	Transition matrix	
	$\boldsymbol{A}_b$	$\boldsymbol{A}_n$
$a_{1,2}$ (REM →Wake)	0.034	0.014
$a_{1,3}$ (Non-REM1→Wake)	0.000	0.000
$a_{1,4}$ (Non-REM2→Wake)	0.008	0.006
$a_{1,5}$ (Non-REM3→Wake)	0.030	0.003
$a_{1,6}$ (Non-REM4→Wake)	0.044	0.000

The elements $a_{1,2}$, $a_{1,5}$, $a_{1,6}$ in Eq. (5) are greater than those in Eq. (6), with a 5% significance level. This means that when body movement occurs in REM, Non-REM3, and Non-REM4 sleep, sleepers tend to switch to AWAKE. Thus, (F4) "AWAKE frequently occurs after body movement" is shown. Figure 4 shows the transition of sleep to a steady state from the WAKE stage for the equation when body movement occurs and no body movement occurs.



(a) Transition of sleep stage probability when body movement occurs



(b) Transition of sleep stage probability when no body movement occurs

Fig. 4　Transition of sleep stage probability

When body movement occurs, the most probable stage is Non-REM2 with a probability of 0.80 and the second most probable stage is REM with a probability of 0.11, whereas when no body movement occurs, the most probable stage is Non-REM2 with a probability of 0.56, the second most probable is Non-REM3 with a probability of 0.25, the third most probable is Non-REM4 with a probability of 0.10 and the fourth is REM with a probability of 0.07. These tendencies show that the sleep transition equation when no body movement occurs demonstrates deeper sleep, whereas that when body movement occurs demonstrates shallower sleep.

4. 2 Optimal estimation of observer and characteristic roots

Here, we determine the gain matrix $\boldsymbol{K}$, which is uniquely calculated if the eigenvalues λ_1-λ_6 of $\boldsymbol{A}$-$\boldsymbol{KI}$ are given. Among the various values of λ_1-λ_6, we select those so that the coincidence rate of measurements $\boldsymbol{y}(k)$ and the most probable state in $\hat{\boldsymbol{x}}(k)$ estimated by the observer for the entire measurement time for the test subjects in Group 1 is maximum, using the genetic algorithm.

Assuming 30 individuals that have λ_1- λ_6 in each generation, digenesis of 200 generations is continuous. Figure 5 shows the highest and the average coincidence rates between the measurements $\boldsymbol{y}(k)$ and the most probable state in $\hat{\boldsymbol{x}}(k)$ estimated by the observer.

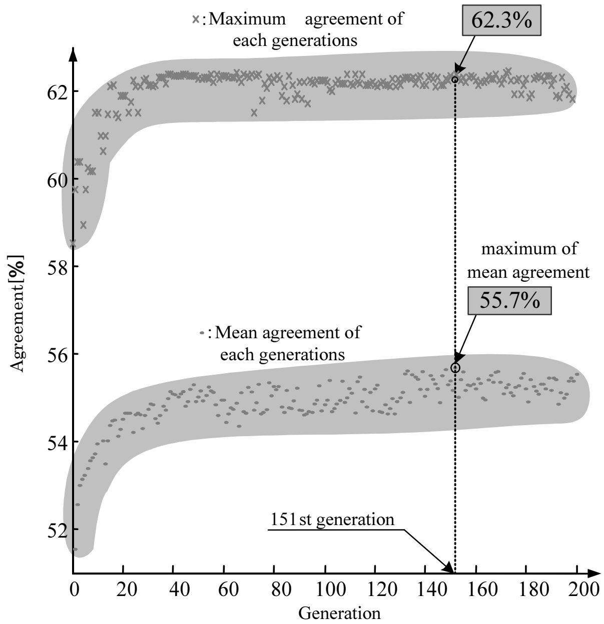


Fig.. 5 Result of genetic algorithm

In Figure 5, increase in coincidence rate is saturated at around 40 generations. Among 200 generations, the genes of λ_1- λ_6 in the 151st generation have an average maximum value of 55.7% and the highest coincidence rate is 62.3%. The genes of λ_1- λ_6 of this generation are:

