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An Intelligent Sensing System for Sleep Motion and Stage Analysis

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Abstract

Monitoring the movements of the human during sleep can potentially give us a good estimation of aspects of the bodily as well as mental state of a human. When such data are combined, either with the knowledge of a sleep pathologist or with a special automated diagnosis system, they could prove quite useful towards the diagnosis of various types of sleep disorders such as parasomnias, insomnia, and dyspnea. Furthermore, such data could also be useful towards diagnosis of various medical conditions, and towards quantitative evaluation of the effects of drug therapy that is administered to a patient who is suffering from poor sleep quality, an important indication of which is the duration and patterns of various sleep stages. The intelligent sensing system that we present consists of a thermal infrared camera, a budget three-electrode budget EEG device, and algorithms for analysis and motion processing which we designed for this system. The main measurables that we derived from our system are of three kinds: a) descriptions of sleep stages (personalized probabilistic model), b) movement graphs, and c) relations between stages and motion. An empirical study with two subjects was carried out, where sensory recordings for multiple nights were captured and analyzed, illustrating the capacity of our sensory system towards providing the above measurables, and quite importantly, towards acting as a strong foundation for future wider deployment of in-home sleep self-monitoring and diagnosis tools.

Keywords: Intelligent sensors; sleep disorders; sleep stages; sleep movement; computer vision

1. Introduction

Assuming that people sleep 8 hours a day on average, people spend about 33% of their lives sleeping. Most importantly, getting a good sleep every night is highly significant as it plays a key role in providing quality time while a person is awake. Studies on sleep have been done in many different ways such as EEG monitoring, body movement tracking using pressure mat [1] or bed temperature monitoring [2]. Sleep monitoring could be crucial in detecting sleep disorders and treatment of sleep disorders [3].

In order to assess the quality of sleep, identifying and measuring the sleep stages that a person is quite useful, as there is a strong correlation between sleep quality and sleep stage duration and patterns. Sleep stages can be subdivided in Non-Rapid Eye Movement (NREM) and Rapid Eye Movement (REM) sleep. People go through what is called as 'Sleep Cycle' that consists of combination of periodic NREM and REM sleep. NREM sleep can be further divided into four stages; N1, N2, N3 and N4 [5]. Sleep stages are traditionally identified using EEG by collecting surface electrical signals arising from internal brain activity, and recognizing the appropriate sleep stage depending on the type and bare frequency of the wave form that arises. Furthermore, monitoring sleep through traditional multi-electrode hospital EEG devices involves direct contact between the user's head and multiple electrodes, which could create discomfort. On the other hand, apart from

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electrical activity, movement during sleep is also an interesting observable.

But what kinds of irregularities of sleep exist? According to Diagnostic and Statistical Manual of Mental Disorders (DSM-IV) [6*], there are more than 80 official sleep disorders, where most of them remain to this day unable to detect and treat. Conventional methods for diagnosis of sleep disorders require the patients to stay some nights in specially designed rooms equipped with special instruments. This examination collects signals generated from the brain and other necessary biometric data from heart, muscles and respiratory function through devices such as EEG, Electrocardiogram sensor (ECG/EKG sensor), etc. The signals and data from these sensors mounted on the body of the patient are collected throughout the night under constant supervision by a technical person and stored in a computer and are presented in different forms. This examination involves continuous recording of the patient with a camera during sleep in order to provide more information about the body movement at specific time to the doctors. All of the above examination leads the patient to unusual sleep due to change in sleep environment and also being watched by another person causes disturbance in normal sleep, so the information that collected by this way from the patient is fictitious and it does not respond to the true picture of the patient's everyday sleep.

