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An EEG-based Sleep Staging method with hybrid entropy computation measures

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Abstract

Sleep is an indispensable physiological need of the human body. Sleep staging is an effective method to objectively assess sleep quality and is helpful for research on sleep and sleep-related diseases. Electroencephalogram (EEG) signals are nonlinear and non-stationary time series, and entropy features are particularly sensitive to these nonlinear characteristics and can reveal information that is difficult to discover with traditional linear analysis methods. We proposed an automatic sleep staging method based on EEG entropy computation, inlcuding signal preprocessing, entropy feature extraction, feature selection and classification modules. The experimental results show that the average accruacy is 91.3% through the fused entropy features.

Keywords: Sleep staging; EEG; entropy; feature selection; classification

Introduction

Approximately one-third of a person's life is spent sleeping. Sleep is a common cyclic physiological phenomenon. It can maintain the normal growth and development of the body, ensure adequate sleep, accumulate energy for the body, restore physical strength, and also allow the brain to get sufficient rest, protect brain function, and keep the body's health. Normal immune balance, etc. Sleep is crucial for everyone.

The study of sleep staging is of great significance for understanding the physiological mechanism of human sleep, diagnosing and treating sleep disorders, and improving people's quality of life. Sleep staging helps reveal physiological changes in the brain and body during sleep, including the characteristics of different sleep stages, such as the characteristics of rapid eye movement (REM) and non-rapid eye movement (NREM) stages (Vallat & Walker, 2021). By studying sleep stages, it can better understand sleep's role in memory consolidation, learning, mood regulation, and physical recovery. In addition, sleep staging is the basis for diagnosing various sleep disorders (such as insomnia, sleep apnea, periodic limb movement disorder, etc.) (Loh et al., 2020; Imtiaz, 2021; Korkalainen et al., 2020). By accurately identifying sleep stages, medicine phsicals can provide patients with more precise treatment options, such as adjusting sleep habits, using medications or recommending specific sleep therapies. Sleep staging studies can also help people understand their sleep patterns and take corrective measures to improve sleep quality.

EEG is high temporal density non-invasive brain signal, which is very suitable for sleep research. There are several good researches related to EEG-based sleep staging (Aboalayon et al., 2016; Tzimourta et al., 2018; Qu et al., 2020; Huang et al., 2021). The related works can be briefly categorized into feature engineering and deep learning methods. For feature engineering, it indicates the sleep staging information represented by feature extraction measurements and then feed the features into a classifier. For deep learning methods, it is an end-to-end learning way which can take the information from the raw sleep EEG data. Therefore,. deep learning method usually can achieve a better classfication accuracy since it adopts the main information of raw EEG data. But it has a lack of interpretability and the training data should be reached a mount of samples. However, EEG data is limited since it is not so many human subjects. Feature engineering method is based on the design of feature extraction, which provides the interpretability and more likely to explore the stable biomarker. Its results. The biomarker is more suitable as a clinical criterion for auxiliary diagnosis. In this work, we use the feature engineering methods to conduct sleep staging research.

Entropy analysis, as a nonlinear method to measure signal complexity and randomness, has shown its unique value in sleep staging. Rearchers have achived some results in using EEG entropy fatures for sleep staging. For instance, Jose Luis Rodríguez-Sotelo et al proposed an EEG-based sleep staging method using entropy and unsupervised pattern analysis technique, the average of 80% clasified stages was obtained (Rodríguez-Sotelo et al., 2014). Li Hui et al used sample entropy analysis for sleep staging (Li et al., 2015). Moreover, Vladimir Miskovic et al explored the mechnisms during the human sleep cycle using multiscale entropy and power-law frequency. They discovered that the entropy of slow wave sleep is decreased at short time scales and increased at long time scales (Miskovic et al., 2019). In summary, the lack of works related to entorpy-base EEG sleep staging as the hybrid measures is not analyzed together or it uses to explore the mechnism other than the classification.

Therefore, we proposed an EEG-based sleep staging method with hybrid entropy computation measures to enhance the feature representation information from differenet aspects of the indicators. It includes the EEG signal preprocessing, the entropy feature extraction, fature selection and classification modules.

Materials and Methods

Our method inlcudes different modules, shown in the Fig. 1, and each module is desicribled in this section.

