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A Non-Invasive Sleep Analysis Approach Based on a Fuzzy Inference System and a Finite State Machine

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ABSTRACT This paper deals with the analysis of sleep quality, which involves a non-invasive sleep stage detection method with home deployability. Some physiological signals, such as heart rate, heart rate variation, and the number of times the subject rolled over, are collected to determine the sleep stage. A fuzzy inference system is adopted to evaluate the division of sleep stage. Then, a preliminary sleep depth is calculated. Furthermore, a finite-state machine is developed to detect the sleep stage changes. The difference between our research and other existing studies is that, first, both the pressure sensors and the heart rate device are employed; then, the fuzzy inference and a finite-state machine are introduced, which give us a higher precision than the traditional methods to evaluate the sleep stage. The experimental results show that the proposed method can well evaluate the sleep quality that is almost consistent with a polysomnography test. The latter is currently recognized as the best way to measure sleep quality, which, however, requires a variety of monitoring sensors and has to be performed by the nursing staff in a professional setting. The reported approach can be used for monitoring sleep quality or sleep disorder screening at home.

INDEX TERMS Sleep analysis, non-invasive, fuzzy inference system, finite state machine.

I. INTRODUCTION

Sleep occupies one-third of our life. Good quality sleep is vital for physical and psychological health. However, as the pressure of modern society increases, sleep disorders have become a growing problem. There are two main methods used clinically for estimating sleep quality. One is self-administered sleep questionnaire (Pittsburgh sleep quality index, PSQI), and the other is Polysomnography (PSG). The questionnaire is supposed to be filled in by the patient upon waking up. The results of the questionnaire are considered to be subjective and inaccurate. Compared with the questionnaire, the PSG technique is more accurate and reliable. The patient goes to a sleep center for a PSG test. Under the supervision of the nursing staff, the electrodes are attached to the subject's head, eyes, lower jaw, heart and legs. The PSG measures the whole night sleep physiological conditions, including Electroencephalogram (EEG), Electrooculography (EOG), Electrocardiography (ECG), Electromyography (EMG), Air flow, Blood pressure, Heart rate (HR), etc.. The cost of a PSG test is expensive, and that many subjects have trouble sleeping due to the multiple sensors, wires, medical staff being present and unfamiliar room and bed. It is uncomfortable and requires the assistance of professional sleep laboratories and nursing staff.

For long-term monitoring, many scholars develop non-invasive sensing methods for home-care sleep analysis.

TABLE 1. The comparison of relevant research with our work.

	Sensor	Signal	Classification	Stage
Watanabe, 2010 [2]	Microphone	Heart rate	Spectrum analysis and Threshold	WAKE; REM; NREM 1–4
Kurihara, 2012 [8]	Pneumatic mattress and PPG	Heart rate; Body movement	Spectrum analysis and Threshold	WAKE; REM; NREM 1–4
Pino, 2015 [10]	Pneumatic mattress and Force sensor	Body movement; Apnea detection	Threshold	N/A
Wei, 2008 [11]	PPG	Heart rate variation	Spectrum analysis and GreyART	WAKE; REM; NREM 1–4
Hung, 2010 [12]	PPG and accelerometer	Heart rate variation; Body movement	Spectrum analysis and GreyART	WAKE; REM; NREM 1–4
Marcos, 2009 [18]	Oxygen saturation and infrared video-recorded	Heart rate variation; Body movement	Spectrum analysis and Threshold	WAKE; REM; NREM 1–3
This article	PPG and force sensor	Heart rate; Body Movement	Fuzzy inference and finite state machine	REM; NREM 1–3

Through extracting physiological signals, such as heart rate, respiratory rate, and the number of times the subject rolled over, we can analyze the changes of REM and NREM phases in a sleep cycle. Existing non-invasive sensing monitor methods include microphone, air mattress, intelligent mattress and pressure sensor. The studies in [2]–[4] improve the microphones to filter the signals of heart rate, rolled over times and snoring. Shin *et al.* [5] and Kurihara *et al.* [7] establish a sleep analysis model with the help of a pneumatic mattress. The study in [6] demonstrates the relationship between heart rate and turning times based on the work in [7]. Kurihara and Watanabe develop a new sleep index system based on intelligent mattresses [8], [9]. Pino *et al.* also report their studies with the aid of air mattress [10]. Utilizing photo plethysmography sensors, the relationship between leg movement and sleep stages is built in [11]. The photo plethysmography and pressure sensors generate two-dimension information [12], [13], but the movement of the human bodies can produce three-dimension images. As the result, some researchers try to assess sleep quality using near-infrared video and oximetry information to make up for the missing dimension [16]–[18]. Other scholars have tried to study the relationships between brain waves and the models of sleep stage from a purely theoretical perspective [19], [20]. Table 1 shows list of relevant research with our work. GreyART and PPG are the abbreviation of Grey Adaptive Resonance Network and Photo PlethysmoGraphy respectively. A PPG is an optically obtained plethysmogram, a volumetric measurement of an organ. A PPG is often obtained by using a pulse oximeter which illuminates the skin and measures changes in light absorption.

In this study, two low-cost sensors are combined to make the method suitable for potential at-home diagnosis. The first is the pillow pressure sensor where the patient sleeps and the second is the heart rate device produced by Mi Company. Most of the above non-invasive sleep monitoring approaches for home care predicate the different sleep phases through threshold values. Fixed thresholds are not well suited for sleep stage determinations for different people. To solve this problem, a fuzzy inference system and a finite state machine are developed in this paper. The collected physiological parameters as input signals are fed into the fuzzy inference system, then a preliminary sleep depth is defuzzified, and finally a finite state machine is used to detect the stage changes in future steps. The combination of fuzzy inference and finite state machine can give us more accurate sleep stage analysis for different patients. The system architecture is shown in Figure 1.

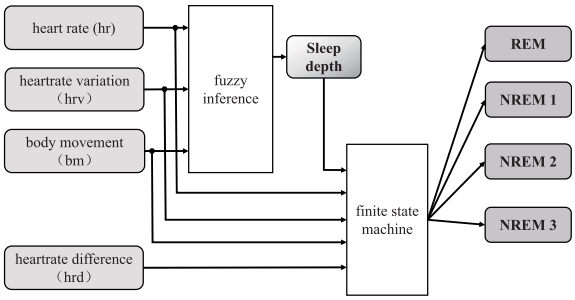


FIGURE 1. System architecture.

The rest of this paper is organized as follows. Section II describes the theoretical background. The proposed fuzzy inference and finite state machine approach are presented in Section III. An application of system is developed in Section IV. Then, three examples to demonstrate the effectiveness of our approaches are shown in Section V. Section VI concludes the paper.