Related research has been done in the past focusing on the relationship between body movement during sleep and condition of health [1], or focusing on generally monitoring sleep in relation to health condition [7]. In [4], it was observed that bodily movements during sleep are associated with the depth of sleep, which may be used to predict the stage of sleep. In that paper, it is described how eye movement and general body motility follow quasi-cyclic patterns. Major body movement during sleep takes place when a person is in REM sleep. Studies on detecting body movement during sleep have been done using various tools such as temperature sensors [2] and bed pressure mat [1]. The method used in [1] provides pressure distributed images that could be used to detect body movement during sleep and also the lying posture, which could be significant information in detection and treatment of pains, caused by inappropriate posture during sleep. Inappropriate posture during sleep could cause serious pains and it can further develop into serious diseases such as cervical or spinal disc. The study in [8] relates EEG patterns during sleep to body movement, eye movement and dreaming. According to [8], EEG, eye movement, and body movement undergo regular cyclic variation and they coincide with the lightest phase of the EEG cycles. Similarly, as we shall see, our results also indicated an interesting relationship between sleep stages identified from EEG and body movement.

Thus, in this paper, we were strongly motivated by all of the above evidence, to create an intelligent sensing system that could be help us study and analyze sleep motion and stages, also possibly round-the-year, in-house and not in a special clinic. We aim to use this sensing system as a basis for further studies concentrating on automated or semi-automated diagnosis of specific pathologies, and for evaluation of treatments. The novel intelligent sensing system that we present consists of three parts: a thermal infrared camera, a budget three-electrode EEG device, and algorithms for analysis and motion processing, which we designed for this system. The main measurables that we derive from our system, are of three kinds: a) descriptions of sleep stages (personalized probabilistic model), b) movement graphs, and c) relations between stages and motion. An empirical study with two subjects was carried out, where sensory recordings for multiple nights were captured and analyzed. Below, we will start by describing our system and methods in detail, and then we will present the numerous and interesting qualitative and quantitative results that have arisen from our experiments.

2. Methods

2.1. System

Our system consists of three main parts: an infrared camera, a budget-priced three-electrode EEG strap and device, and analysis algorithms (Fig.1). In more detail:

2.1.2 Infrared camera

In order to be able to easily detect and localize spatiotemporally body movement during sleep, we used an IR thermal imaging camera. The model of the thermal camera that we used is 'PathFindIR' manufactured by FLIR [9] (Fig.2 (a)) which can sense in the infrared wavelength and its video output signal has a resolution of 320 by 240 pixels with a refresh rate of 7,5 Hertz and thermal sensitivity 100 mK at +25°C. This device enables us to easily discriminate the image of a person, even if he or she is sleeping in very dark environments, and makes it simple for us to differentiate a human body from the background, due to the temperature difference. There exists some thermal occlusion from bedsheets and covers, but for our experiments, as we shall see, this proved not to be a problem. The resolution, the frame rate as well as accuracy of the camera, proved to be certainly adequate for our needs.

