Sleep-States-Transition Model by Body Movement and Estimation of Sleep-Stage-Appearance Probabilities by Kalman Filter

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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. Kalman filter based on the two sleep models with no body movement and with body movement was designed. Sleep stages judged by three different scorers were rejudged by the filter. The two sleep models were stochastically estimated from biosignals from 15 nights' data and the rejudged scores by the filter were evaluated by the data from 5 nights. 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 0.90, 0.93, and 0.84, respectively. Those of sleep stages determined from the most and second most probable were 0.92, 0.94, and 0.89 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 filter are expressed by probabilistic manner, which are more reasonable in expression than those given by deterministic manner. The expression could compensate the uncertainties in each judgmentsand thus were more accurate than the direct judgments.**

***Index Terms*—R–K method, sleep-stage-state variable equation, sleep-stage transition probability matrix, sleep stages.**

I. Introduction

SLEEPING is 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 noninvasive techniques for measuring sleep conditions [4]–[10].

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 [11] at time intervals divided independently for all-night sleep. The stages are AWAKE, Rapid eye movement (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 biosignals mentioned previously. 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 [12].

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 [13], [14], but our model and method are different in which we use a new sleep-transition model and apply a Kalman filter 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 Kalman filter. The measurements used for the filter are the temporal changes in sleep stages judged by a scorer or automatic sleep-stage estimator. The state variables estimated by the filter 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 the Kalman filter.

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. Despite 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.

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II. Method

A. Sleep-Stage-Transition Probability Matrix

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], [15] 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 stage to another, as described previously; 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 $a_{j,i}$, 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:

$$a_{j,i} = \begin{cases} P(E_{j,i}|E_i, E_b) \\ P(E_{j,i}|E_i, E_n) \end{cases} \text{when} \quad \begin{matrix} \text{(body movement occurs)} \\ \text{(no body movement occurs)} \end{matrix} \tag{1}$$

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

B. 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 $k (k = 1, 2, 3, ..., T_{ib})$ be a discrete time of every 1 min with the sleep stage judged within that time, and let $x_1(k)$, $x_2(k)$, $x_3(k)$, $x_4(k)$, $x_5(k)$, and $x_6(k)$ be the probabilities of how surely the sleep stages belong to 1, 2, 3, 4, 5, and 6, respectively.

Furthermore, let the vector $\boldsymbol{x}(k) = [x_1(k), x_2(k), x_3(k), x_4(k), x_5(k), x_6(k)]^T$ be the state vector. The sleep-stage state vector $\boldsymbol{x}(k)$ transits to $\boldsymbol{x}(k+1)$ following to the relation $\boldsymbol{x}(k+1) = \boldsymbol{A}\boldsymbol{x}(k)$ in the transition time from k to $k+1$. The state vector $\boldsymbol{x}(k)$ is corrupted by the uncertainties of the transition relation which is referred to as system noises. Let the vector

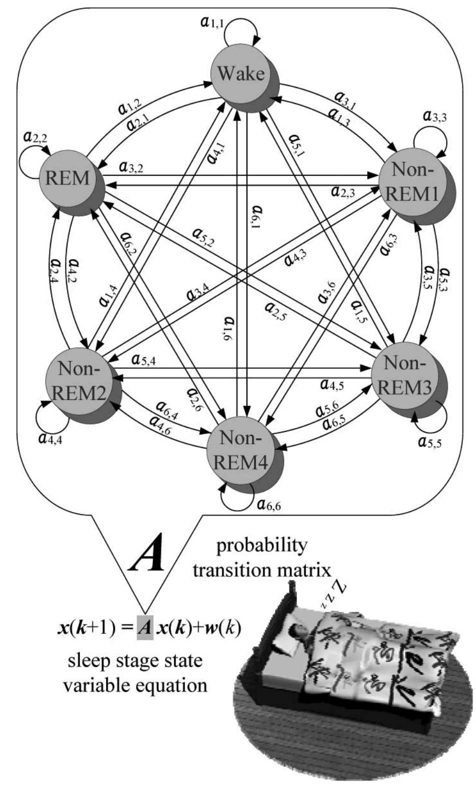

Fig. 1. Shannon diagram of sleep-stage transition.