II. PRELIMINARIES

We review some sleep knowledge in this section. The sleep stages are divided into rapid eye movement (REM) and non-rapid eye movement (NREM). The early classification of sleep stages is mainly based on the R–K method proposed by Rechtschaffen and Kales in 1968 [1], who split a sleep cycle into six stages, namely Awake, REM, NREM 1, NREM 2, NREM 3, and NREM 4. This division is based on the EEG, EOG and EMG measurements. Because NREM 3 and

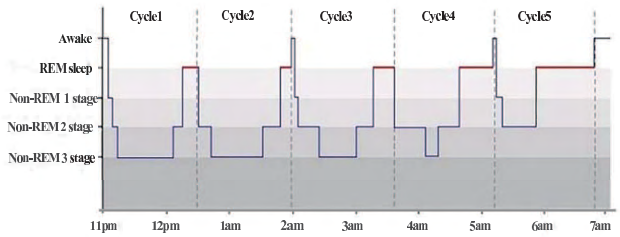


FIGURE 2. A full night's sleep and five sleep cycles [15].

NREM 4 are not much different, the American Academy of Sleep Medicine [14] redefined a sleep cycle into five stages in 2007, which are Awake, REM, NREM 1, NREM 2, and NREM 3. Figure 2 shows a full night's sleep and five sleep cycles. During the night's sleep time, the Awake stage rarely happens. Even if it occurs, it does not mean that one is really awake, but pseudo-conscious. In the latest American Academy of Sleep Medicine sleep manual [23], it is also called arousal. In fact, it is very difficult to detect the arousal phenomenon, which needs the help of EEG and EMG (Chin electromyogram). The latest sleep manual shows the conditions for detecting the Awake state in the sleep time: ''there is an abrupt shift of EEG frequency including α, θ and/or frequencies greater than 16 Hz (but not Spindles) that lasts at least 3 seconds, with at least 10 seconds of stable sleep preceding the change. Scoring of arousal during REM requires a concurrent increase in submental EMG lasting at least 1 second''. Since this study only uses PPG and pressure sensors, it is impossible to detect the Awake stage. In addition, the Awake stage has very limited impact on the analysis of sleep disorders, and thus we incorporate it into the REM stage. This article considers REM and NREM stages only.

REM can be seen as a period of brain repair. In this phase, the brain is very active, therefore dreaming often happens during the REM period, and the dream content is easier remembered when people wake up. The heart rate and respiratory rates are as irregular as in the sane moments, and the eyes move quickly. The brain shows α, β, θ and Sawtooth waves. The REM phase accounts for 25% of the total sleep time. If the REM period is too short or does not occur, the brain cannot repair itself. Obviously, the REM period is an important index of sleep quality.

NREM is known as a period of physical repair, which is mainly divided into three stages: NREM 1 and NREM 2 in shallow sleep and NREM 3 in deep sleep. NREM 1 is classified as shallow sleep, which is a transition period from REM to NREM 2. At this phase, the brain shows θ wave, and the eyeballs have slower movements. The heart rate and respiratory rate will be faster and more regular than in REM, and the turning action appears a lot of times. Each NREM 1 period lasts about 5 minutes. NREM 2 is also a shallow sleep, the eyeballs are no longer moving during this phase, and the heart rate, respiratory rate and body temperature gradually drop. Spindle and K complex waves appear at this time. The NREM 2 stage lasts for 10–15 minutes. NREM 3 is defined as deep sleep. In this stage, the eyeballs do not move, and the heart rate, respiration rate and body temperature further decrease. The frequency of heartbeat will drop to about 20–30% than awake, and the body barely moves. The brain shows δ wave. The NREM 3 stage lasts about 30–60 minutes. More deep sleep always means more rest of the body, thus the total duration of NREM 3 is another important index of sleep quality.

Once an ideal sleep cycle starts at REM and ends at NREM 3, via NREM 1 and NREM 2 on the way, and finally back to REM. The stages keep cycling all night. There are about 4–6 cycles a night, 90–120 minutes for each cycle, and a full night's sleep lasts about 7.5 hours [1]. Note that in the real sleep time, sometimes people may cause some confusing stage changes in different sleep cycles. The characteristics of each stage are shown in Table 2 [15].

III. A NON-INVASIVE SLEEP ANALYSIS APPROACH

A. INDEXES SETTING

For convenience of description, four indexes are introduced. One is heart rate, and the others are heart rate variation, body movement and heart rate difference. All indexes are formally quantified as follows:

1) HEART RATE (hr)

$$hr(x) = \frac{\sum_{i=-30}^{x} heartrate(i)}{30} \tag{1}$$

where $heartrate(i)$ is the current heart rate at i-th time. The average of 30 samples is taken as a heart rate value. Today's ECG and EEG are based on an average of 30 samples as a parameter. Corresponding descriptions are shown in [23]: on page 13, Section III, Technical and Digital Specifications: ''To accommodate older equipment, filter settings in the range of 30–35 Hz may be used to comply with the recommendations of 35 Hz. This applies most specifically in the context of EEG and EOG high filter settings''; and on page 19, Section IV, Sleep Staging Rules Part 1: Rules for Adults: ''Score sleep stages in 30-second, sequential epochs commencing at the start of the study''. In order to facilitate comparison with other research, we also follow the conventions. Higher heart rate usually means lighter sleep depth, and vice versa.

2) HEART RATE VARIATION (hrv)

$$hrv(x) = \sum_{j=-10}^{x} |hr(j) - hr(j-1)| \tag{2}$$

where $hr(j)$ is the j-th time heart rate. If the heart rate is sampled once per second, i.e., in Eq. (1) the parameter i is in seconds, then the sampling period of j is at least every 30 seconds. In Eq. (2), heart rate values are sampled ten times; as a result, it takes at least five minutes to sample one heart rate variation. The study in [21] suggests that the five minutes

TABLE 2. The characteristics of each stage [15].

	REM	NREM 1	NREM 2	NREM 3
Nickname	Paradoxical sleep	Null	Null	Slow wave sleep
Eyeball movement	Rapid	Slow	No	No
Heart rate	Less rhythmical	Rapid and rhythmical	Slow and rhythmical	Slower 20–30% than being awake
Body movement	50%	90%	30%	10%
Respiration	Less rhythmical	Rhythmical	Slow and rhythmical	Slowest
Body temperature	High	Low	Low	Low
Brain waves	α, β, θ and Sawtooth waves	θ wave	Spindle wave and K complex wave	δ wave
Percentage of total sleep	25%	5%	45%	25%

hrv better be applicable for screening the variation in the heart rate of subjects, which is taken as our standard. This heart rate variation value is used to observe whether the heart rate is irregular and drastically changed within a sampling period.

3) BODY MOVEMENT(bm)

$$bm(x) = \sum_{i=-300}^{x} bm(i) \tag{3}$$

where $bm(i) = 1$ if the pressure sensor detects a movement in the current i-th time, else $bm(i) = 0$. The system records the number of times the subject rolled over in five minutes as the body movement index when the parameter i is in seconds.