λ_1= -1.09×10^{-2}, λ_2= -3.52×10^{-2},
λ_3= -3.44×10^{-4}, λ_4= -6.93×10^{-3},
λ_5= -9.03×10^{-3}, λ_6= -6.79×10^{-3}

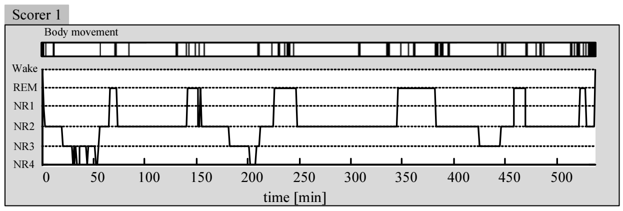
and we select the genes as characteristic roots of the observer or the eigenvalues of $\boldsymbol{A}$-$\boldsymbol{KI}$. Thus, the gain matrix $\boldsymbol{K}$ is determined as follows:

When body movement occurred:

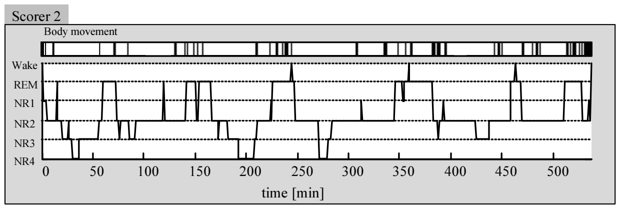
$$\boldsymbol{K}_b = \begin{bmatrix} 0.344 & 0.034 & 0.000 & 0.008 & 0.030 & 0.044 \\ 0.103 & 0.764 & 0.318 & 0.023 & 0.000 & 0.011 \\ 0.154 & 0.106 & 0.273 & 0.002 & 0.067 & 0.066 \\ 0.410 & 0.131 & 0.409 & 0.959 & 0.127 & 0.066 \\ 0.000 & 0.000 & 0.000 & 0.015 & 0.741 & 0.198 \\ 0.000 & 0.000 & 0.000 & 0.000 & 0.044 & 0.622 \end{bmatrix} \quad (7)$$

When no body movement occurred:

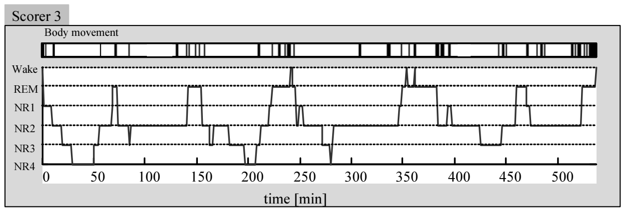
$$\boldsymbol{K}_n = \begin{bmatrix} 0.344 & 0.014 & 0.000 & 0.006 & 0.003 & 0.000 \\ 0.167 & 0.901 & 0.167 & 0.014 & 0.000 & 0.000 \\ 0.000 & 0.014 & 0.333 & 0.001 & 0.000 & 0.000 \\ 0.500 & 0.106 & 0.500 & 0.958 & 0.059 & 0.000 \\ 0.000 & 0.000 & 0.000 & 0.028 & 0.888 & 0.145 \\ 0.000 & 0.000 & 0.000 & 0.000 & 0.059 & 0.862 \end{bmatrix} \quad (8)$$



(a) Sleep stage judged by Scorer 1



(b) Sleep stage judged by Scorer 2



(c) Sleep stage judged by Scorer 2

Fig. 6 Sleep stages judged by scorers

Table 5 Kappa statistics evaluating reliability of judgment

Group	Sub-ject	Age	Scorer 1 vs Scorer 2	Scorer 1 vs Scorer 3	Scorer 2 vs Scorer 3
Group 1	A1	22	0.85	0.88	0.76
	A2	22	0.78	0.86	0.81
	B1	21	0.83	0.89	0.75
	B2	22	0.86	0.89	0.87
	C1	23	0.81	0.92	0.79
	C2	23	0.85	0.89	0.76
	C3	23	0.76	0.78	0.81
	D1	22	0.81	0.86	0.82
	D2	22	0.80	0.88	0.75
	D4	23	0.81	0.84	0.78
	E1	18	0.86	0.81	0.82
	F1	22	0.85	0.91	0.84
	F2	23	0.74	0.85	0.82
	H1	23	0.77	0.83	0.85
	J1	25	0.81	0.88	0.85
	Mean	22.3	0.81	0.87	0.81
	S.D.	1.5	0.04	0.04	0.04
Group 2	D3	23	0.81	0.94	0.85
	E2	18	0.86	0.92	0.79
	G1	23	0.79	0.81	0.79
	I1	22	0.88	0.90	0.79
	J2	25	0.90	0.90	0.81
	Mean	22.2	0.85	0.89	0.81
	S.D.	2.6	0.05	0.05	0.03

