2C5-OS-21b-5

Sleep Pattern Discovery and Visualization based on Clustering of Sound Events

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The good sleep quality is important for a healthy life. At present, a number of sleep analysis products have arisen on the market, however in many cases they require additional hardware, or there is a lack of scientific evidence regarding their clinical efficacy. In this research, a novel method for sleep pattern discovery via clustering of sound events is proposed. The sleep-related sound clips are extracted from the sound recording of sleep. Then various types of Self-Organizing Map algorithms were applied on extracted sound data. We demonstrated the superiority of Kullback-Leibler divergence, and obtained the cluster maps to visualize the distribution and changing of sleep-related events during the sleep. Also, we performed a comparative interpretation between sleep stage sequences and obtained cluster maps. This proposed method requires few additional hardware, and by taking the consistency with the medical evidence, its reliability has been proven.

1. Introduction

Sleep is an important physiological state of human body. Almost a third of the time in people's life has been spent in sleep. However, most of us have experienced trouble sleeping at one time or another. Therefore, sleep monitoring technology has become an indispensable content in modern medical diagnosis.

The primary tool of sleep study is Polysomnography (PSG) [Chokroverty 13]. PSG is mainly used in medical science and medical treatment by medical doctors [Kato 11]. Since its professional property and financial cost, PSG is limited to clinic. Beside traditional PSG, actigraphy also has been used as an alternative, there are also many actigraphy based products, including Beddit*1, etc. One of the problems of these products is that they are invasive to users which means that users have to wear an additional device or place a device on their bed during sleep. On the other hand, additional devices will add extra financial burden to the user. The efforts in the market to reduce the cost are mostly through mobile apps. Mobile apps use the smartphone's built-in sensors, and hence users do not need to purchase additional hardware. Therefore, according [Behar 13], very few of the apps are based on any published scientific evidence.

In this paper, a method for sleep analysis based on clustering of sound data is proposed. We extracted sound clips of events from the recorded sound data, get the frequency spectrum as input vectors, and then applied various types of Self-Organizing Map (SOM) [Kohonen 95] algorithms on them to get cluster maps. The main features of our method are as follows:

Fine-grained sleep process visualization: We proposed a novel algorithm to cluster the sleep-related events on spatio-temporal dimensions. The transition of sleep state is visualized on the cluster map. It provides a clear and easy way to understand the analysis report.

Non-invasive: The sound data can be recorded by any recording device placed near user's bed during sleep, hence no burden will be added to the user.

No extra financial cost: Any off-the-shelf equipment with microphone could be used as the recording device, including smartphone, recording pen and personal computer.

Scientifically validated: By taking the consistency with the medical evidence from PSG, the reliability of this method was proved.

2. Methodology

In this section, we introduce the key methodologies that being applied in this research.

2.1 Burst extraction algorithm

Manually searching the sleep-related sound events in the sound record will waste a lot of time and definitely unacceptable. In this paper, the sound events were extracted by the statistical burst extraction method [Kleinberg 03]. The burst extraction method estimates the maximum likelihood state sequence to the sound event. This method is able to extract a variable length sound event based on the amount of activity of the signals. We leverage the method in [Fukui 11] to differentiate the steady noise from sleep-related sound events.

2.2 Clustering algorithms

In this research, we generate cluster maps by clustering algorithms based on Self-Organizing Map (SOM), including standard SOM, Kullback-Leibler Kernel SOM (KL-KSOM)

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*1 http://www.beddit.com/

and Sequenced-based Kernel SOM. SOM is an artificial neural network, and originally a model of associative memory, but has recently been widely used for visual data mining.

We use the frequency spectrum as input vectors. The standard SOM uses Euclidean distance as a similarity measure of data points, so the distribution structure of a frequency spectrum cannot be captured since each discrete point is treated as an independent variable. In [Fukui 11], they proposed the use of Kullback-Leibler (KL) divergence to introduce a distribution structure into a similarity measure of frequency spectrum of acoustic emission events and obtained good effect. In the present study, to make a comparison, KL-KSOM that applied the KL divergence to SOM through the kernel function [Andras 02] was also be used to cluster the sleep related sound events.