4) HEART RATE DIFFERENCE (hrd)

$$hrd(x) = \sum_{j=-10}^{x} (hr(j) - hr(j-1)) \tag{4}$$

It looks that the index hrd is very similar with the index hrv. The $hrd(x)$ focuses more on the continuity of heart rate change, and $hrv(x)$ concerns the severity of change. Generally, the continuous positive value implies that the patient sleeps more and more shallowly, and vice versa.

B. FUZZY INFERENCE IN ANALYSIS OF SLEEP PHASES

A fuzzy inference system is presented in this subsection, and its block diagram is shown in Figure 3. The fuzzy inference system includes three parts: input membership function (fuzzifier), output membership function (defuzzifier) and fuzzy rule library (fuzzy rule base and fuzzy inference engine). The membership functions are established based on the knowledge of expert systems and the summary of experimental data. The experimental data are from [22], where there is a comprehensive website that provides resources about sleep disorders in patients with different URLs. We have analyzed approximately 300 subjects information and generated input and output membership functions. The triangular membership function stands out from other expression curves: trapezoidal, gaussian, bell-shaped and sigmoid because of its practicality. The fuzzy rule base is derived from our experiments. We employ professional medical equipment

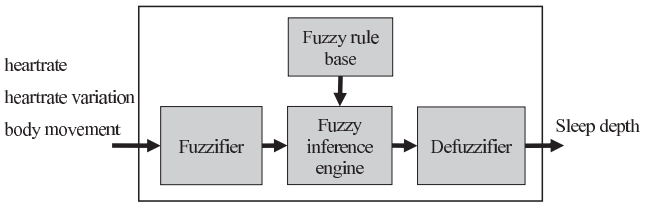


FIGURE 3. Fuzzy inference system.

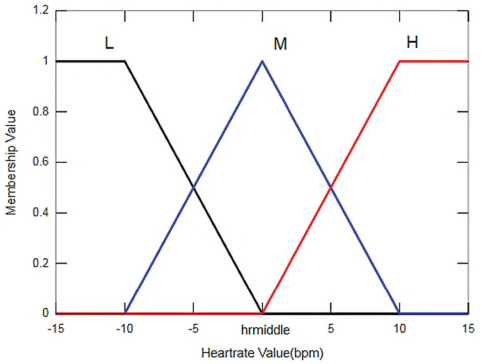


FIGURE 4. Heart rate membership function.

NicoletOne EEG to collect the subjects' brain waves. Different sleep stages correspond to different brain waves, which is described in Table 2 early. Based on the subjects' brain waves, we identify the current sleep stage, and record the heart rate, heart rate variation, and body movement at the same time. Following this way, we summarize the rules in Table 3 from about 200 experiments. Subsequently, a preliminary sleep depth conclusion can be reached after the fuzzy calculation. The indexes defined in Section III-A are sampled within five minutes as an observation period.

C. INPUT MEMBERSHIP FUNCTIONS

The input membership functions to heart rate, heart rate variation, and body movement are expressed in Eqs. (5), (6) and (7), respectively. Because each person's heart rate is different, the range of heart rate functions varies with each person's heart rate. Therefore, we propose a concept of *hrmiddle* in the membership functions, which is calculated by the average

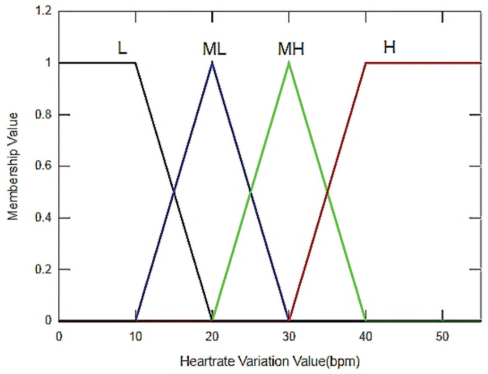


FIGURE 5. Heart rate variation membership function.

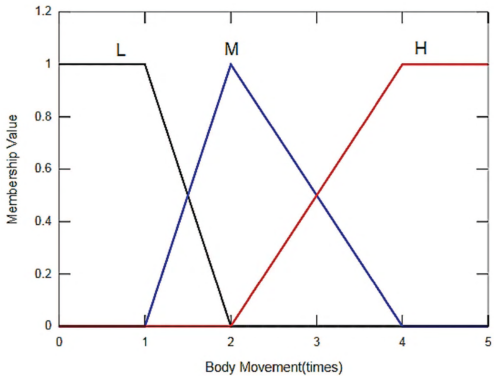


FIGURE 6. Body movement membership function.

from sleep onset to the first time that we detect the subject's heart beats to be 10 less than the average value per minute (that is also denoted as the first stage of NREM 3). The function curves are also shown in Figures 4, 5, and 6.

$$\mu_1^L(x_1) = \begin{cases} 1 & x_1 < hrmiddle - 10 \\ (hrmiddle - 10)/10 & hrmiddle - 10 \\ & \le x_1 < hrmiddle \\ 0 & x_1 \ge hrmiddle. \end{cases} \tag{5a}$$

$$\mu_1^M(x_1) = \begin{cases} 0 & x_1 < hrmiddle - 10 \\ (x_1 - hrmiddle + 10)/10 & hrmiddle - 10 \\ & \le x_1 < hrmiddle \\ (hrmiddle + 10 - x_1)/10 & hrmiddle \le x_1 \\ & < hrmiddle + 10 \\ 0 & x_1 \ge hrmiddle + 10. \end{cases} \tag{5b}$$

$$\mu_1^H(x_1) = \begin{cases} 0 & x_1 < hrmiddle \\ (x_1 - hrmiddle)/10 & hrmiddle \le x_1 \\ & < hrmiddle + 10 \\ 1 & x_1 \ge hrmiddle + 10. \end{cases} \tag{5c}$$

$$\mu_2^L(x_2) = \begin{cases} 1 & x_2 < 10 \\ (20 - x_2)/10 & 10 \le x_2 < 20 \\ 0 & x_2 \ge 20. \end{cases} \tag{6a}$$

$$\mu_2^{ML}(x_2) = \begin{cases} 0 & x_2 < 10 \\ (x_2 - 10)/10 & 10 \le x_2 < 20 \\ (30 - x_2)/10 & 20 \le x_2 < 30 \\ 0 & x_2 \ge 30. \end{cases} \tag{6b}$$

$$\mu_2^{MH}(x_2) = \begin{cases} 0 & x_2 < 20 \\ (x_2 - 20)/10 & 20 \le x_2 < 30 \\ (40 - x_2)/10 & 30 \le x_2 < 40 \\ 0 & x_2 \ge 40. \end{cases} \tag{6c}$$

$$\mu_2^H(x_2) = \begin{cases} 0 & x_2 < 30 \\ (x_2 - 30)/10 & 30 \le x_2 < 40 \\ 1 & x_2 \ge 40. \end{cases} \tag{6d}$$

$$\mu_3^L(x_3) = \begin{cases} 1 & x_3 < 1 \\ 2 - x_3 & 1 \le x_3 < 2 \\ 0 & x_3 \ge 2. \end{cases} \tag{7a}$$

$$\mu_3^M(x_3) = \begin{cases} 0 & x_3 < 1 \\ x_3 - 1 & 1 \le x_3 < 2 \\ (4 - x_3)/2 & 2 \le x_3 < 4 \\ 0 & x_3 \ge 4. \end{cases} \tag{7b}$$

$$\mu_3^H(x_3) = \begin{cases} 0 & x_3 < 2 \\ (x_3 - 2)/2 & 2 \le x_3 < 4 \\ 0 & x_3 \ge 4. \end{cases} \tag{7c}$$