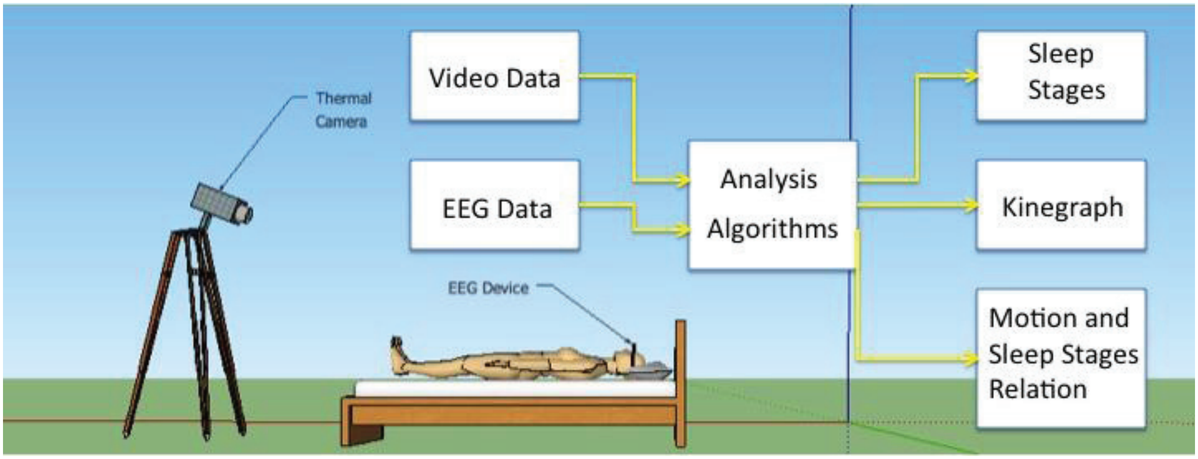


Fig. 1. System Architecture: experimental subject, infrared camera, EEG strap, analysis algorithms, and results

2.1.2 Triple-electrode EEG strap

To be able define the sleep stages we used a budget wireless EEG device with three dry electrodes manufactured by Zeo Inc. The model we used can be seen in Fig.2(b), and gives us as output an estimation of the sleep stage of a human every 30 seconds as well as a more stable filtered version every 5 minutes, using proprietary analysis. Our experimental subjects reported that the strap was not obstructing normal sleep and movements, and was quite convenient to wear.

(a)

(b)

Fig. 2. Experimental equipment. (a) IR thermal imaging camera; (b) EEG device

2.2. Experiments

The experiments were performed in the sleeping room of the apartment of each subject, where we had placed the thermal camera on a tripod to a point where it is possible to observe all the possible movement area see Fig.3. The user wore the EEG device on his head before sleep and when he was ready to sleep he started recording the data from the EEG device and the video from the thermal camera. In the experiments took part two subjects aged 21 and 28 years for 5 and 4 consecutive nights respectively, including weekend for one of the two subjects. Both of the subjects were working at the university, and their everyday duties mainly were office work involving small muscle activity during the day, which translated to little physical fatigue. The average sleep duration for the experiments was about 7 hours per day and the end of sleep was caused by external factors (alarm).

(a) (b)

Fig. 3. Experiment environment. (a) experimental setup: FLIR Camera & Strap; (b) infrared image of subject

2.3. Movement detection and video processing

This part was one of the most important parts in this project since detecting body movement during sleep through computer vision required careful tuning of our algorithms in order to give out meaningful results. We have used MATLAB [10] for our coding, and also utilized the computer vision toolbox. We experimented with various methods to analyze the video, such as optical flow, frame-by-frame comparison, and background estimation. Given the nature of the movements, we finally used two methods: optical flow and frame-by-frame comparison. The final output of our algorithms for motion analysis was a kinegraph, i.e. a visualization of motion quantity over time, such as the example of Fig.4 below.

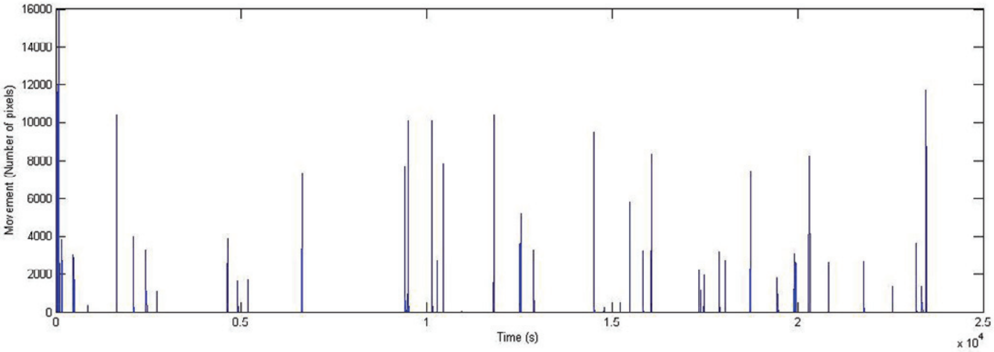


Fig. 4. Example of a KineGraph: visualization of sleep quantity over the duration of a whole night's sleep

