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RESEARCH ARTICLE

Multimodality Sensor System for Sleep- Quality Monitoring

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Abstract— ***Multimodality is the mixture of textual, audio, and visual modes in combination with media and materiality to create meaning. The influence of sleep conditions to human health and performance is currently well known but still underestimated and monitoring devices are not widespread. This paper describes methodology and prototype design of a sleep monitoring. Sleep monitoring is an important issue and has drawn considerable attention in medicine and healthcare. Given that traditional approaches, such as polysomnography, are usually costly, and often require subjects to stay overnight at clinics, there has been a need for a low-cost system suitable for long-term sleep monitoring. In this paper, we propose a system using low-cost multimodality sensors such as video, passive infrared, and heart-rate sensors for sleep monitoring. We apply machine learning methods to automatically infer a person's sleep state, especially differentiating sleep and wake states. This is useful information for inferring sleep latency, efficiency, and duration that are important for long-term monitoring of sleep quality in healthy individuals and in those with a sleep-related disorder diagnosis. Our experiments show that the proposed approach offers reasonable performance compared to an existing standard approach (i.e., actigraphy), and that multimodality data fusion can improve the robustness and accuracy of sleep state detection.***

I. INTRODUCTION

Sleep scoring belongs currently to the most innovative multimodal diagnostic methods, and is investigated by dozens of scientists all around the World. Since during the sleep all regulatory functions are under the sole control of the autonomous nervous system, sleep scoring benefits from the absence of voluntary behavior control from the subject under investigation [12]. Sleep laboratories require expensive infrastructure and well trained laboratory staff to provide reliable patient description. Sleep occupies more than one-third of human life. Sleep deprivation due to sleep-related disorders may introduce severe physical effects, cognitive impairments, and mental health complications [1]. An economical and minimally-invasive method to monitor sleep state and differentiate it from waking can provide valuable information about a person's health, an early warning for, and long-term monitoring of response to therapies for sleep-related disorders.

In practice, self-rated questionnaires and sleep diaries are routinely used for the assessment of sleep quality [2], [3]. Among the questionnaires, the Pittsburgh Sleep Quality Index (PSQI) has been a most widely used instrument [3]. It contains nineteen self-rated questions which form seven component scores. Each component score has a range of 0–3.

The sum of the subscale scores yields a global score of sleep disturbance between 0–21. Higher scores indicate more severe sleep disturbance. However, retrospective assessments of subjective quality have limited capabilities and are the least reliable.

According to the American Academy of Sleep Medicine, there are 81 official sleep disorders, presented in [1]. Seventy million people in the USA have a sleep disorder, the vast majority of which remain undiagnosed and untreated. It is estimated that sleep-related problems incur $15.9 billion to national healthcare budget. There is then great need for automatic non-intrusive methods for sleep disorder recognition that patients can use in their homes. This would not only help decrease healthcare costs but also increase the number of diagnosed patients.

Polysomnography (PSG)[5], a standard approach for sleep monitoring and objective sleep quality measurements, is usually conducted at specialized centers or in hospitals. PSG involves recordings of multiple physiologic variables including electro-encephalogram (EEG), electro-cardiogram (ECG), electro-myogram (EMG), and electro-oculogram (EOG). PSG data are scored by human examiners based on the standard criteria [6]. PSG recordings provide the accurate assessment of sleep architecture and quality. However, its high cost ~$1000/study makes it impractical for long-term sleep monitoring. Also, with so many sensors attached to the user's body, it is highly intrusive. It can disturb the users' usual sleep, so the measured data may not accurately represent the users' actual sleep behavior.