D. FUZZY RULE BASE

A fuzzy rule base is presented in Table 3, which includes three input parameters, one output sleep stage and 26 rules. In theory, there are 32 rules can be created. However some brain wave boundaries are blurry, and they are not very easy to be recognized by our instruments. We will develop them in future work with new equipments or processes.

E. OUTPUT MEMBERSHIP FUNCTIONS

The output membership functions are shown in Eq. (8) and Figure 7. Their appearance makes it possible to calculate the center gravity of each sleep stage, which is a necessary step to defuzzifying.

$$\mu_4^{REM}(x_4) = \begin{cases} 1 & x_4 < 20 \\ (x_4 - 20)/20 & 20 \le x_4 < 40 \\ 0 & x_4 \ge 40. \end{cases} \tag{8a}$$

$$\mu_4^{NREM1}(x_4) = \begin{cases} 0 & x_4 < 20 \\ (x_4 - 20)/20 & 20 \le x_4 < 40 \\ (60 - x_4)/20 & 40 \le x_4 < 60 \\ 0 & x_4 \ge 60. \end{cases} \tag{8b}$$

TABLE 3. Fuzzy rule base.

Rule Number	Heart rate	Heart rate Variation	Body Movement	Sleep Stage
1	H	H	L	REM
2	H	MH	H	REM
3	L	H	H	REM
4	H	H	H	REM
5	M	H	H	REM
6	M	MH	L	REM
7	M	H	L	REM
8	M	MH	H	REM
9	H	L	L	NREM 1
10	M	ML	L	NREM 1
11	M	MH	M	NREM 1
12	H	ML	H	NREM 1
13	L	MH	M	NREM 1
14	M	H	M	NREM 1
15	L	H	M	NREM 1
16	M	ML	H	NREM 1
17	H	L	L	NREM 1
18	H	MH	L	NREM 1
19	H	L	L	NREM 1
20	M	ML	M	NREM 2
21	H	ML	L	NREM 2
22	L	MH	L	NREM 2
23	L	H	L	NREM 2
24	M	L	L	NREM 2
25	L	ML	L	NREM 3
26	L	L	L	NREM 3

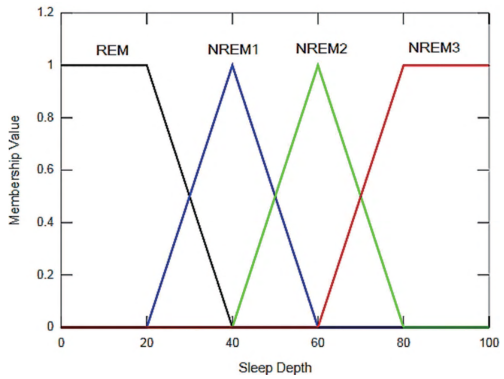


FIGURE 7. Sleep stage membership function.

$$\mu_4^{NREM2}(x_4) = \begin{cases} 0 & x_4 < 40 \\ (x_4 - 40)/20 & 40 \le x_4 < 60 \\ (80 - x_4)/20 & 60 \le x_4 < 80 \\ 0 & x \ge 80. \end{cases} \tag{8c}$$

$$\mu_4^{NREM3}(x_4) = \begin{cases} 0 & x_4 < 60 \\ (x_4 - 60)/20 & 60 \le x_4 < 80 \\ 1 & x_4 \ge 80. \end{cases} \tag{8d}$$

F. FUZZY INFERENCE ANALYSIS OF SLEEP STAGE ALGORITHM

We can discover all center point of functions in Figure 7 with the help of Eq. (9) to defuzzify the gravity of each curve. Corresponding to different functions REM, NREM 1, NREM 2 and NREM3, the X-coordinate values of these center points are 15.6, 40, 60, and 84.4, respectively.

$$g(k) = \frac{\int x_4 \cdot u_4^k(x_4)dx}{\int u_4^k(x_4)dx} \tag{9}$$

where $k \in \{REM, NREM1, NREM2, NREM3\}$.

Eq. (10) is further adopted to solve the final weight for each sleep stage, which helps us understand the sleep stages under the current input parameters.

$$\mu_5^k = \max_{1 \le l \le 26} [\min(\mu_{i,l}^k(x_i))] \tag{10}$$

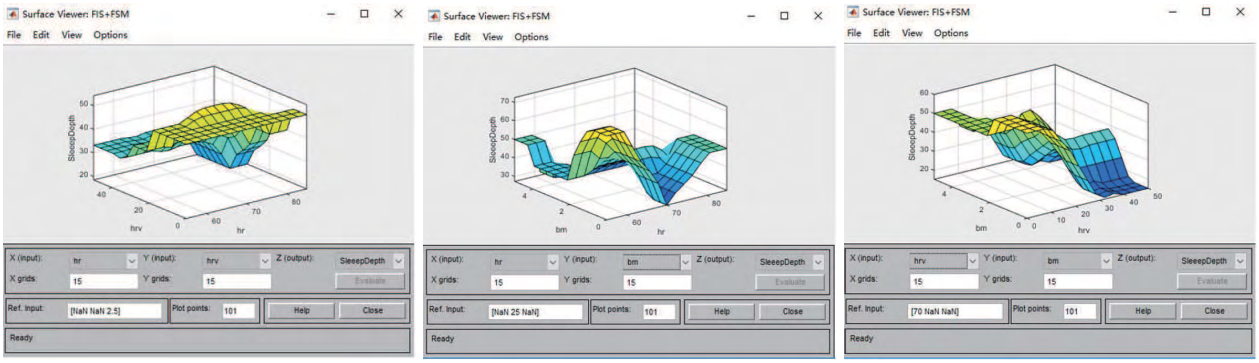
where $k \in \{REM, NREM1, NREM2, NREM3\}$, $i \in \{1, 2, 3\}$ and l is the rule number in Table 3. $u_{i,l}^k(x_i)$ is a value chosen from $u_i(x_i)$, $i \in \{1, 2, 3\}$, and l and k are rule number and sleep stage corresponded to the current $u_i(x_i)$ in Table 3, respectively.