The two different results, one from each method, i.e. subtraction versus optical flow, were compared, and as was expected, the outputs obtained from each method were very similar and therefore, we decided to use the much simpler frame-by-frame subtraction method, since it could process lengthy video in a few minutes whereas optical flow required more time, almost the length of the video to process since it required the whole video to be played from the beginning to the end. The frame-by-frame method was simply implemented by subsampling, and more specifically taking one frame from each second of the video, and comparing it to the previous frame. The previous frame is subtracted from the next frame, and then the individual pixel differences were compared to the threshold. The threshold value was determined using trial and error, by analyzing a video with an empty bed and no movement, in order to determine the usual noise levels. Several values of threshold were tested, and the best chosen threshold was applied in analyzing the videos. After thresholding, the logical "1" entries of the resulting binary image are added, and therefore the number of pixels with significant change is counted. The thermal image made this process highly effective for our purpose since the human pixels have a significantly higher temperature than the background. Furthermore, processing were very fast; approximately 1 minute processing time was required for every hour of video, running on an i5 processor at 2.5GHz.

3. Results

As mentioned in the introduction, the main measurables that we derive from our system are of three kinds: a) descriptions of sleep stages (personalized probabilistic models), b) movement graphs, and c) relations between stages and motion. Let us consider each in turn.

3.1. Sleep stage descriptions

In order to analyze the data that we have obtained from our budget EEG device, we have extracted the data from Zeo device that contained sleep stage information every 30 seconds, as well as every 5 minutes. The first step was to determine which data to use since data from every 30 seconds and every 5 minutes gave out different results when analyzed. It was noticed that the 30 second sampling rate data appeared to have many more sleep stage transitions than the 5 minute sampling rate data. This could be the case either because there exist micro-stages with abrupt transitions, or because the Zeo classification contains more errors due to noise and inadequate integration time of the device, at this sampling rate. After consulting with the usual sleep stage durations, it became apparent that the second cause was the case. Therefore the slow stream of data sampled every 5 minutes was used as our primary source for sleep stages.

The next step towards creating our desired sleep stage description, was to generate a transition matrix by counting the number of each type of transition that had taken place. After generating a transition matrix, a Markov chain model was constructed (see for example Fig.5). Furthermore, we gathered statistics for the duration of each sleep state – and generated histograms for them. Thus, the total probabilistic model that was generated, contained both a transition matrix, as well as a state duration statistics. From such a model, the average sleep quality can be estimated, as a function of the durations. An example of such a total model is given below in Fig.5 and Fig.6.

