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Using off-the-shelf lossy compression for wireless home sleep staging

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HIGHLIGHTS

- We examine the effects of off-the-shelf lossy compression on an all-night PSG dataset, in the context of automated sleep staging.
- The popular compression method Set Partitioning in Hierarchical Trees (SPIHT) was used.
- A rule-based automatic sleep staging method was used to classify the sleep stages.
- The result shows that the system can achieve more than 60% energy saving and a high accuracy (>84%) in classifying sleep stages.
- The feasibility of using off-the-shelf lossy compression for wireless home sleep staging was demonstrated.

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ABSTRACT

Background: Recently, there has been increasing interest in the development of wireless home sleep staging systems that allow the patient to be monitored remotely while remaining in the comfort of their home. However, transmitting large amount of Polysomnography (PSG) data over the Internet is an important issue needed to be considered. In this work, we aim to reduce the amount of PSG data which has to be transmitted or stored, while having as little impact as possible on the information in the signal relevant to classify sleep stages.
New method: We examine the effects of off-the-shelf lossy compression on an all-night PSG dataset from 20 healthy subjects, in the context of automated sleep staging. The popular compression method Set Partitioning in Hierarchical Trees (SPIHT) was used, and a range of compression levels was selected in order to compress the signals with various degrees of loss. In addition, a rule-based automatic sleep staging method was used to automatically classify the sleep stages.
Results: Considering the criteria of clinical usefulness, the experimental results show that the system can achieve more than 60% energy saving with a high accuracy (>84%) in classifying sleep stages by using a lossy compression algorithm like SPIHT.
Comparison with existing method(s): As far as we know, our study is the first that focuses how much loss can be tolerated in compressing complex multi-channel PSG data for sleep analysis.
Conclusions: We demonstrate the feasibility of using lossy SPIHT compression for wireless home sleep staging.

1. Introduction

Point-of-care (POC) patient monitoring refers to near-patient testing, usually outside the central hospital or primary care facility. One important POC application is to measure and track sleep quality. Human beings spend approximately one third of their lives sleeping, and condition such as insomnia and obstructive sleep apnea can seriously affect the quality of life. According to a survey, 50–70 million people suffer from sleep disorders in the United States (Colten and Altevogt, 2006).

Sleep staging is probably the most important piece of information in the analysis of sleep. Polysomnography (PSG) is the gold standard used in hospitals for sleep staging, and this method continuously and simultaneously records multiple physiological signals during sleep, such as electroencephalogram (EEG),

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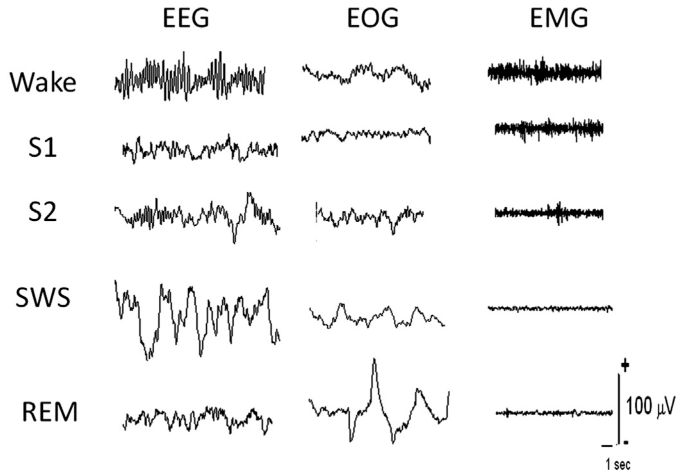

Fig. 1. Typical polygraphic recordings during the wake, stage 1 (S1), stage 2 (S2) light sleep, slow-wave sleep (SWS) associated with deep sleep, and rapid-eye movement (REM) states. Each column shows EEG, EOG and EMG obtained during the corresponding sleep stage.

electromyogram (EMG), electrooculogram (EOG), electrocardiogram (ECG), and blood oxygen saturation data. EEG records electrical activities of the brain which have distinct patterns in different sleep stages, such as a sleep spindle or delta rhythm. EOG records eye movement during sleep, which is critical to differentiate the rapid eye movement (REM) sleep stage from the other sleep stages. EMG records bioelectrical signals generated by the activities of skeletal muscles, and play an important role in distinguishing Wake from REM sleep. Fig. 1 shows typical PSG recordings corresponding to various sleep stages.