$\boldsymbol{w}(k) = [w_1(k), w_2(k), w_3(k), w_4(k), w_5(k), w_6(k)]^T$ be the system noise vector, which is unbiased but has variances ξ_1^2, ξ_2^2, ξ_3^2, ξ_4^2, ξ_5^2, and ξ_6^2, respectively. Then, the sleep-stage-state variable equation is given as follow:

$$\boldsymbol{x}(k+1) = \boldsymbol{A}\boldsymbol{x}(k) + \boldsymbol{w}(k). \tag{2}$$

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

And let the vector $\boldsymbol{y}(k) = [y_1(k), y_2(k), y_3(k), y_4(k), y_5(k), y_6(k)]^T$ be the sleep stage judged by a certain method such as the R–K method by scorers. $\boldsymbol{y}(k)$ is deterministically given corresponding to the judgment of sleep stage as follows:

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

In the decision of sleep stages via the R–K method by scorers, there may occur the errors due to the subjective judgments error. The error due to the judgment can be referred to observation noise. Let the vector $\boldsymbol{v}(k) = [v_1(k), v_2(k), v_3(k), v_4(k), v_5(k), v_6(k)]^T$ be the observation vector, which is unbiased but has variances τ_1^2, τ_2^2, τ_3^2, τ_4^2, τ_5^2, and τ_6^2, respectively. Then, the measurement equation is given as follows:

$$\boldsymbol{y}(k) = \boldsymbol{I}\boldsymbol{x}(k) + \boldsymbol{v}(k). \tag{3}$$

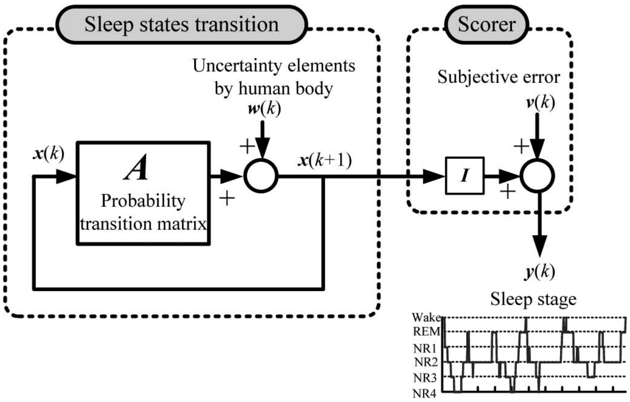

Fig. 2. Block diagram of the sleep-states-transition model.

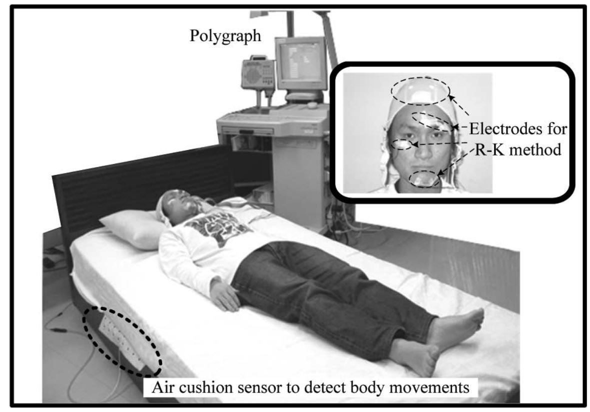

Fig. 3. Measurement system.

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

$$\boldsymbol{x}(0) = \boldsymbol{x}(T_{ib}) = [1\,0\,0\,0\,0\,0\,0]^T.$$

Fig. 2 shows a block diagram of the sleep-state-transition model.

C. Kalman Filter to Estimate Sleep-Stage-Appearance Probability

Here, we consider Kalman filter to estimate the probability of how surely the sleep belongs to each sleep stage based on the state-variable equation. The Kalman filter is a state estimator for an object whose characteristics are given by an *a priori* mathematical model described as the state variable equations (2) and (3) [16]. It estimates all state variables from measurements corrupted by noise. The state variable in (2) is the probability, thus, we estimate the probability from the sleep judgments (measurements), which may include errors.