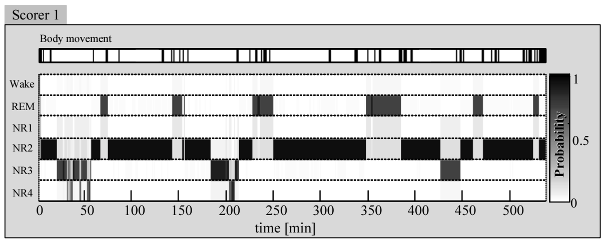
4. 3 Sleep stage judgment by R-K Method

Figure 6 shows the markers for which body movement occurred and the sleep stages judged by Scorer 1, Scorer 2 and Scorer 3 for the third night's data for a subject. The kappa statistics between Scorer 1 and Scorer 2 is 0.81, that between Scorer 1 and Scorer 3 is 0.87, and that between Scorer 2 and Scorer 3 is 0.81 for G1 and 0.85, 0.89 and 0.81 for G2. These are high and the trend characteristics are similar. However, Scorer 2 and Scorer 3 tend to judge AWAKE more frequently than Scorer 1, and Scorer 2 frequently judged REM sleep. Thus, details of the judgments are different.

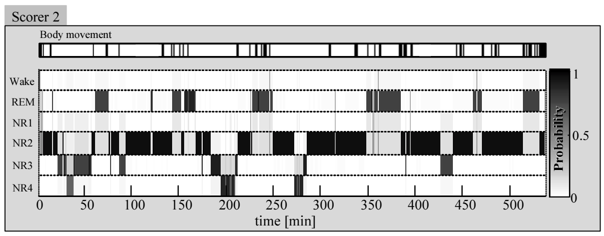
Table 5 shows the kappa statistics between scorers for sleep data in Groups 1 and 2. The statistics all exceed 0.74 and the reliability of judgment is high.

4. 4 Estimation of Sleep stage appearance probability

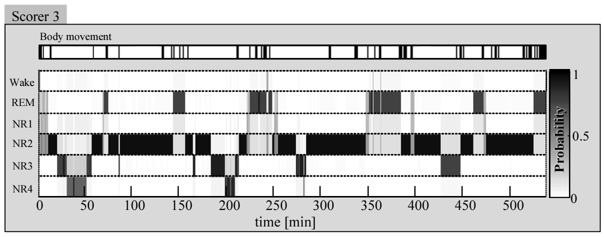
The sleep stages judged by the three scorers are employed as the measurements $\boldsymbol{y}(k)$ of the observer given by Eq. (4) using the optimal gain matrix $\boldsymbol{K}$. The estimate $\hat{\boldsymbol{x}}(k)$ of the state vector $\boldsymbol{x}(k)$ provides the probability of appearance of each sleep stage for each discrete time. Figure 7 shows the markers for which body movement occurred and the output from the observer for the subject. The probabilities are shown by gray scale; the darker the lightness, the higher the probability. When we compare (a), (b) and (c) in Figure 7, the differences in deterministic judgment in the confusin time intervals 10–50, 70–80, 170–180, 220–240, 350–380, and 450–470 min in Figure 6 are statistically compensated. In a deterministic expression, these differ, but in a statistic expression, the probabilities are shown.