Diagnosis of sleep disorders using PSG is typically performed in hospitals and sleep centers, and subjects are thus often kept on a waiting list for a considerable period of time, which in the United States, ranges from a few weeks to more than one year (Flemons et al., 2004). Moreover, sleeping in an unfamiliar environment, such as a hospital, may cause the first-night effect in subjects (Agnew et al., 1966), leading to less REM sleep, shorter total sleep time, and lower sleep efficiency. Sleep recording at home can reduce the first-night effect (Edinger et al., 1997) and decrease the waiting time for sleep evaluation. Recently, there has been increasing interest among both the academics (Chang et al., 2012; Griessenberger et al., 2013; Kelly et al., 2012; Lubecke and Boric-Lubecke, 2009) and practitioners in at-home sleep monitoring through the use of lightweight, wearable wireless PSG systems. However, with PSG signals, even a small amount of recording can generate very large amounts of data, and wireless transmission is a major contributor to power consumption in portable devices (Casson and Rodriguez-Villegas, 2007). In addition, with the surging popularity of cloud computing, many studies have proposed providing remote sleep monitoring as a cloud service for elderly patients at nursing homes (Biswas et al., 2010; He et al., 2013; Hossain, 2013). However, since most ISPs charge subscribers based on the volume of traffic, minimizing the amount of data to be transmitted is clearly a desirable aim (Peng et al., 2012).

Lossy compression generally achieves much higher compression ratios than lossless compression, but at the cost of imperfections in the reconstructed signal. A trade-off thus exists between the amount of loss in signal fidelity that can be tolerated, and the compression ratio that can be achieved. Percentage Root-Mean Squared Difference (PRD) is a common measure of the loss of signal fidelity between two signals. The smaller the PRD, the lower the distortion introduced by the compression process, and although higher compression ratios are wanted, they result in larger PRD. This paper considers a remote sleep monitoring system, as shown in Fig. 2. Our architecture consists of a wearable PSG system that records, compresses and wirelessly transmits the PSG data to a remote "server" that is responsible for analyzing the PSG signal. Through the use of an automatic rule-based sleep staging method (Liang et al., 2012), our goal is to examine how the sleep staging performance is affected by different compression levels.

We used the popular off-the-shelf Set Partitioning in Hierarchical Trees (SPIHT) (Said and Pearlman, 1996) compression algorithm to compress PSG signal. SPIHT consists of two steps: first, SPIHT employs the Discrete Wavelet Transform (DWT) to decompose the signal into the wavelet coefficients. It then encodes the resulting coefficients into a binary stream based on the Embedded Zerotree Wavelet (EZW) coder (Shapiro, 1993).

All-night PSG sleep recording data from 20 healthy subjects was used for testing. The data were compressed at a range of levels and passed through the automatic sleep staging system. The objective of this work is to understand the effectiveness of an off-the-shelf compression algorithm with regard to the performance of sleep stage detection.

Numerous studies have attempted the compression of different physiological signals, such as those obtained from EEG (Daou and Labeau, 2012; Higgins et al., 2013; Srinivasan et al., 2013, 2011), ECG (Adel et al., 2012; Isa et al., 2012, 2014; Rubio et al., 2013; Shridhar and Mohankrishnan, 1984), EMG (Norris and Lovely, 1995), EOG (Bhandari et al., 2007) and echocardiogram (Cavero et al., 2013), and these generally focus on how to maximize the compression ratio using different coding techniques (Wegener, 2010). For example, Cárdenas-Barrera et al. (2004) proposed an algorithm to minimize power consumption when compressing EEG data. Our study is close to the work of Higgins et al. (2010), which investigated how an off-the-shelf lossy compression algorithm, such as JPEG2000 (Skodras et al., 2001), will affect the performance of seizure detection using EEG data. However, while all the prior works only consider the use of single-channel data, such as EEG or ECG, more phenomena can be discovered using multi-channel data (Kuo et al., 2013). For example, the characteristics of in S1 and REM stages are very similar in EEG data (see Fig. 1) but different and can be easily distinguished in EOG and EMG data. Our study focuses on the amount of loss in signal fidelity that can be tolerated when compressing complex multi-channel PSG data for sleep staging analysis.

2. Data source and methodologies

2.1. Subjects and recordings

All-night PSG sleep recordings were obtained from 20 healthy subjects (12 males and 8 females) ranging from 19 to 23 years in age (mean = 21.2 ± 1.1). The data from five subjects were used to generate the system, and data from the other fifteen subjects were used for testing. The recordings included six EEG channels (F3-A2, F4-A1, C3-A2, C4-A1, P3-A2, and P4-A1, according to the international 10–20 standard system), two EOG channels (positioned 1 cm lateral to the left and right outer canthi), and a chin EMG channel (Siesta 802 PSG, Compumedics, Inc.). The sampling rate was 256 Hz with 16-bit resolution. The 20 PSG sleep recordings were visually scored by a sleep specialist using the Rechtschaffen & Kales (R&K) rules (Rechtschaffen and Kales, 1968) with a 30-s interval (termed the epoch). According to AASM and R&K rules' suggestion which is the gold standard of manual sleep scoring, C3-A2 is used as the main EEG channel for manual sleep scoring. Therefore, we follow their suggestion and adopt the use of C3-A2 as the EEG channel in our work.