Let $\hat{\boldsymbol{x}}(k\,|\,k)$ be the estimate of $\boldsymbol{x}(k)$ at k, and let $\hat{\boldsymbol{x}}(k\,|\,k-1)$ be the predict of $\boldsymbol{x}(k)$ at $k-1$. Let $\boldsymbol{Q}$ and $\boldsymbol{R}$ be the covariance matrices of the noises $\boldsymbol{w}(k)$ and $\boldsymbol{v}(k)$, respectively, and $\boldsymbol{P}(k\,|\,k-1)$be the co-variance matrix of the error between the state vector $\boldsymbol{x}(k)$ and the predicted state vector $\hat{\boldsymbol{x}}(k\,|\,k-1)$. Then, the matrix $\boldsymbol{K}(k)$ referred to Kalman gain is determined so that it minimizes the value of $\boldsymbol{P}(k\,|\,k-1)$ from the matrices $\boldsymbol{A}$, $\boldsymbol{Q}$, and $\boldsymbol{R}$. The Kalman filtering processing is given as follows:

$$\hat{\boldsymbol{x}}(k\,|\,k) = \hat{\boldsymbol{x}}(k\,|\,k-1) + \boldsymbol{K}(k)\left\{\boldsymbol{y}(k) - \hat{\boldsymbol{x}}(k\,|\,k-1)\right\} \quad (4)$$

with

$$\begin{aligned}\hat{\boldsymbol{x}}(k\,|\,k-1) &= \boldsymbol{A}\hat{\boldsymbol{x}}(k-1\,|\,k-1)\\ \boldsymbol{K}(k) &= \boldsymbol{P}(k\,|\,k-1)\left\{\boldsymbol{P}(k\,|\,k-1) + \boldsymbol{R}\right\}^{-1}\\ \boldsymbol{P}(k+1\,|\,k) &= \boldsymbol{A}\left\{\boldsymbol{P}(k\,|\,k-1) - \boldsymbol{K}(k)\boldsymbol{P}(k\,|\,k-1)\right\}\boldsymbol{A}^T + \boldsymbol{Q}.\end{aligned}$$

Because the initial and final times in the sleeping are in the "Wake" stage, we let the initial condition $\hat{\boldsymbol{x}}(1\,|\,0)$ and the final condition $\hat{\boldsymbol{x}}(T_{ib}\,|\,T_{ib}-1)$ be $\hat{\boldsymbol{x}}(1\,|\,0) = \hat{\boldsymbol{x}}(T_{ib}\,|\,T_{ib}-1) = [1\,0\,0\,0\,0\,0\,0]^T$.

The values of ξ_1^2, ξ_2^2, ξ_3^2, ξ_4^2, ξ_5^2, ξ_6^2 and τ_1^2, τ_2^2, τ_3^2, τ_4^2, τ_5^2, τ_6^2 are optimally determined by genetic algorithm [17]. 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 $\hat{\boldsymbol{x}}(k\,|\,k)$ estimated by the filter for the entire measurement time for the test subjects.

III. 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. Fig. 3 shows the sleep conditions. We obtained informed consent from each subject. Sleep stage was evaluated by the international 10/20 method [15] and so electroencephalogram (EEG) at points C4-A1 and C3-A2 of the head, eye movement, and electromyography (EMG) at submental muscles were measured. Electrocardiograms were measured using the I-induction correction method [15]. 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 1 min, 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 0.5 s [15]. We detected body movements using this detection procedure. The method was verified by comparison with the pneumatic body-movement detection method [6]. Sleep stages were judged by three different scorers.

A. Estimation of Sleep-Stage-Transition Equation

First, we estimated the transition matrix $\boldsymbol{A}$. The data from the 20 nights were randomly divided into Group 1 and Group 2: Group 1 consisting of 15 nights' data, and Group 2 consisting of the remaining 5 nights' data. The Group 1 data was used to estimate the transition matrices and the Group 2 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

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

When no body movement occurred

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

Fig. 4 shows the Shannon diagram of the sleep-transition equation. 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 Fig. 4 or the transition matrices (5) and (6) satisfy the sleep feature (F1)–(F4) in conjunction with body movement, as described in Section II. Table I shows the value of elements $a_{3,2}$, $a_{3,5}$, and $a_{3,6}$ in $\boldsymbol{A}_b$ and $\boldsymbol{A}_n$.

The elements in (5) when body movement occurred are greater than those in (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 II shows the values of elements $a_{5,5}$ and $a_{6,6}$.