II. PROPOSED SYSTEM FOR SLEEP MONITORING

The widely-adopted objective measuring device, the actigraph, [1] is a watch-like device which contains motion accelerometers to measure limb movements. It has been used for many medical research applications, especially for monitoring motion-related sleep disorders [7], [8]. Actigraphy has been used to study sleep–wake patterns for at least 30 years since Kupfer *et al.* reported significant correlation between the wrist activity, EEG signals, and wakefulness in 1972 [9]. Sadeh *et al.* concluded that normal subjects showed more than 90% agreement [10] in comparisons of actigraphy with PSG. By 1995, sufficient analysis eventually enabled the Standards of Practice Committee of the American Sleep Disorders Association (now the American Academy of Sleep Medicine:AASM)to support the use of actigraphy in evaluating certain aspects of sleep disorders such as insomnia, circadian sleep–wake disturbances, and periodic limb movements [7]–[9]. Although only one physiological variable (i.e., limb motion) is measured, the advantage of actigraphy over PSG is that sleep and wake can be recorded continuously for weeks or even longer. It provides a convenient way for long-term sleep-monitoring. However, the device is still intrusive in that some people find wearing a wrist-watch type device during sleep troublesome and the devices are still relatively expensive (>$1000). In addition, actigraphy is less useful in detecting some disorders when limb motion is not involved [12] and the preparation and processing of data can require extensive personnel time.

Sleep monitoring has been an active research area for decades and other devices have been developed but are mostly used in research studies and not clinical practice. Body movements during sleep are monitored with customized systems [7], [8], [13] that identify sleep–wake states from wrist activity data. Hidden Markov models (HMM) and neural networks have been applied to detect arousal and abnormal breathing events during sleep [4]. Wantanabe [13] derived an algorithm for the relationship between sleep stages, and measured bio-signals based on pneumatic methods.

In contrast to these previous methods, which often involve costly devices that are seldom affordable and suitable for use by the general public, we propose to use relatively low-cost multimodality sensors for sleep and wake monitoring. Several sleep related disorders show certain motion (e.g., limb movements, parasomnias) or audio (e.g., snoring) phenomena. Moreover, among the nineteen questions in the PSQI, eight of them can be detected via non-intrusive low-cost motion and audio sensing devices. Therefore, it is interesting to investigate the use of simple video, passive infrared (PIR), and audio sensors for sleep monitoring (although the audio modality is not included in our current study due to the lack of audio data from the subjects we tested).

In this paper, we show that using a video or a PIR sensor, and machine learning techniques [7], we can analyse a nonintrusive and low-cost sleep–wake detection system which could be useful for long-term sleep monitoring, detection of early symptoms of sleep related disorders, and response to treatment. The addition of a low-cost heart-rate (HR) sensor, albeit a bit intrusive, is useful for symptoms without body movements or audio sounds. We also show that by combining different data modalities (e.g., motion and HR data), more robust performance can be achieved in detecting sleep and wake states under different circumstances such as primary insomnia that does not involve limb or other types of body movements. Although a HR sensor may not be appropriate for a nonintrusive system, we expect that in general, the improved robustness of the proposed multimodality sensor fusion framework can be extended to other types of nonintrusive sensors such as audio.

To reduce the privacy concern of video sensors, we only extracted low-level features such as motion information instead of recording the actual video such that identifiable features of the subjects was not possible. PIR sensors actually help reduce the privacy concern because visual data is not captured at all.

The low-cost nature of the system makes long-term sleep monitoring possible. Moreover, with machine learning techniques, the proposed system learns how to distinguish various sleep conditions using multimodality features. It does not require technical highly trained experts to manually assign inference rules. The client sensors can either send the multimodality data to a home computer for feature extraction or directly extract features from embedded integrated circuits

(ICs). The extracted features are then sent to a server, either at the user's home or at a remote clinical monitoring center through the Internet, for sleep–wake state determination.