2.3 Proposed method: Sequenced-based kernel SOM

In order to provide a clear and easy to understand analysis report of user's sleep, a fine-grained map that depicts the distribution and changing of sleep-related events is necessary. On the other hand, the comparison of the clustering results between standard SOM and KL-KSOM demonstrated that KL divergence provides better performance in current study.

Based on aforementioned premises, a novel algorithm called Sequenced-based Kernel SOM (Sb-KSOM) is proposed. This algorithm is an extension of Sequence-based SOM (SbSOM) [Fukui 08]. Different from the normal SOM that deals with static data, SbSOM introduces Sequencing Weight Function (SWF) into SOM, it is able to visualize transition of cluster dynamics since spatio-temporal neighborhood is converted into topological neighborhood by the neighborhood function. The proposed Sb-KSOM kernelized SbSOM by replaced the Euclidean distance with the KL divergence to make it able to handle frequency spectrum data.

In the SbSOM, let v-dimensional N inputs be $x_n = (x_{n,1}, ..., x_{n,v}), (n = 1, ..., N)$ (discrete points of frequency power spectrum), the position of M neurons in the visualization layer be $r_j = (\xi_j, \eta_j), (j = 1, ..., M)$, and the reference vector corresponding to the j^{th} neuron be m_j (v-dimension). The winner reference vector for data x_n is determined by spatio-temporal distance utilizing SWF $\psi(n, \xi_j)$ as follows:

$$c(x_n) = arg \min_j \psi(n, \xi_j) \|x_n - m_j\|. \tag{1}$$

The n^{th} data is located at ratio of n/N within the data sequence, and the j^{th} neuron is located at ratio of ξ_j/ξ_M to certain direction on the topology of SOM neurons (in this case, ξ-direction). Let the absolute value of those difference be $\epsilon = |\xi_j/\xi_M - n/N|$. The SWF is defined so as to be able to take a balance between spatio/temporal resolution, in case of NOT allowing reversal of data order, the SWF is given as:

$$\psi_{strict}(n, \xi_j) = \begin{cases} 1 & if \quad \epsilon < \frac{1}{2K} \\ \infty & otherwise \end{cases}, \tag{2}$$

Table 1: Subject and sound data information

Subject id	Age	Gender	Recording date	Duration
1	21	F	2014/05/13	08:05:22
2	22	M	2014/05/27	08:16:15
3	22	M	2014/06/03	08:01:09
4	23	M	2014/07/29	08:23:01
5	24	M	2014/01/20	08:17:34
6	23	F	2015/03/03	08:30:30
7	20	F	2015/06/02	07:18:30

where K is the number of neurons to ξ-direction. Sb-KSOM replaced the normal Euclidean distance calculation in eq.(1) with kernel function:

$$c(x_n) = arg \min_j \psi(n, \xi_j) d_{j,n}. \tag{3}$$

$d_{j,n}$ is the dissimilarity between j^{th} reference vector and n^{th} data point in KL-KSOM.

2.4 Weighted pairwise F-measure (wPF)

To evaluate our method, we labeled the extracted events based on the synchronous PSG data scored by medical specialist, and calculated the weighted pairwise F-measure (wPF) [Fukui 12] as the validity measure of each cluster map. Original pairwise F-measure evaluates correlation between cluster assignment and class label. However, especially in SOM visualization, neighborhood relation is also important. The wPF introduces likelihood function indicating a degree that a data pair belongs to the same cluster instead of the actual number of data pairs.

3. Experiment

In the first part of the experiment, we applied standard SOM and KL-KSOM on the extracted sound data first, and compared the performance of these two algorithms via wPF using events scored through PSG as ground truth labels.

Then in the second part, we used Sb-KSOM on the data to get the spatio-temporal dimensional cluster map, and discussed the relationship between the transition of sleep stages and cluster dynamics of sound events.

3.1 Experimental setting

The data we used in the paper is prepared by Graduate School of Dentistry in Osaka University. The study protocol was approved by the clinical research ethics Committee of the Osaka University Graduate School of Dentistry. Written informed consent was obtained from all subjects. All the subjects were asked to sleep in a specific room from 22:30 to 8:00. The recording device is LA1250 (Ono Sokki)[*2] and R-4 Pro (Roland)[*3]. The microphone was placed 50 centimeters from the head of the subjects. The sound data was recorded on single channel (mono) and 48 kHz sample rate. Also in this experiment, all subjects were measured by PSG simultaneously as well.