These are the probabilities of maintaining the same sleep stage. Those in (5) are less than those in (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 III shows the values of elements $a_{2,1}$–$a_{2,6}$, except $a_{2,2}$, and $a_{1,2}$–$a_{6,2}$. The elements $a_{2,3}$ and $a_{2,4}$ in (5) are greater than those in (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 $a_{1,2}$, $a_{3,2}$, and $a_{4,2}$ in (5) are greater than those in (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 IV shows the values of elements $a_{1,2}$, $a_{1,5}$, and $a_{1,6}$. The elements $a_{1,2}$, $a_{1,5}$, and $a_{1,6}$ in (5) are greater than those in (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

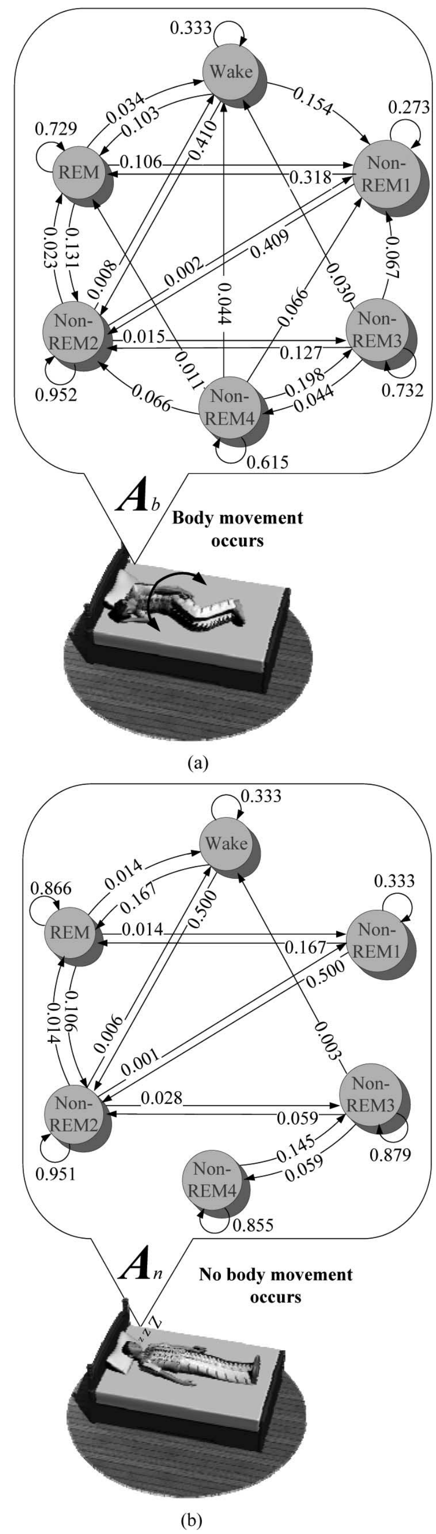

Fig. 4. Shannon diagram of the matrix $\boldsymbol{A}$. (a) Body movement occurs. (b) No body movement occurs.

TABLE I
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

TABLE II
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

TABLE III
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

TABLE IV
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

after body movement" is shown. Fig. 5 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. 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.

B. Decision of the Optimal Variances of the Noise

Here, we determine the values of $\xi_1^2, \xi_2^2, \xi_3^2, \xi_4^2, \xi_5^2$, and ξ_6^2 and $\tau_1^2, \tau_2^2, \tau_3^2, \tau_4^2, \tau_5^2$, and τ_6^2. Among the various values of $\xi_1^2 = \xi_6^2$ and $\tau_1^2 - \tau_6^2$, we select those so that the coincidence rate of measurements $\boldsymbol{y}(k)$ and the most probable state in $\hat{\boldsymbol{x}}(k \mid k)$ estimated

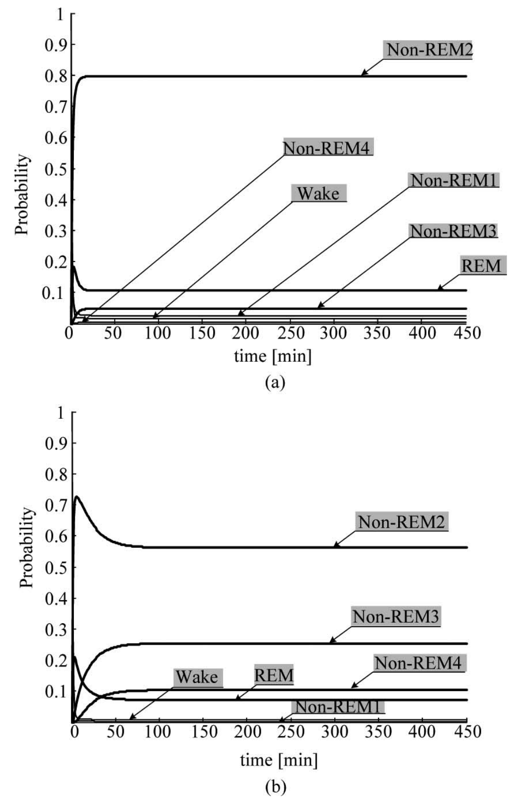

Fig. 5. Transition of sleep-stage probability.