Furthermore, a concept of sleep depth $f(z)$ is defined in Eq. (11). The sleep depth takes into account the final weight of each sleep stage, as well as the center gravity value of every output membership function, thereby obtaining a weighted average value. Then, Table 4 is used to map the sleep depth to the corresponding sleep stage. Algorithm 1 shows the details of each step. Note that the standards in Table 4 are also obtained from experimental data analysis.

$$f(z) = \frac{\sum \mu_5^k \cdot g(k)}{\sum \mu_5^k} \tag{11}$$

where $k \in \{REM, NREM1, NREM2, NREM3\}$.

Let us discuss the time complexity of Algorithm 1. All steps, except for the first step, can be considered to complete in unit time. Assume that $M = 26$ (M is the number of all the rules in Table 3). In the worst case, three input parameters are solved by Eqs. (5), (6) and (7), and the generated results



(a) (b) (c)

FIGURE 8. Control surfaces of fuzzy inference system. (a) X-axis:hr, Y-axis:hrv, and Z-axis:sleep depth. (b) X-axis:hr, Y-axis:bm, and Z-axis:sleep depth. (c) X-axis:hrv, Y-axis:bm, and Z-axis:sleep depth.

TABLE 4. The value of $f(z)$ corresponding to different sleep stage.

$f(z)$	$0 \sim 30$	$30 \sim 50$	$50 \sim 70$	$70 \sim 100$
Sleep Stage	REM	NREM 1	NREM 2	NREM 3

Algorithm 1 Fuzzy Inference Analysis of Sleep Stage Algorithm

Input: Heart rate (hr), Heart rate Variation (hrv), and Body Movement (bm)

Output: Sleep stage (REM, NREM 1, NREM 2, NREM 3)

Step 1: According to the input parameters with the data hr, hrv and bm, the Eqs. (5), (6) and (7) are used to calculate u_i values, $(i = 1, 2, 3)$;

Step 2: Obtain the center gravity of each sleep phase according to Eq. (9);

Step 3: Calculate the final weight of each sleep stage by using Eq. (10);

Step 4: Combining the results of **Steps 2** and **3**, find a weighted average sleep depth value with the help of Eq. (11);

Step 5: Based on the value of **Step 4**, we map the data into Table 4. Output the corresponding sleep stage, and then the algorithm stop.

correspond to all terms in the fuzzy rule base. Therefore, its total cost is $O(M)$.

Using the Fuzzy Logic Toolbox, the fuzzy control surfaces are generated by MATLAB. There are three input parameters in the fuzzy logic designer: hr, hrv, and bm, and one output parameter: sleep depth. The Mamdani-type inference is applied in the fuzzy logic designer. Figure 8(a), (b) and (c) are 3D images, where their output Z-axis is settled by sleep depth parameter, and the X-axis and Y-axis are synthesized by two sets of three input parameters. The control surface in Figure 8 shows the dependency of one of the outputs on any two of the inputs for the fuzzy inference system.

G. AN ILLUSTRATION OF ALGORITHM

We give an example to explain the algorithm in the following. Suppose that we have the following data: Heart rate is *hrmiddle* + 4, Heart rate Variation is 33, and Body Movement is 3.

i). According to the input membership functions, the different u_i, $i = \{1, 2, 3\}$ can be calculated as:

Heart rate: M(0.6), H(0.4)

Heart rate Variation: MH(0.7), H(0.3)

Body Movement: M(0.5), H(0.5)

ii). Based on the values above, Table 5 is generated (ignore the two columns *Rule Weight* and *Final Weight* for now), which is filtered from Table 3. Furthermore, Eq. (10) is applied to find the final weight of each sleep stage. Generally, we find the smallest value as the rule weight of this row first. For example, in the first line of Table 5, there are three values: heart rate(0.4), heart rate variation(0.7) and body movement(0.5). We choose the minimum value 0.4 as the rule weight of this row. This value is filled in the corresponding *Rule Weight* column in Table 5. Among all the rule weights in the same sleep stage, we pick up the largest one as the final weight of this stage. For example, the first four lines in Table 5 all belong to the same REM sleep stage, and their rule weights are 0.4, 0.3, 0.3 and 0.5, respectively. Obviously, the value 0.5 is the best choice as the final weight, which is also recorded in the last column of Table 5.

iii). Through Eq. (9), we know that the center gravities of REM and NREM 1 are 15.6 and 40, respectively. The sleep depth is calculated as $f(z) = \frac{\sum \mu_5^k \cdot g(k)}{\sum \mu_5^k} = \frac{15.6 \times 0.5 + 40 \times 0.5}{0.5 + 0.5} = 27.8$.

iv). Compared to Table 4, the sleep depth value 27.8 falls between 0 and 30. As a result, the current sleep stage may be REM.

H. FINITE STATE MACHINE IN ANALYSIS OF SLEEP PHASES

As mentioned in Section II, not every cycle is perfect from REM to NREM 3 end. Sometimes, stage confusing changes will occur. Some alterations are allowed if the changes are caused by the patient's own physical condition, but some deviations are not if those irregular stage changes may be touched by the problem with the collected parameters.

TABLE 5. The third step of Algorithm 1 applied to Example 1.

Rule number	Heart Rate	Heart Rate Variation	Body Movement	Rule Weight	Sleep Stage	Final Weight
2	H(0.4)	MH(0.7)	H(0.5)	0.4	REM	
4	H(0.4)	H(0.3)	H(0.5)	0.3	REM	
5	M(0.6)	H(0.3)	H(0.5)	0.3	REM	0.5
8	M(0.6)	MH(0.7)	H(0.5)	0.5	REM	
11	M(0.6)	MH(0.7)	M(0.5)	0.5	NREM 1	
14	M(0.6)	H(0.3)	M(0.5)	0.3	NREM 1	0.5

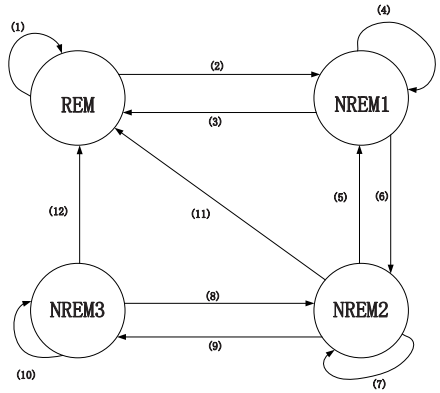


FIGURE 9. Finite state machine in analysis of sleep phases.