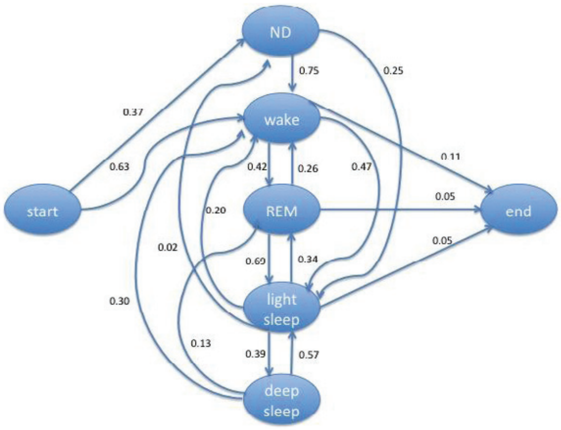
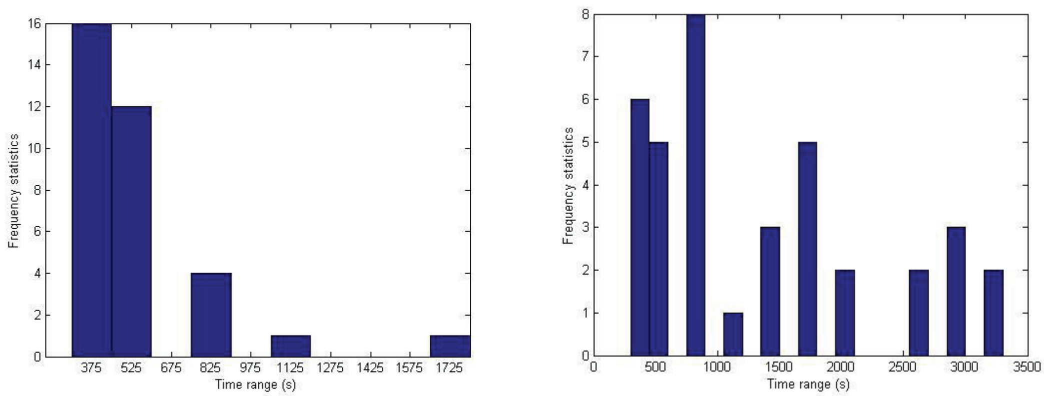
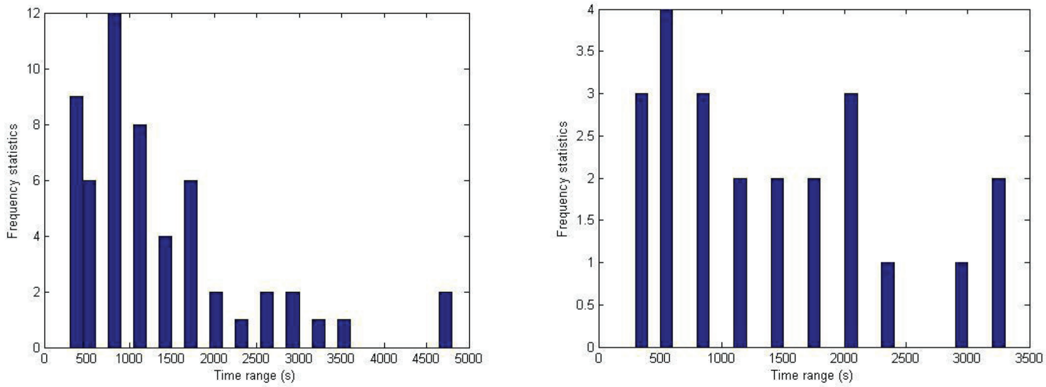


Fig. 5. Markovian model of sleep stages



(a) (b)



(c) (d)

Fig. 6. Histograms of state durations. (a) wake; (b) REM; (c)light sleep; (d)deep sleep

3.2. Movement graphs

We generated kinegraphs for all of the observed nights. A lot of detail was also apparent when zooming in near the high intensity episodes, for example as shown below in Fig.7.

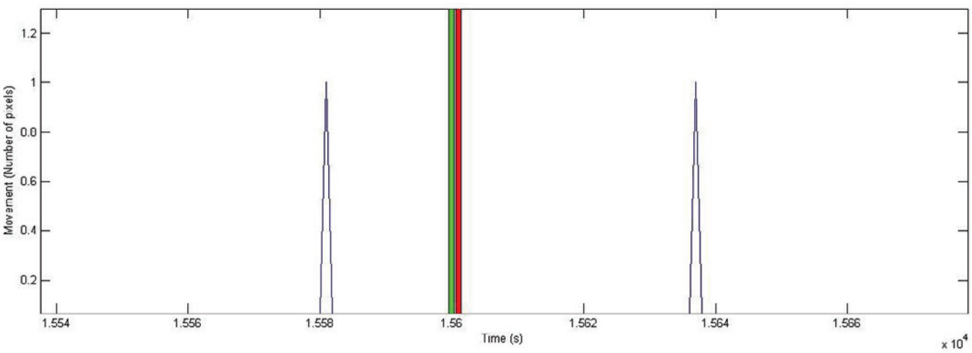


Fig. 7. Magnifying a movement episode around a stage transition

In the above example of a movement episode, there is a transition between Light Sleep and REM occurring at time 15600; roughly 20 seconds later, there is a large movement occurring, followed by two smaller ones, the first of which 100 seconds later from the transition mark, and the second 120 or so.