(a) Sleep stage appearance probability judged by Scorer 1



(b) Sleep stage appearance probability judged by Scorer 2



(c) Sleep stage appearance probability judged by Scorer 3

Fig. 7 Sleep stage appearance probability and body movement

5. Discussion

The results appear to show that the proposed algorithm is a simple smoother or low-pass filter, but it is not. The Luenberger observer is a state estimator for an object whose dynamics are given by an a priori mathematical model, and it is designed by using the a priori information of the object as described in Section 3.3. Thus, state estimation by the observer is different from simple smoothers and/or low-pass filters which do not use the a priori information of the object. The observer has a smoother (low-pass filter) function, and the cut-off frequency which shows the degree of smoothness can be controlled by the eigenvalues of the observer coefficient matrix i.e., the characteristic roots of the observer itself. These values should be determined so that the measurement noise is filtered out. In this paper, the eigenvalues are automatically determined by the genetic algorithm from the measurements i.e., the judgment results of three scorers. The cut-off frequency is automatically and optimally determined to compensate the fluctuations in judgment by the three scorers in the sense of maximizing the coincidence rates of their judgment results.

Table 6 compares the sleep stages by the three scorers for the most probable stage; by the mean value of the kappa statistic, that between Scorer 1 and Scorer 2 is 0.89, that between Scorer 1 and Scorer 3 is 0.92, and that between Scorer 2 and Scorer 3 is 0.85 for G1 and 0.91, 0.92 and 0.85 for G2. These are all higher than the corresponding mean values of 0.85, 0.89 and 0.81 in Table 5. Furthermore, when we select the sleep stage from the most probable and the second most probable, the kappa statistic between Scorer 1 and Scorer 2 is 0.92, that between Scorer 1 and Scorer 3 is 0.95 and that between Scorer 2 and Scorer 3 is 0.89 for G1 and 0.94, 0.96 and 0.90 for G2. Similarly, when we select the sleep stage from the most probable, the second most probable and third most probable, the kappa statistic between Scorer 1 and Scorer 2 is 0.94, that between Scorer 1 and Scorer 3 is 0.97 and that between Scorer 2 and Scorer 3 is 0.93 for G1 and 0.95, 0.97 and 0.92 for G2. The kappa statistics are increased. For the judgment of the sleep stage for G2, which we did not use for estimating the sleep stage transition matrix, the reliability is improved.

As shown in Table 6, when we use the three most probable judgments, the average value of the kappa statistics among the three scorers is over 0.92 and is highly reliable statistical judgment. Furthermore, the confusing judgment by scorers as shown in Figure 7 can be shown statistically, which is a more accurate description of the sleep stage. If the probability of the most probable sleep stage is low, we can understand that the sleep is hardly judged as one of the six categories.

Table 6 Kappa statistics of each sleep stage appearance probability

Group	Subject	Scorer 1 vs Scorer 2			Scorer 1 vs Scorer 3			Scorer 2 vs Scorer 3		
		1st	2nd	3rd	1st	2nd	3rd	1st	2nd	3rd
Group 1	A1	0.88	0.92	0.94	0.89	0.94	0.96	0.77	0.87	0.91
	A2	0.87	0.94	0.95	0.90	0.96	0.97	0.82	0.90	0.92
	B1	0.91	0.95	0.95	0.95	0.96	0.97	0.90	0.92	0.93
	B2	0.91	0.93	0.95	0.91	0.96	0.97	0.87	0.91	0.94
	C1	0.88	0.92	0.95	0.95	0.97	0.98	0.89	0.90	0.93
	C2	0.91	0.93	0.94	0.95	0.96	0.97	0.88	0.91	0.92
	C3	0.82	0.91	0.92	0.79	0.93	0.94	0.82	0.85	0.95
	D1	0.86	0.89	0.96	0.91	0.94	0.96	0.83	0.92	0.93
	D2	0.89	0.90	0.93	0.96	0.96	0.97	0.87	0.88	0.91
	D4	0.88	0.92	0.94	0.94	0.96	0.97	0.82	0.89	0.94
	E1	0.94	0.91	0.94	0.91	0.95	0.96	0.86	0.87	0.91
	F1	0.89	0.92	0.94	0.93	0.95	0.97	0.85	0.88	0.94
	F2	0.91	0.93	0.94	0.93	0.96	0.98	0.87	0.90	0.92
	H1	0.90	0.93	0.95	0.91	0.96	0.97	0.88	0.89	0.93
	J1	0.85	0.94	0.95	0.92	0.96	0.97	0.86	0.91	0.92
	Mean	0.89	0.92	0.94	0.92	0.95	0.97	0.85	0.89	0.93
	S.D.	0.03	0.01	0.01	0.04	0.01	0.01	0.03	0.02	0.01
Group 2	D3	0.92	0.96	0.97	0.95	0.97	0.98	0.92	0.94	0.95
	E2	0.87	0.90	0.93	0.93	0.95	0.96	0.79	0.87	0.89
	G1	0.90	0.92	0.96	0.92	0.96	0.97	0.85	0.89	0.92
	I1	0.91	0.94	0.95	0.90	0.95	0.96	0.86	0.90	0.91
	J2	0.93	0.94	0.96	0.91	0.95	0.96	0.81	0.92	0.93
	Mean	0.91	0.94	0.95	0.92	0.96	0.97	0.85	0.90	0.92
	S.D.	0.02	0.02	0.02	0.02	0.01	0.01	0.05	0.02	0.02