*2 https://www.onosokki.co.jp/English/hp_e/products/keisoku/s_v/la1200.html
*3 http://proav.roland.com/products/r-4_pro/

Table 2: Comparison of wPF between SOM and KL-KSOM clustering results

Subject id	SOM		KL-KSOM	
	Mean	SD	Mean	SD
1	0.537	0.033	0.604	0.037
2	0.521	0.041	0.573	0.038
3	0.506	0.031	0.551	0.031
4	0.559	0.040	0.592	0.037
5	0.602	0.039	0.629	0.039
6	0.543	0.033	0.600	0.035
7	0.483	0.042	0.523	0.047
Mean	0.535	0.037	0.581	0.037

Most of the experimental subjects are university students from Osaka University, hence the age of the subjects are mostly around 20 to 24. Male to female ratio is basically balanced. Table 1 shows information of the subjects and recorded sound data that used in this research.

3.2 Event extraction

We selected 7 nights of sound data in this study. Based on the burst extraction method, we obtained totally 6775 sound events. These events contain sleep disorder events and other sound events like outdoor traffic noise. Fast Fourier Transform was applied on the extracted sound data to get the frequency power spectrum. From 24 Hz to 20 kHz, at intervals of 4 Hz, 4995 discretized points as an input for SOM were obtained for every sound data.

3.3 Clustering by standard SOM and KL-KSOM

In this experiment, the number of neurons was set to 15×15 with a two-dimensional regular grid. In general, the number of neurons is not sensitive to these results in the sense that the SOM captures the data distribution in the feature space. Gaussian function was used as the neighborhood function in SOM and KL-KSOM. We used the sound data from each subject as a respective dataset, and compared the wPF values of SOM and KL-KSOM for each subject. In order to avoid initial value dependency, the experiments were run for 50 times, and the average values were computed. The mean wPF values and standard deviation (SD) are showed in Table 2, the average of wPF has been improved about 10% from standard SOM, that indicated KL-KSOM has a better performance in this research.

3.4 Sleep pattern analysis by Sb-KSOM

According to [Chokroverty 13], the stages of sleep include rapid eye movement sleep (REM), Non-REM (NREM) and awakening , sleep proceeds in cycles of REM and NREM, usually four or five times every night. The American Academy of Sleep Medicine (AASM) divides NREM into three stages: NREM Stage 1 (N1), NREM Stage 2 (N2), and NREM Stage 3 (N3). In this experiment, we made a comparative analysis between cluster maps generated by Sb-KSOM and sleep stage sequences trying to reveal the relationship between them. Fig.1(a) shows the result via Sb-KSOM applied on the sound data from Subject 4, the number of neurons was set to 50×10 with a two-dimensional grid. Subject 4's sleep stages were scored by medical specialists based on PSG data from the same night, and the time window size is 30 seconds. The sleep stage sequence is showed in Fig.1(b), the awaking stage is showed as "W". We defined the periods that contain continuous N3 stages with intervals of other stages that less than 3 minutes as deep sleep periods, and periods except deep sleep periods and REM stages as light sleep periods. We marked out the deep sleep periods in the figure by gray box. The grayscale parts in Fig.1(b) indicate REM stages. Since REM stage is a unique phase in the sleep process, we discussed it separately.

The sleep periods of Subject 4 were interpreted as follows:

Deep Sleep Periods (0:13:30 - 0:31:30), (2:09:30 - 2:42:00), (5:09:30 - 05:33:00), (7:25:30 - 7:45:30): There are many snoring events at these periods, very few body movements, and no tooth grinding. We found out that a cluster center of snoring event is mostly associated with a deep sleep period.

REM Stages (1:33:00 - 1:43:00), (3:02:00 - 3:19:30), (4:43:00 - 4:51:30), (6:00:00 - 6:05:30), (6:07:30 - 6:44:00), (7:50:30 - 8:07:00): Compared with other stages, REM stages have a stronger association with clusters of body movement, and less related to clusters of snoring or tooth grinding.