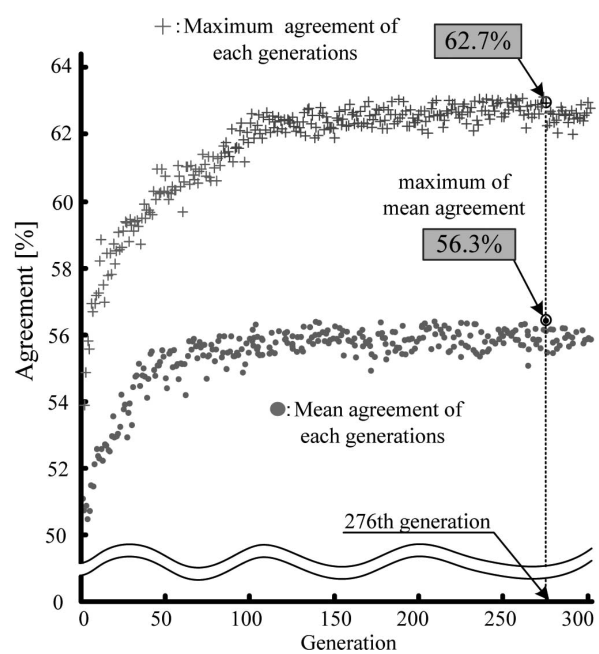

Fig. 6. Result s of genetic algorithm.

by the Kalman filter for the entire measurement time for the test subjects in Group 1 is maximum, using the genetic algorithm. Assuming 30 individuals that have $\xi_1^2 - \xi_6^2$ and $\tau_1^2 - \tau_6^2$ in each generation, digenesis of 300 generations is continuous. Fig. 6 shows the highest and the average coincidence rates between the measurements $\boldsymbol{y}(k)$ and the most probable state in $\hat{\boldsymbol{x}}(k \mid k)$ estimated by the Kalman filter.

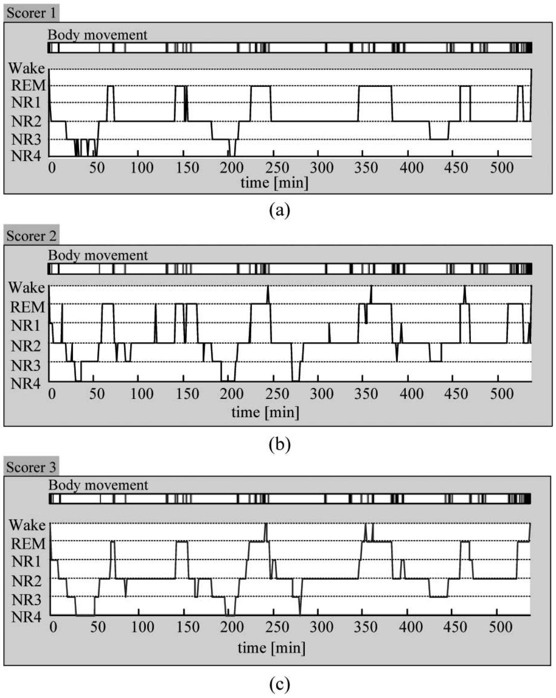

Fig. 7. Sleep stages judged by scorers.

In Fig. 6, increase in coincidence rate is saturated at around 100 generations. Among 300 generations, the genes of $\xi_1^2 - \xi_6^2$ and $\tau_1^2 - \tau_6^2$ in the 276th generation have an average maximum value of 56.3% and the highest coincidence rate is 62.7%. The genes of $\xi_1^2 - \xi_6^2$ and $\tau_1^2 - \tau_6^2$ of this generation are as follows:

$$\xi_1^2 = 2.14 \times 10^{-2} \quad \xi_2^2 = 4.35 \times 10^{-2} \quad \xi_3^2 = 2.26 \times 10^{-2}$$
$$\xi_4^2 = 1.98 \times 10^{-2} \quad \xi_5^2 = 1.27 \times 10^{-2} \quad \xi_6^2 = 2.54 \times 10^{-2}$$
$$\tau_1^2 = 0.61 \times 10^{-1} \quad \tau_2^2 = 1.32 \times 10^{-1} \quad \tau_3^2 = 3.11 \times 10^{-1}$$
$$\tau_4^2 = 1.84 \times 10^{-1} \quad \tau_5^2 = 0.92 \times 10^{-1} \quad \tau_6^2 = 1.12 \times 10^{-1}$$

and we select the genes as the values of the variances.