6. Conclusion

This paper describes a novel sleep stage transition equation in which the transition matrix is switched depending on whether or not body movement occurs during sleep. The transition matrix is statistically determined by 15 nights' sleep data on 10 normal sleepers. An observer was built to estimate the probability of how surely the sleep belongs to the six different stages. Sleep stages judged by three different scorers were compared using kappa statistics.

If we select the sleep stage from the most probable three judgments on the group of data by which the transition matrix was estimated, the kappa statistic between Scorer 1 and Scorer 2 is 0.89, that between Scorer 1 and Scorer 3 is 0.92, and that between Scorer 2 and Scorer 3 is 0.85. Furthermore, for sleep not used to estimate the transition matrix, the kappa statistic between Scorer 1 and Scorer 2 is 0.91, that between Scorer 1 and Scorer 3 is 0.92 and that between Scorer 2 and Scorer 3 is 0.85. The reliability of judgment is high and accurate in the sense that the results are statistically described.

In this paper, we built the sleep transition equation, a sleep mathematical model using the sleep data of young healthy subjects.

The sleep modes change as people get older. For example, the occurrence rate of Non-REM4 sleep decreases almost linearly in proportion to age. Thus, sleep transition might also change as people get older. Therefore, in order to apply the proposed algorithm, the sleep transition matrix must be defined and estimated for different generations. Furthermore, the sleep stages vary much more for subjects with sleep disorders, and so the sleep transition matrix must be prepared for each sleep disorder.

References

[1] R. Kawahara, H. Maeda and S. Yoshioka "Sleep disorder as present age disease," Nippon-Hyoron-Sha Co., Ltd., 2000.

[2] S. Chiba and K. Honma "Clinical study of circadian rhythm sleep disorder," Shinkoh Igaku Shuppan Co., Ltd., 2003.

[3] Ministry of Economy, Trade and Industry of Japan. Health service creation support project report, March 2005. Available from: http://www.meti.go.jp/policy/servicepolicy/contents/healthcare-service.pdf

[4] A. Rechtschaffen and A. Kales, Eds. "A Manual of Standardized Terminology, Techniques and Scoring System for Sleep Stage of Human Subjects," Washington, D.C.; Public Health Service, U.S. Government Printing Office, 1968.

[5] C.W. Whitney, et al. "Reliability of Scoring Respiratory Disturbance Indices and Sleep Staging," Sleep, 21, 7, 749-57, 1998.

[6] B. Kemp "A Model-Based Monitor of Human Sleep Stages," Biol. Cybern. 57: 365-378, 1987.

[7] M. Schwaibold "Artificial intelligence in sleep analysis (ARTISANA)-modeling visual processes in sleep classification," Biomed Tech 46, 129-32, July 2001.

[8] Handbook of Sleep Science and Sleep Medicine: Asakura (The Japanese Society of Sleep Research), 1998.

[9] O'Reilly J. "Observer for linear system," Academic Press, 1983.

[10] D. E. Goldberg "Genetic Algorithms in Search, Optimization and Machine Learning," Kluwer Academic Publishers, Boston, MA, 1989.

[11] Watanabe K. et al. "Noninvasive Measurement of Heartbeat, Respiration, Snoring and Body Movement of a Subject in Bed via Pneumatic Method," IEEE Trans. BME, Vol. 52, No. 12, pp. 2100-2107, 2005.