Light Sleep Periods: In every light sleep period, there were some clusters of tooth grinding and body movement event, only a few of snoring event.

In this experiment, we found out that the distribution of sound event clusters changed along with the sleep stage changing on Subject 4. Also this analysis was made on other subjects, although each subject's primary sleep disorders and changing pattern of sleep stages are different, similar conclusions are drawn. For example, on Subject 2, the deep sleep periods also obviously associated with the clusters of snoring, the number of body movement is notably more in light periods and REM stages than in deep periods, and no snoring clusters were found in REM stages.

There are similar discussions in other researches. According to [Fairbanks 03], conventional snoring is most likely to occur in deep sleep stage, also likely in light sleep stage, but unlikely in REM stage. And REM stages always associated with dreaming [Hobson 00], which will trigger lots of body movements.

Through this experiment, we found out that there is a relationship between the transition of cluster dynamics and the changing of sleep stage. Since sleep stage sequence is an important tool in the study of sleep pattern, this relationship provides the possibility to discover the sleep pattern based on the cluster map of sleep-related sound data from Sb-KSOM.

4. Conclusion

In the present study, a novel approach to discover the sleep pattern through analyzing the sleep-related sound events based on clustering algorithms is proposed. By this

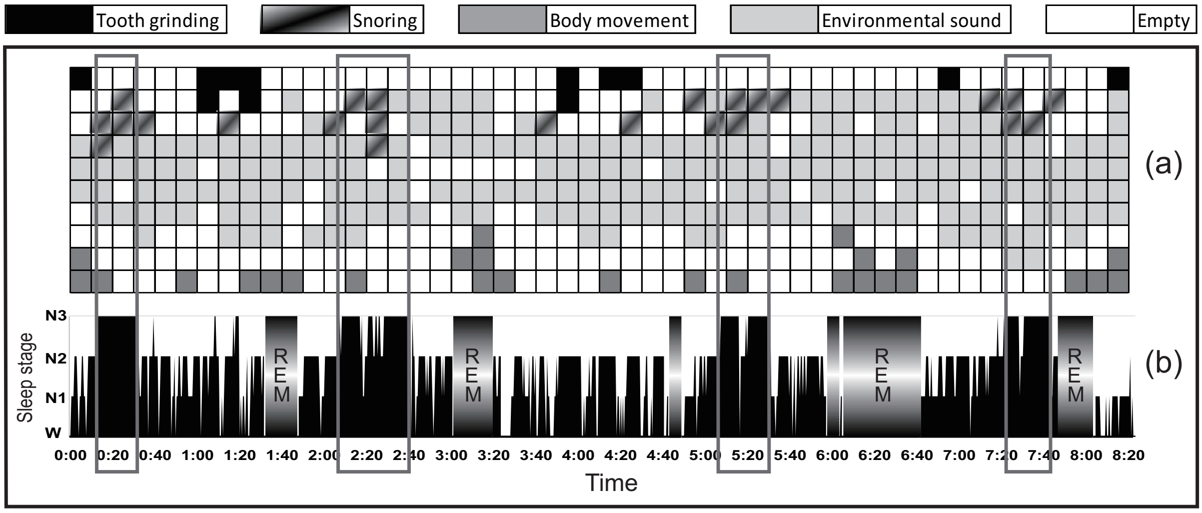

Fig 1: Cluster map via Sb-KSOM on Subject 4

method, we got a fine-grained map that depicts the distribution and changing of sleep-related events. By taking the consistency with the clinical evidence from PSG, we evaluated the clustering results based on validity measure, and proved the reliability of the method. Also, we compared the cluster results from our method to the sleep stage sequences from PSG, found out the relevance, and provided a new train of thought for studying the sleep pattern.

As future work, for a further verification, the Sb-KSOM algorithm will be applied to the data of several nights from same subject. Also, since it is difficult to use PSG scoring in practice, we will develop an annotation tool that a user can easily annotate their clusters.

Acknowledgments

This research is partially supported by the Center of Innovation Program from Japan Science and Technology Agency, JST, the Grant-in-Aid for Scientific Research (B)(#25293393) from the JSPS, and Challenge to Intractable Oral Diseases from Osaka University Graduate School of Dentistry.

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