C. Sleep-Stage Judgment by R–K Method

Fig. 7 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 C.

The kappa statistics between Scorer 1 and Scorer 2 is 0.76, that between Scorer 1 and Scorer 3 is 0.78, and that between Scorer 2 and Scorer 3 is 0.81. 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 V shows the kappa statistics between scorers for sleep data in Groups 1 and 2. The mean of 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 Group 1, and 0.85, 0.89, and 0.81 for Group 2.

The statistics all exceed 0.74 and the reliability of judgment is high.

TABLE V
KAPPA STATISTICS EVALUATING RELIABILITY OF JUDGMENT

Group	Subject	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

D. Estimation of Sleep-Stage-Appearance Probability

The sleep stages judged by the three scorers are employed as the measurements $\boldsymbol{y}(k)$ of the Kalman filter given by (4) using the optimal Kalman gain $\boldsymbol{K}(k)$. The estimate $\hat{\boldsymbol{x}}(k \mid k)$ of the state vector $\boldsymbol{x}(k)$ provides the probability of appearance of each sleep stage for each discrete time. Fig. 8 shows the markers for which body movement occurred and the output from the filter for the third night's data for the subject C. The probabilities are shown by gray scale; the darker the lightness, the higher the probability. When we compare (a), (b), and (c) in Fig. 8, the differences in deterministic judgment in the confusing time intervals 20–50, 70–80, 170–180, 220–250, 350–380, and 430–570 min in Fig. 7 are statistically compensated. In a deterministic expression, these differ, but in a statistic expression, the probabilities are shown.

IV. Discussion

The results appear to show that the proposed algorithm is a simple smoother or low-pass filter, but it is not. The Kalman filter 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 II-C. Thus, state estimation by the Kalman filter is different from

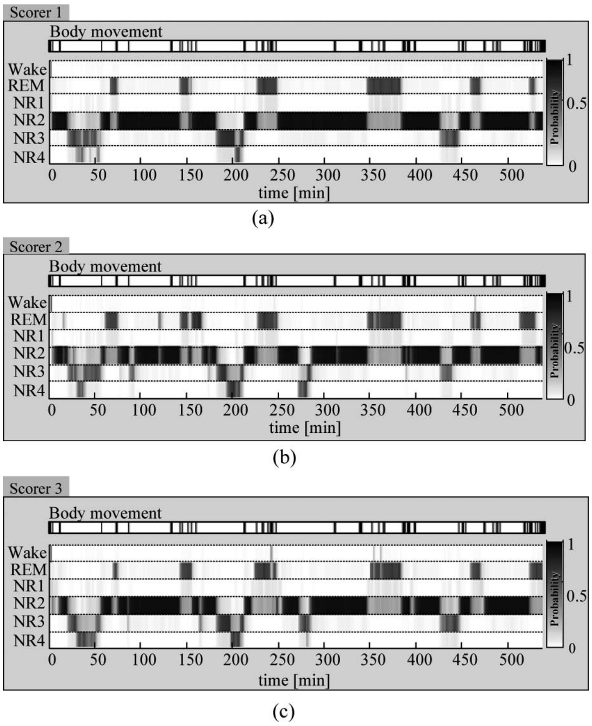

Fig. 8. Sleep-stage-appearance probability and body movement.

simple smoothers and/or low-pass filters which do not use the a priori information of the object.