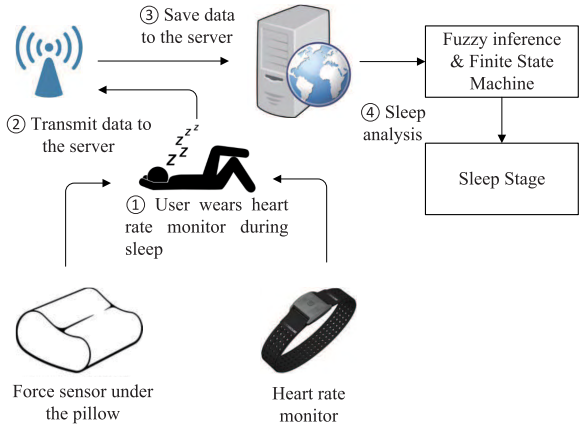


FIGURE 10. The system configuration.

Section III-B can only make preliminary sleep calculations according to the input parameters. If we want to make accurate decision, especially in the face of such irregular changes, the introduction of finite state machines is necessary. The preliminary sleep stage analysis result, three original input parameters (hr, hrv and bm) and the heart rate difference (hrd) are served as the inputs to the finite state machine. Then a finite state machine further refines the analysis result depending on state transition rules to reveal the reasonable sleep stage alterations. The following rule numbers correspond to the labels next to edges in Figure 9.

State transition rules:

(1) $f(z) < 30$, hrv > 30, and bm > 3.
(2) $30 < f(z) < 50$, hrv > 30, and bm > 3.
(3) $f(z) < 30$ and hrv < 20.
(4) $30 < f(z) < 50$, hrv > 20, and bm > 3.
(5) $30 < f(z) < 50$.
(6) $30 < f(z) < 50$ and hrv > 20.
(7) $50 < f(z) < 70$ and hrd < 10.
(8) $50 < f(z) < 70$.
(9) $f(z) > 70$.
(10) $f(z) > 70$, hrv < 10, and bm < 3.
(11) $f(z) < 30$ and hrd > 25.
(12) $f(z) < 30$.

For example, in the last five minutes, the parameters collected are hr $=$ *hrmiddle* $-$ 2, hrv $= 16$, and bm $= 1$; and the sleep stage is decided as NREM 2. Now, we obtain four new parameters: hr $=$ *hrmiddle* $+$ 4, hrv $= 33$, bm $= 3$, and hrd $= 30$. As a result, the sleep depth is 27.8 (we have used these parameters as an illustration of Algorithm 1 in Section III-B), which is in the REM sleep stage. Apparently, the development of the sleep situation does not follow the perfect cycle from the last moment of NREM 2 to the next moment of NREM 3, and there is a slight stage deviation. Check the current confusing stage change, we observe that this alteration is permissible in Figure 9 and the four new parameters entered are also in accordance with rule (11). Consequently, the result REM stage is accepted. Let us make a counter example. If the last sleep stage is NREM 1, the current parameters (hr $=$ *hrmiddle* $-$ 8, hrv $= 13$, and bm $= 1$) are calculated, and then the sleep stage will be supposed as NREM 3. After comparing the result with Figure 9, we find that this situation is impossible, no matter what the heart rate difference is. It implies that the parameters collected at this time are incorrect, which may be caused by environmental factors or sensor failure. Therefore, the NREM 3 prediction is discarded.

IV. APPLICATION

The system configuration is displayed in Figure 10. Some force sensors are placed under the pillow and a heart rate monitor is worn on the subject's hand. When the subject has falling asleep, the physiological parameters are collected and transmitted to the server. Each sampling period is 5 minutes. As soon as the subject is awake, the system will assess the sleep quality based on the percentage of different sleep stages throughout the night.

To implement the description in Figure 10, the actual application scenario is shown on the left part of Figure 11.

TABLE 6. Comparison of different sleep stage evaluation criteria.

No.	Heart rate	Heart rate Variation	Body Movement	Sleep Stage determined by [8]	Sleep Stage determined by this article
1	63	15	1	NREM 3	NREM 3
2	59	17	1	NREM 3	NREM 3
3	54	27	7	NREM 1	NREM 2
4	50	28	4	NREM 1	NREM 2
5	48	27	1	NREM 1	NREM 2
6	54	27	3	NREM 3	NREM 3
7	49	27	3	NREM 1	NREM 2
8	65	25	2	NREM 2	NREM 2
9	71	25	4	REM	REM
10	69	50	2	NREM 1	NREM 1
11	60	50	2	NREM 1	NREM 1

The red circle is the wearing of a Bluetooth heart beat monitor, the yellow oval dotted line is the pressure-sensing Arduino chip placed under the pillow, and the green rectangle is the user interface of system. The top right portion of Figure 11 expresses the details of the parameter collection and transmission. The force sensors connect with 1 $M\Omega$ resistances and 5 V pin of Arduino chip to form series circuits. Then, we can predict pressure changes by measuring variations in pin voltage. A Zigbee network is used to transmit the body movement parameter back to the server. Subsequently, a Bluetooth heart beat monitor is adopted to collect the hr, hrv, and hrd parameters and links with computer through Bluetooth 4.0 protocol. The user interface of system is presented in the bottom right part of Figure 11. In the user interface, the red dotted line box is the setting of system factors, including the communication port and USB Dongle. When the user presses the *Start System* button, the system begins to collect the subject's parameters and analyze the sleep stages, the corresponding sections are shown in the black and blue dashed boxes of the user interface.

V. EXPERIMENTAL RESULTS

A total of 24 subjects were requested to use the proposed system for more than 200 sleep analysis experiments. Three pressure-sensing Arduino chips are placed under the pillow, as shown in Figure 12, and a Mi model 3 heart rate monitor is worn on the subject's wrist. The Mi model 3 heart rate monitor uses a triaxial acceleration and photoplethysmography (PPG) sensors to analyze the heart rate, which can accurately collect hr, hrv and hrd parameters. To facilitate the comparison of experiments, we also invite professional staff to perform PSG tests for the subjects at the same time, and encourage the subjects to fill up self-administered sleep questionnaires to record their feelings upon waking up.

Example 1: We apply the experiment on the same subject employing the proposed method and the one in [8]. All night sleep data are collected, and the heart rates are sampled every 30 seconds (epoch). The main purpose is to compare the difference in determining sleep stage between the fixed threshold and the fuzzy inference system plus finite state machine. One of the experiment results is shown in Figure 13

TABLE 7. Sleep information of subject 001.

Subject information			
Subject ID	001	Age	23
Height	184 cm	Weight	82 kg
Sleep information analyzed by our system			
Total sleep time	396.5 min	REM time	66 min (16.65%)
NREM 1 time	55.5 min (14%)	NREM 2 time	128 min (32.28%)
NREM 3 time	147 min (37.07%)		
Sleep information analyzed by PSG			
Total sleep time	402.5 min	Light sleep time	254.5 min (63.23%)
Deep sleep time	148 min (36.77%)		

with two subgraphs: Figure 13(a) employs the way in [8] and Figure 13(b) utilizes the method in this article. It is clear that many jitters are generated by the fixed threshold method. Taking the red oval circle as an example, we select representative eleven points in this area, and show their physiological signals in Table 6. This patient has coronary heart disease, and his average heart rate is 55, which is lower than the normal 70. If the normal human heart rate is used as the threshold of the input parameter for sleep determination, some misjudgments will occur. For example, the patient is currently in the NREM 2 stage, but is considered as in the NREM 1, which can also be seen at the peak in the red oval circle in Figure 13(a). Comparing the fixed threshold, the proposed method in this paper can effectively eliminate the jitters, as shown in Figure 13(b). The sleep stages determined by different methods are listed in the last two columns of Table 6.