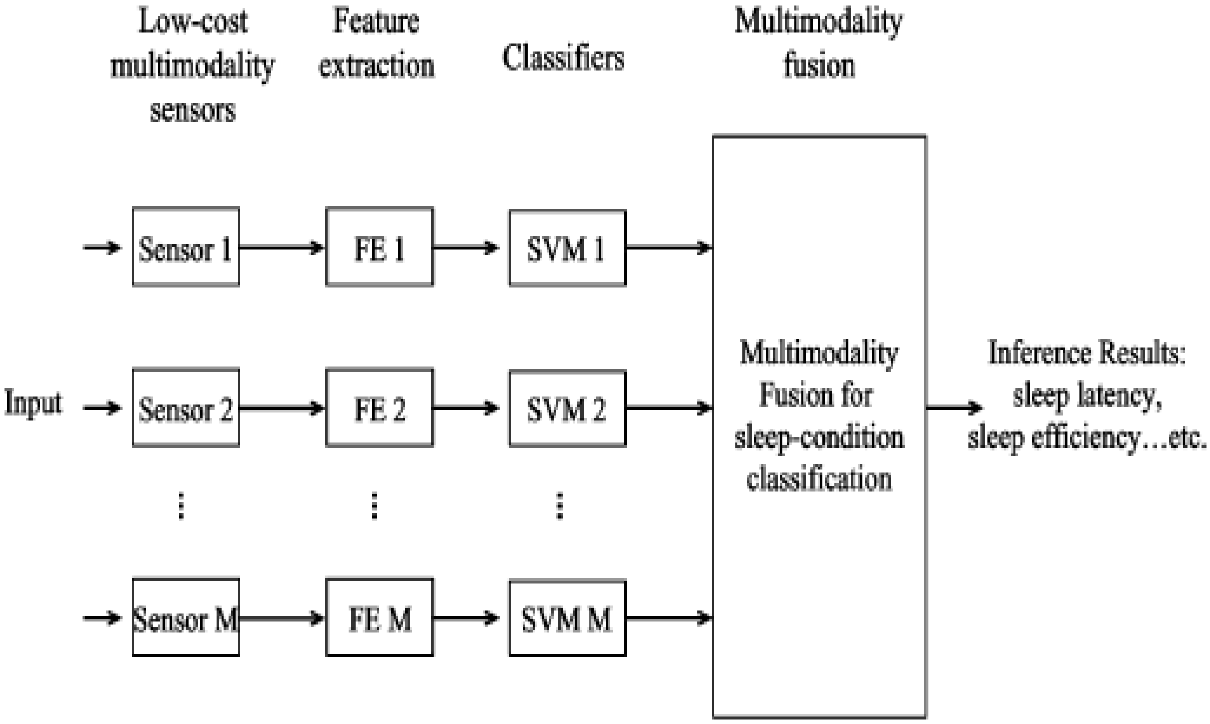


Fig .1 Proposed multimodality sensor system for sleep condition classification and sleep quality inference

The contributions of this paper include: 1) proposing a system for combining low-cost multimodality sensors (e.g., video, PIR, and HR sensors, where a less-robust but nonintrusive monitoring system can also be achieved if the HR sensor is not used) and machine learning schemes (i.e., support vector machine classifier and classifier fusion) for sleep condition monitoring and sleep quality measurements; 2) showing a set of features for each sensor and how to combine the information from different sensors for sleep–wake detection; and 3) analyzing competitive performance in preliminary experiments by comparing our system to actigraphy. Our novel system is not meant to replace existing standard methods (i.e., PSG or actigraphy) to measure sleep, but it provides an alternative approach, which has potential advantages for long-term monitoring.

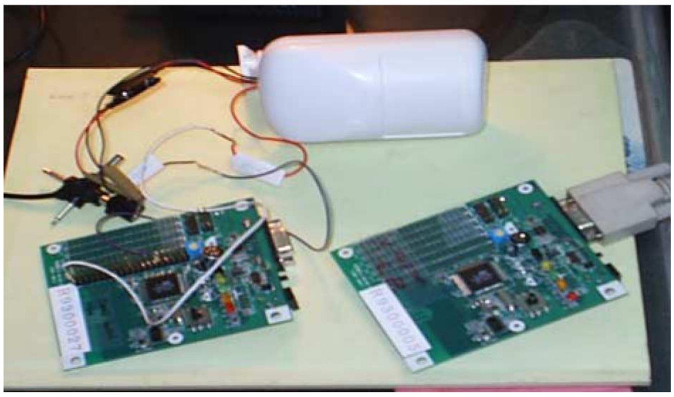
III. PROPOSED SYSTEM FOR SLEEP-WAKE DETECTION

The proposed multimodality sensor system for sleep state inference is shown in Fig. 1. Multimodality data are first acquired from various sensors. Features are extracted from each data modality and are used for classification using support vector machines (SVM) [8]. Results of individual classifiers are fused together to infer the sleep state condition. Data collected from the training stage are divided into two sets. One is for the training of individual modality classifiers, and the other is used as a validation set for optimal parameter selection of each modality classifier (e.g., the length of analyzed window, the classifier kernel, etc.). Motion and HR are the major modalities investigated in this work .

For motion monitoring, we use either an infrared night-vision video webcam or a PIR sensor for data capturing. The infrared night-vision video webcam3 acquires motion information by applying motion estimation between two consecutive video frames (with a frame rate of 1 frame per 6 s). The video webcam is shown in Fig. 2(a), which costs about $20.