3.3. Relation between sleep stages and motion

Once having acquired the sleep stage timeseries as well as the kinegraphs, one can start searching for interesting relations between the two. The main question asked was: Q1) is there any overall relation between stage transitions and movement? And furthermore Q2) what can one say regarding observed motion and the specific types of stages or transitions? Let us consider these questions in detail. In order to investigate Q1, we followed the following procedure:

First, we created timewindows of varying duration around sleep stage transitions, and observed the motion taking place within these timewindows, in comparison to the motion taking place outside (Fig.8). By varying the time window length, we derived interesting results, as shown for example in figure 10 below. In that example, it was observed that 60% of all movements with amplitude greater than 50, occurred within 5 minutes around state transitions.

Now, let us move on to Q2: what can one say regarding observed motion and the specific types of stages or transitions? Our empirical data also provided strong indications that the transition from light sleep to deep sleep contains no moves in a time window of 5 minutes, and that the stages with greater movements overall were REM, and Light sleep

Furthermore, we are collecting more data, and have started to create a number of other relevant interesting questions worth investigating: for example, we have decided to try to quantify which transition types have more movement associated with them, how characteristic sleep movements are with regards to the identity of the experimental subject, as well as many other interesting questions that arise.

Most importantly, having designed, created, and demonstrated the capabilities of our intelligent sensing system, we are now starting a collaboration with a sleep expert aimed towards targeting specific pathologies, which could be potentially diagnosed, and their treatment monitored, through our system.

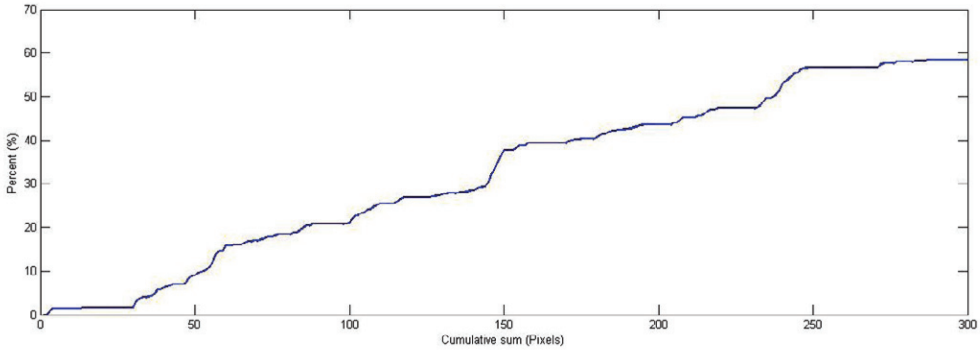


Fig. 8. Percentage of large movements (amplitude greater than 50) occurring within a timewindow of duration t around a sleep stage transition where horizontal axis is time window duration (sec) and vertical axis is percentage

4. Conclusion

Towards our ultimate goal of in-house non-obtrusive sleep monitoring and sleep quality improvement for everyone, which will benefit the health, productivity, and happiness of a significant percentage of people worldwide, in this paper we have presented an intelligent sensing system which we have constructed as our prototype for our further studies, which will be focused towards specific types of sleep disorders. The intelligent sensing system that we have presented consists of a thermal infrared camera, a budget three-electrode budget EEG device, and algorithms for analysis and motion processing which we designed for this system. The main measurables that we have derived from our system are of three kinds: a) descriptions of sleep stages (personalized probabilistic model), b) movement graphs (kinegraphs), and c) relations between stages and motion. An empirical study was carried out, where sensory recordings for multiple nights were captured and analyzed, illustrating the capacity of our sensory system towards providing the above measurables, and quite importantly, towards acting as a strong foundation for future wider deployment of in-home sleep self-monitoring and diagnosis tools.

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