Example 2: The sleep time and percentages of each sleep stage of subject 001 are shown in Figure 14. It is shown that the subject has an REM period of about 17%, and the NREM 3 period exceeds 30% overnight, which means that he has difficulty falling asleep, but the quality of sleep is not bad. More details are given in Table 7. In the PSG test, all sleep stages except NREM 3 are regarded as light sleep. The PSG test values are very close to our conclusions. For instance, its deep sleep time (NREM 3 stage) is 36.77%, and our result is 37.07%. Meanwhile, after examining his self-administered questionnaire, we find that he feels hard to sleep, but he feels energetic during the day. This is consistent with our experimental analysis results.

The sleep time and percentages of each sleep stage of subject 002 are shown in Figure 15 and Table 8. We can clearly

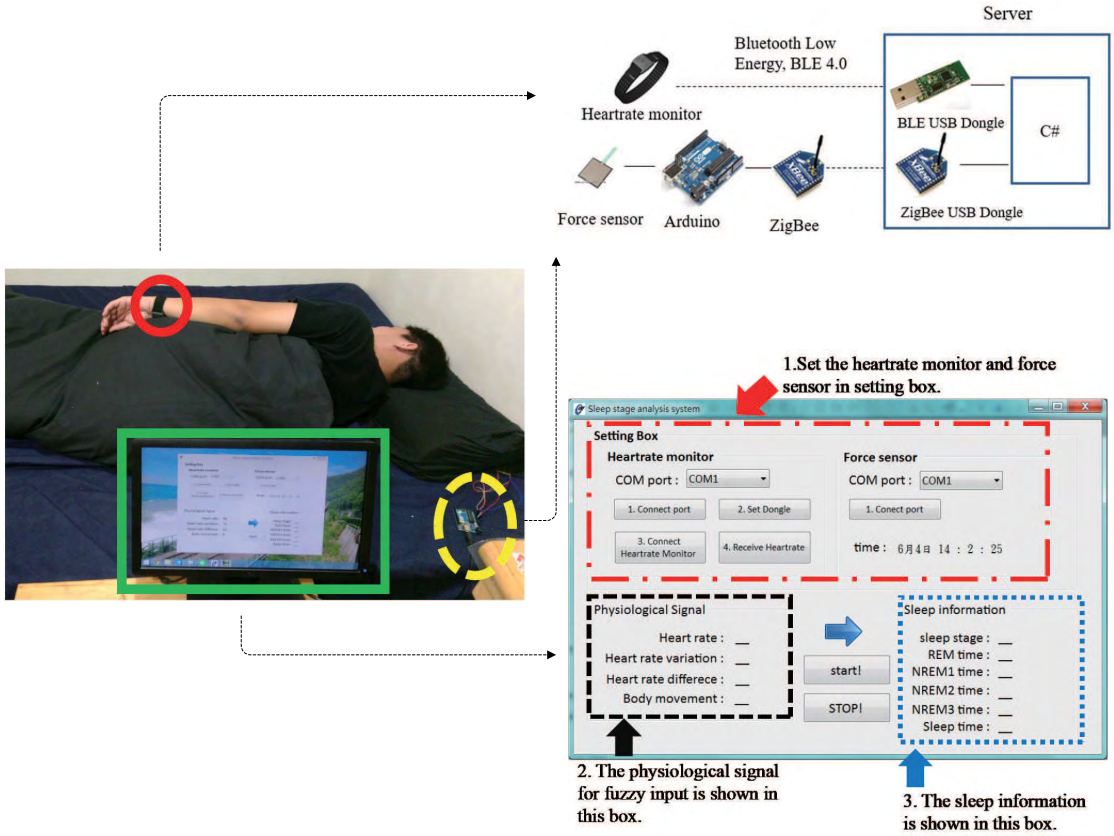


FIGURE 11. The application of system.

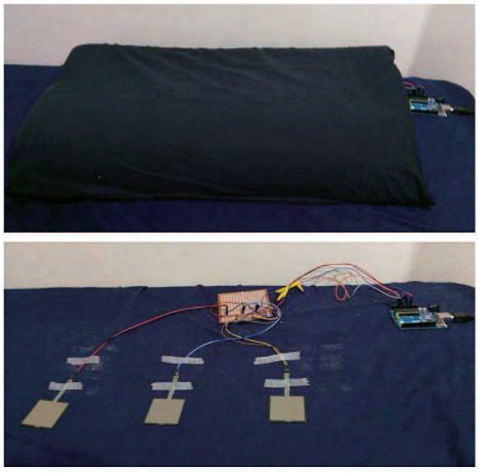


FIGURE 12. Three pressure sensors place under the pillow.

see that the REM period is less than 9%, and the NREM 2 and NREM 3 periods are 36% and 44%, respectively. That means he has a good rest in the physical body, but the brain repair time is not enough. The subject says that he falls asleep normally, but he often wakes up in a nightmare, and he feels tired after getting up. The experimental conclusions are also consistent with the PSG test and his sleep questionnaire.

TABLE 8. Sleep information of subject 002.

Subject information			
Subject ID	002	Age	24
Height	177 cm	Weight	68 kg
Sleep information analyzed by our system			
Total sleep time	456 min	REM time	40.5 min (8.88%)
NREM 1 time	49.5 min (10.86%)	NREM 2 time	165 min (36.18%)
NREM 3 time	201 min (44.08%)		
Sleep information analyzed by PSG			
Total sleep time	449 min	Light sleep time	272 min (60.58%)
Deep sleep time	177 min (39.42%)		

Example 3: To illustrate that the proposed approach works well across different subjects, we list all patients' information in Table 9. There are 24 subjects, including 13 males and 11 females. The 24 subjects have different age levels. A total of more than 200 sleep experiments are performed in our results. For each subject, we performed sleep measurements for 10 days continuously, with the least number of subjects being measured 5 times and the most patients being measured 10 times in the period; the PSG, PSQI, and our method are adopted in each sleep test. The light sleep includes REM + NREM 1 + NREM 2 and the deep light sleep represents NREM 3. We measure the patients' light sleep time, deep sleep time, and total sleep time in different ways, and then average the results of multiple cases. The percentage values of each column of the PSG and our method are the corre-

TABLE 9. The sleep data information of 24 subjects.