A low-cost PIR sensor4 is commonly used in daily life for security applications. Its sensor-head is typically divided into several sectors/zones. Each sector/zone is defined by specific boundaries. Detection occurs when a heat-emitting source crosses two adjacent sector boundaries or crosses the same boundary twice within a specified sensing time. To acquire motion information, we modified the PIR sensor to have a granularity of a two-second resolution period. The PIR on-off stream showing the motion situation is recorded. The PIR device set is shown in Fig. 2(b), which costs about $40.


(a) (c)



(b)

Fig.2 Sensors required for system. (a) Night-vision video webcam. (b)Modified PIR motion sensor, including a PIR sensor connected to a wireless transmitter and a wireless receiver interfaced with the computer. (c) HR sensor.

A wearable watch with a sensor belt is used to continuously capture the user'sHR.5The sensed HR data are usually noisy with irregular sampling intervals due to the loose contact between the sensing belt and the subject's chest. We analyze preprocessing on the noisy data to exclude unlikely noisy values (e.g., though the HR in fit subjects may drop below 50 beats per min (bpm) during sleep, we only eliminated isolated spikes with values below 50 bpm and above 100 bpm) and then repeat or skip samples according to the desired sampling rate based on the assumption that the missing sensing sample has the same value as the previous value. The cost of the HR sensor in our analysis is about $200. The HR detector used in our pilot system is shown in Fig. 2(c).

We currently use the integrated microphone of a PC with the Windows audio recording software to work as the audio sensor to capture sounds from the subject and the environment during sleep. In the future, the audio sensor could be integrated with the video sensor in a low-cost device, and connects to the PC through wireless connections. However, in this study, audio did not have an effect on analysis because the participants were healthy and did not make loud snoring sounds and other noises. Thus, the audio component will not be discussed in this paper. In future work, when the system is applied to patients with symptoms involving audio, the audio sensor could be a useful component.

We have analyzed the sleep monitoring prototype system in a distributed, client-server architecture. On the client side, sensed data from the HR and video sensors are recorded into the computer while the PIR data are transmitted by a wireless transmitter to a wireless receiver connected to the computer. The sensor data are processed to extract the features for the classifiers. The results from the classifiers are then fused to infer the sleep condition. Diagnostic results including detected sleep conditions along with important factors for sleep quality measurements (e.g., sleep latency, duration, and efficiency) can be either recorded on the central server or the client machines for sleep logging.

IV. MULTIMODAL SLEEP PATTERNS

A. *Description of Database*

For the needs of our analysis, we collected data from 7 different individuals simulating their sleep habits. Each individual lied on the bed for a period of time and performed the actions that they would normally perform if they went to bed. That involved getting in bed, staying still for periods of time in different postures, changing body postures , moving parts of the body like the arms or the legs, and getting out of the bed. The different actions performed; during that period of time were recorded using 2 different sensors. The first one was a bed pressure mat (see Sect. 1) that we put under the sheets, and the second one was a

Microsoft Kinect sensor (see Sect. 2) that we mounted on the ceiling. The recorded data were then manually annotated according to the various classes of interest, such body posture, motion occurrence, etc.

1).Data collected from FSA bed pressure mat

The FSA bed mat system produced by Vista Medical Ltd. provides a 1,920 mm x 762 mm sensing area which contains an array of 32 x 32 pressure sensors. Each of the sensors can capture a measurement in the range 0–100 mmHg (1.93 PSI) with a scan frequency of up to 5 Hz. The measurements can be recorded over a period of time and can be exported as a set of time stamped vectors containing the values of each of the 1,024 pressure sensors for each time stamp. To make visualization easier, we can consider each of these vectors as a frame of a video. Each of the sensors can be considered as pixel of a gray-scale image with an intensity ranging from 1 to 100. Thus, each frame can be considered as a 32 x 32 pixel image.