Table VI 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 0.86 for Group 1 and 0.90, 0.93, and 0.84 for Group 2. These are all higher than their corresponding mean values of 0.81, 0.87 and 0.81 for Group 1 and 0.85, 0.89 and 0.81 for Group 2 in Table V. The kappa statistics for the Group 1 increased by 0.06 on average, and for the Group 2 increased by 0.04 on average. Regarding Group 1, we compared the kappa statistics in Table V with those of the most probable stage in Table VI by Wilcoxon rank sum test. As a result, all the kappa statistics between Scorer 1 and Scorer 2, Scorer 1 and Scorer 3, and Scorer 2 and Scorer 3 in Table VI are higher than the kappa statistics in Table V at a significant level of 1%. Regarding Group 2, in the same manner, all the kappa statistics between Scorer 1 and Scorer 2, Scorer 1 and Scorer 3, and Scorer 2 and Scorer 3 in Table VI are higher than those in Table V at a significant level of 5%. As aforementioned, the kappa statistics for the Group 1 is increased by 0.06 on average and for the Group 2 is increased by 0.04 on average. We compared the mean values of the kappa statistics between Group 1 and Group 2 by Welch's t-test. As the results, the mean values for Group 1 is higher than those for the Group 2 at a significant level of 5%. Therefore, this method is more effective for Group 1 than for Group 2 since the state-transition matrix was based on the data used for Group 1.

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 0.90 for Group 1 and 0.92, 0.94, and 0.89 for Group 2. 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 0.96, and that between Scorer 2 and Scorer 3 is 0.93 for Group 1 and 0.95, 0.97, and 0.92 for Group 2. The kappa statistics are increased.

TABLE VI
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	0.89	0.91	0.93	0.88	0.93	0.95	0.78	0.88	0.92
	A2	0.88	0.93	0.94	0.91	0.95	0.96	0.83	0.91	0.93
	B1	0.90	0.93	0.95	0.94	0.96	0.98	0.89	0.91	0.92
	B2	0.89	0.92	0.94	0.92	0.95	0.96	0.89	0.90	0.93
	C1	0.89	0.91	0.92	0.94	0.96	0.97	0.90	0.91	0.94
	C2	0.88	0.92	0.93	0.94	0.96	0.98	0.87	0.90	0.93
	C3	0.83	0.91	0.93	0.80	0.92	0.95	0.83	0.86	0.94
	D1	0.87	0.93	0.95	0.90	0.93	0.97	0.83	0.91	0.92
	D2	0.88	0.91	0.92	0.95	0.96	0.97	0.86	0.89	0.91
	D4	0.86	0.91	0.94	0.93	0.95	0.96	0.83	0.91	0.95
	E1	0.94	0.90	0.92	0.92	0.94	0.96	0.86	0.88	0.92
	F1	0.90	0.93	0.95	0.92	0.94	0.96	0.86	0.91	0.93
	F2	0.91	0.92	0.94	0.94	0.95	0.97	0.88	0.91	0.93
	H1	0.91	0.92	0.96	0.92	0.94	0.95	0.87	0.88	0.91
	J1	0.86	0.91	0.93	0.93	0.96	0.97	0.87	0.90	0.92
	Mean	0.89	0.92	0.94	0.92	0.95	0.96	0.86	0.90	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	0.91	0.93	0.96	0.95	0.96	0.97	0.91	0.93	0.96
	E2	0.88	0.92	0.95	0.94	0.95	0.96	0.80	0.85	0.88
	G1	0.89	0.91	0.94	0.91	0.92	0.98	0.83	0.90	0.91
	I1	0.90	0.93	0.94	0.91	0.94	0.95	0.85	0.88	0.92
	J2	0.92	0.92	0.95	0.92	0.94	0.97	0.82	0.91	0.92
	Mean	0.90	0.92	0.95	0.93	0.94	0.97	0.84	0.89	0.92
	S.D.	0.02	0.01	0.01	0.02	0.02	0.01	0.04	0.03	0.03

For the judgment of the sleep stage for Group 2, which we did not use for estimating the sleep-stage-transition matrix, the reliability is improved.

As shown in Table VI, 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 Fig. 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.

V. 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. Kalman filter 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 0.86. Furthermore, for sleep not used to estimate the transition matrix, the kappa statistic between Scorer 1 and Scorer 2 is 0.90, that between Scorer 1 and Scorer 3 is 0.93, and that between Scorer 2 and Scorer 3 is 0.84. The reliability of judgment is high and accurate in the sense that the results are statistically described. This method is effective although the only used stage is the most probable one, which might provide sufficient information in some clinical environments. In other clinical environments where more strict analyses are required, however, the second and the third most probable stages provide more detailed information.

In this paper, we built the sleep-transition equation, a sleep mathematical model using the sleep data of young healthy subjects. As for our future work, we are considering using more test data to validate this method. 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.

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