Subject ID	Ages	Gender	Experimental Cases	PSG		Our Method		Sleep Disorders (≤25%)
				Light sleep	Deep sleep	Light sleep	Deep sleep	
001	23	Male	10	63.23%	36.77%	62.93%	37.07%	No
002	24	Male	9	60.58%	39.42%	55.92%	44.08%	No
003	19	Female	8	70.91%	29.09%	68.62%	25.96%	No
004	22	Female	8	91.69%	8.31%	87.22%	8.22%	Yes
005	22	Male	10	77.01%	22.99%	75.22%	21.44%	Yes
006	27	Male	9	67.63%	32.37%	59.96%	32.00%	No
007	26	Male	10	81.73%	18.27%	71.44%	28.56%	No
008	30	Female	8	69.64%	30.36%	64.70%	26.51%	No
009	30	Male	9	93.36%	6.64%	84.34%	6.52%	Yes
010	30	Male	8	91.64%	8.36%	75.21%	7.77%	Yes
011	28	Female	5	78.51%	21.49%	68.73%	18.20%	Yes
012	33	Male	7	72.83%	27.17%	65.67%	25.81%	No
013	**33**	**Female**	**8**	**74.31%**	**25.69%**	**75.13%**	**24.87%**	**PSG:No; Our:Yes**
014	37	Female	8	80.34%	19.66%	67.85%	17.52%	Yes
015	39	Female	10	85.88%	14.12%	68.94%	12.34%	Yes
016	41	Male	8	60.80%	39.20%	50.93%	37.53%	No
017	45	Male	10	65.73%	34.27%	55.56%	33.57%	No
018	40	Female	8	75.81%	24.19%	64.74%	23.35%	Yes
019	51	Male	9	81.43%	18.57%	66.39%	17.80%	Yes
020	63	Male	8	65.86%	34.14%	64.12%	29.76%	No
021	52	Female	10	76.76%	23.24%	72.79%	21.02%	No
022	52	Male	7	93.98%	6.02%	79.34%	20.66%	Yes
023	**55**	**Female**	**6**	**77.55%**	**22.45%**	**73.30%**	**26.70%**	**PSG:Yes; Our:No**
024	65	Female	10	92.26%	7.74%	86.55%	7.60%	Yes
Total		M(13), F(11)	203	77.61%	22.39%	68.02%	23.45%	No

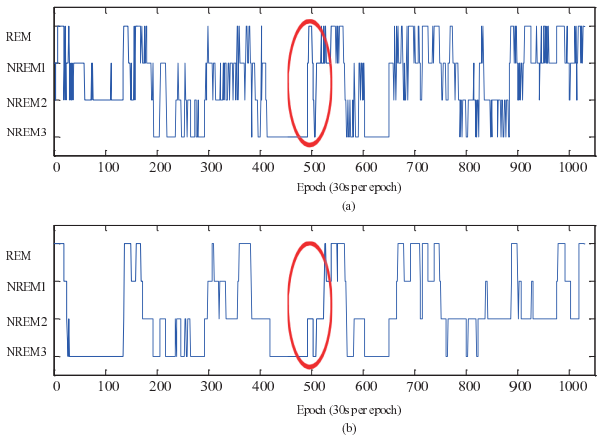


FIGURE 13. The comparison of sleep stage determining between the fixed threshold [8] with the proposed fuzzy inference system plus finite state machine work.

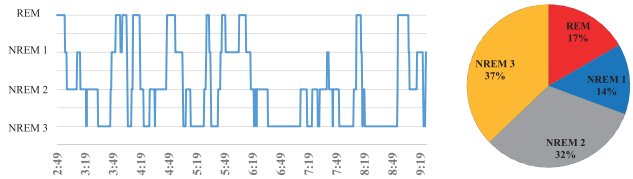


FIGURE 14. Sleep time and proportion of subject 001.

sponding sleep time divided by the total sleep time. If the PSG method is used as a standard, 12 people have severe sleep disorders (deep sleep time is less than 25% [23]). Two subjects are misjudged by our method, and their ID are 013 and 023. Each sleep stage of them is shown in Table 10, where the upper row of data for each patient is collected by the PSG method, and the next row of data is adopted by our method. It clearly shows that our method basically determines the sleep stages accurately, no matter the age, gender, insomnia or not; offsets are within the allowable range, and the overall accuracy rate reaches 83% ($(1 - \frac{2}{12}) \times 100\%$). In contrast, if we still use the PSG method as the benchmark, adopting the same population, and applying the Mi band and pressure-sensing pillow separately, the proportions of subjects who can be detected severe sleep disorders are only 70.2% and 51.6%, respectively. This also validates our previous assumptions that more physiological signals can get a more accurate decision of sleep analysis, as long as we can organize the signals together. However, deciding how to effectively integrate these signals is a challenging task, which deserves in-depth research.

The proposed method also has its limitations. First, due to the lack of brain wave collection, it is impossible to distinguish the Awake stage. Second, many physiological parameters, such as respiratory, oxygen saturation, and oxygen index reduction etc., which are closely related to sleep quality, cannot be applied in the presented method.

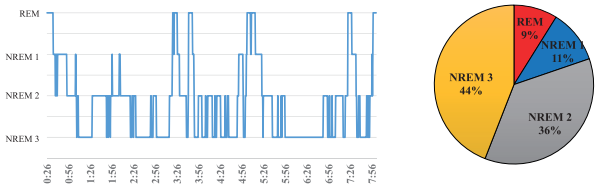


FIGURE 15. Sleep time and proportion of subject 002.

TABLE 10. A detailed presentation of misjudged data.

Subject ID	REM	NREM 1	NREM 2	NREM 3	Total sleep time
013	21.5	99	203.5	112	436
	8	123	117.7	82.3	331
023	17	133	192	99	441
	23	155	117.55	107.65	403.2

Third, the PSG method can split between, moderate, and severe sleep disorders, which is not possible to fulfill in the proposed approach. All in all, the way shown in this article is suitable for perform at home as a supplement to medicine.

VI. CONCLUSION

In this paper, we present a non-invasive sleep analysis approach, which can help us to evaluate the overall quality of sleep. Through the fuzzy inference, we can get a preliminary sleep depth by optimizing the division of sleep stage. Then, a finite state machine is proposed to evaluate the sleep stage alterations. Experimental results show that the sleep analysis conclusions obtained by the proposed approach are consistent with the PSG test. In future, more rules will be expanded into the fuzzy rule base and some dynamic correction parameters will be introduced in Section III-H when a state change is denied by the finite state machine. Dynamic parameters can help us locate the next reasonable state alteration as much as possible, instead of simply discarding all the collected values. We will discuss this in the next paper. In the future we will analyze the sleep phases by using Petri nets and their related analysis methods [24]–[27].

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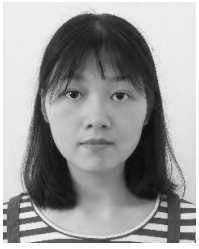

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