2).Data collected from Kinect

Kinect is a motion sensing input device designed by Microsoft for the Xbox 360 video game console [1]. Kinect outputs 3 different data streams, RGB video stream, depth sensing video stream and audio. The video output frame rate is 30 Hz. The RGB video stream uses 8-bit VGA resolution (640 x 480 pixels), while the monochrome depth sensing video stream is in VGA resolution (640 x 480 pixels) with 11-bit depth, which provides 2,048 levels of sensitivity. In our analysis, we used only the depth sensing video stream. The depth sensor consists of an infrared laser projector combined with a monochrome CMOS sensor, which captures video data in 3D under any ambient light conditions. That feature makes the Kinect usable even in very low lighting conditions, which is usually the case during the night sleep. Furthermore, the 3D input that we get regarding the subject's body posture is more informative compared to the 2D information that we could get from the RGB video. The value of each pixel in a depth video stream frame is the distance, in millimeters, of the corresponding surface part of the object from the sensor (Fig. 3).

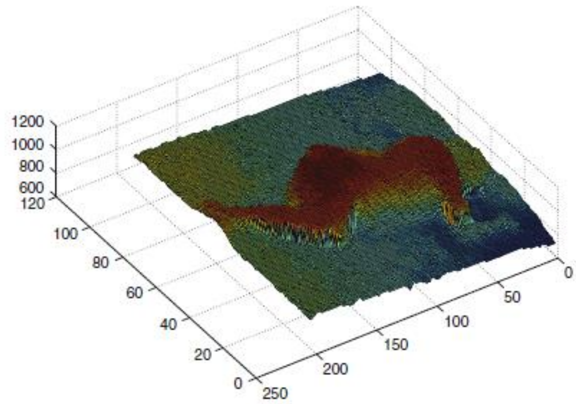


Fig 3. A 3D representation of the input obtained by the Kinect depth sensor

B. Data analysis and Classification

The detection/recognition of sleep disorders usually boils down to the recognition of a set of symptoms that are related to a specific sleep problem. Such symptoms are as follows: how long it takes for the person to fall asleep, how many times (if any) they wake up during the night, how often do they move during their sleep time, how many hours on average do they sleep, etc. These indicators are difficult to monitor at home. Our immediate goal is to create a system that can recognize these indicators and make them easily accessible to the physicians. The long term goal is to create a system that will be able to automatically detect specific sleep disorders based on training data from previous known cases.

To achieve all requirements, we break our problem into a set of classes and we employ a combination of rule-based and supervised learning methods to classify the various instances into one of those classes. To evaluate the classification accuracy, we perform leave-one-out cross-validation experiments where every time we test the classification accuracy on the data collected from one user, by training it on data collected from the other users. In more detail, we are attempting to recognize the following situations: (1) if the person is in bed or not, (2) when does motion occur while in bed, (3) what type of motion is that, and (4) while the person does not move what is their body posture in bed. Being able to detect and recognize the above situations and then combining them together can be a very rich information source with regard to the symptoms that we want to identify. In the following sub-sections, we will describe how we approach each of the above situations and how efficient our system is in terms of recognition accuracy.

1) Detecting if person is in bed or not.

The first case of interest in our experiments would be to detect whether the person is in bed or not. This is useful in cases, for example, where we want to know how many hours in total does the person spend in bed and how often do they get up during their sleep time[11]. It turns out that this is a very easy problem to solve by just using the bed pressure mat. All we had to do is just define a threshold of the total amount of pressure that we get in the pressure mat. If the total pressure exceeds that threshold, it means that the person is in bed. Using this approach, we got 100 % accuracy in detecting whether the person is in bed or not in our analysis. Note that we did not consider cases where somebody puts something heavy on the bed that might confuse our system, since we assume that participants are willing to be analyzed and they are not willing to mislead the system.

2) Motion Detection

Another case of interest is to detect when motion occurs while the person lies on bed. The detection of motion can be related to various sleep disorder symptoms. For example, it can be an indication of how long does the person take to fall asleep after they go to bed or how often do they wake up during the night.

To detect motion, we used the standard computer vision technique of frame differencing. That means that we compared consecutive frames by subtracting the frame n from the frame n+i, where i >=1 depending on the frame rate, and summing up the absolute differences. The value of that sum S is a very good indicator of the existence of motion in the time slot between the two frames.

3) Recognition of body types and body postures

After detecting motion, our next step was to recognize the motion type, when motion occurred, and the subject's body posture, when there was not motion. To do that, we first used our motion detection method to segment the data steams into sequences of frames which are part of a motion and sequences of frames where there is no motion[1]. Then, we classified each of those sequences into one of the motion classes or body posture classes.

The basic motion classes that we defined were the following:

1. Changing body posture.
2. Moving arms or legs.
3. Getting in bed or out of bed.
4. Making bed.

The first class refers to the case where the subject is changing sides, for example, they are sleeping on their back, and then, they turn their left. The second class refers to more subtle motion types where the subject moves a part of their body, usually a limb, but they do not completely change their body position. The third class occurs when the person gets in or out of the bed. This motion type differs from the previous two considerably. The last class refers to the case where the person is not actually in bed but there is still some type of motion detected by the pressure mat or the Kinect. This is usually the case when someone makes their bed.

Regarding the body postures we defined the following classes:

1. Back
2. Left side
3. Right side
4. Stomach
5. Sitting on bed

To recognize the body postures, we analyzed with two different techniques. The first one is a Computer Vision-based technique, called Template Matching (TM), which has been used in face detection [10] and other similar applications. The idea behind this technique is that for each posture, we pick a representative frame to use it as a template, after possibly cropping it appropriately, and then for every other frame to be classified, we compare it with all the templates and see which one matches better according to some distance criterion. In our case, we used the simple frame difference as a distance criterion. That means we calculated the sum of absolute differences of each pixel of the template subtracted from the corresponding pixel in the frame to be classified. To accommodate for cases where the subject lied in a different position of the bed compared to the template or they were taller/shorter compared to the subject used in the template, we tried different scales and different centering positions of the template.

The second technique that we analyzed was based on supervised learning. In order to perform supervised learning, we converted each frame to a feature vector where each pixel represented a feature.

- Be aware of the different meanings of the homophones "affect" and "effect", "complement" and "compliment", "discreet" and "discrete", "principal" and "principle".
- Do not confuse "imply" and "infer".
- The prefix "non" is not a word; it should be joined to the word it modifies, usually without a hyphen.
- There is no period after the "et" in the Latin abbreviation "et al.".
- The abbreviation "i.e." means "that is", and the abbreviation "e.g." means "for example".

An excellent style manual for science writers is [7].

V. THE IMPORTANCE OF SLEEP MONITORING SYSTEM

Researchers at the University of California at San Diego have identified four major categories for sleep problems that came along with aging:

1. Health issues:-Sleep issues increase with age primarily due to health problems that might include depression, pain from disease like arthritis or cancer, neurological disorder such as dementia, and organ system failure like pulmonary or coronary disease.

2. Medications:-The second reason for poor sleep with age is the potential for poly-pharmacy issues from the variety of medications older adults take to treat medical and psychiatric conditions.

3. Sleep disorders:-Sleep disorders that are more common with age include restless legs syndrome and sleep apnea[12]. Other researchers have identified general insomnia, or trouble falling or staying a sleep , as a most common sleep disturbance in older adults.

4. Circadian Rhythm:-The biological clock changes with age , causing sleepiness in the early evening and waking earlier in the morning. Although older adults still need about the same amount of sleep as people of younger age ,they tend to sleep more lightly because they spend less time in REM (rapid eye movement) sleep.

VI. CONCLUSION

In this paper, we analyze an economical system consisting of multimodality sensors with machine learning approaches for human sleep–wake detection and sleep-quality measurements.

It demonstrates the usefulness of both video and PIR sensors for capturing motion information and show comparable results with actigraphy in terms of sleep–wake detection for the tested subjects. These analysis also show that inference accuracy can be boosted by fusing the motion and the HR modalities together, especially under the occasion of inactive sleepers when actigraphy may fail to detect wakefulness. Also, It gives analysis of sleep patterns using non-invasive sensors and applying a combination a rule-based and Machine Learning methods. Also it gives results on real user data sets show that the task of analyzing sleep patterns with the intent to detect symptoms related to sleep disorders can be successfully analysed. Although the available dataset was relatively small, the classification accuracy results are promising and show that the proposed tools and methods could be used in the future for the detection of sleep disorders and other related diseases affecting sleep quality.

In the future, we can plan to apply the system to large-scale clinical tests and we believe that it will be possible to associate our findings with pathological cases such as SDB, RBD RLS/PLMS, as well as depression. The big challenge is the diagnosis of diseases by recognizing the sleep patterns, which may lead to more focused medical treatments. The more focused treatments are expected to enhance the quality of life for millions of patients suffering from sleep disorders.

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Thanking you,

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