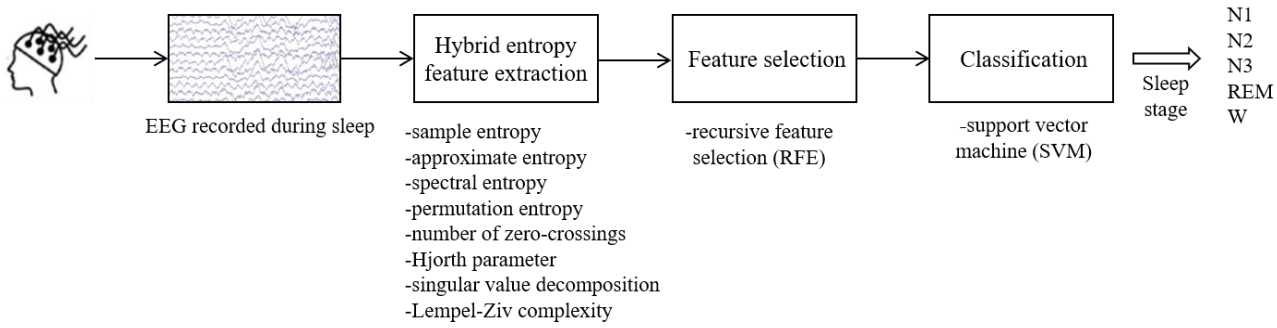

Figure 1. Flowchart of the proposed method

2.1 Experimental Dataset

The sleep EEG data used in this paper comes from the Danish Center for Sleep Medicine (DCSM) sleep stage data set. (The URL is Public Archive: db553715ecbe1f3ac66c1dc569826eef (ku.dk)). The data set randomly selects the actual sleep measurement data of 6 subjects throughout the night, with a total of 6 sets of EEG data. The male to female ratio is 1:1, the average age is 32.83, the sampling rate is 512Hz, and it contains 12 channel data. The layout of EEG electrodes is as shown in Fig. 2.

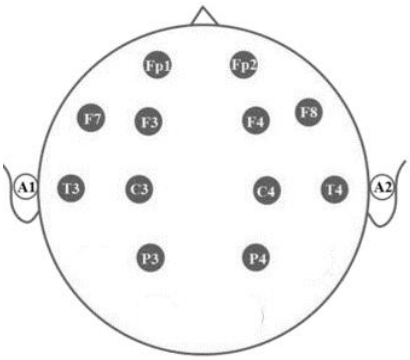

Figure 2. Layout of the EEG electrodes

No drugs were used to interfere during the test. The sleep staging results were manually annotated by sleep experts per 30 seconds, and the expert annotation results were used as labels to test the staging accuracy of the method proposed. Define 30 seconds of EEG as a sample. The distribution of sleep samples of the 6 subjects is shown in the Table 1.

Table 1. Sample distribution of each sleep stage

Subject	W	N1	N2	N3	REM	Total
n3	136	49	347	279	188	999
n5	10	49	413	303	232	1007
n10	66	2	261	308	215	852
nfle1	18	11	425	279	217	950
nfle2	199	22	424	243	87	975
nfle3	136	72	419	209	261	1097

2.2 EEG Preprocessing

EEG is easily affacted by various noises and artifacts. In sleep scenario, maily indicates the eyemovements, electromyography artifacts, machine noise, etc. Therefore, preprocessing is required before feature extraction. In this work, we adopted independent component analysis (ICA) ultized from eeglab (Brunner et al., 2013) to remove the common artifacts and used the wavelet decomposition[13] to remove the artifact and noise further.

2.3 Hybrid Entropy Feature Extraction

We computated different kind of entropy measurements covering the structural and dynamical entropies (Liang et al., 2015). The priciples are given in this subsection.

1) Sample entropy

Sample entropy (SampEn) is a statistical tool used to measure the complexity and regularity of time series data and is used to quantify the self-similarity of a signal and the uncertainty of its prediction. The core idea of sample entropy is to calculate the frequency of similar patterns in a time series and compare it with a shorter set of patterns. Specifically, sample entropy calculates the difference between the number of approximate matches for an m-dimensional vector pattern and the number of approximate matches for an (m+1)-dimensional vector pattern under a given tolerance r, excluding matches to itself, the main difference from approximate entropy is that sample entropy does not match itself. The core calculation formula is given as follows:

$$\mathrm{SampEn}(\mathrm{m},\mathrm{r}) = -\ln\left(\frac{\mathrm{B}^{\mathrm{m}+1}(\mathrm{r})}{\mathrm{B}^{\mathrm{m}}(\mathrm{r})}\right) \tag{1}$$

Where $\mathrm{B}^{\mathrm{m}}(\mathrm{r})$ is the approximate probability of the m-dimensional vector,and $\mathrm{B}^{\mathrm{m}+1}(\mathrm{r})$ is the approximate probability of the (m+1)-dimensional vector. We set the embedding demision m=2, r=0.2. The smaller the value of sample entropy, the stronger the regularity of the time series; the larger the value, the higher the complexity and randomness of the time series.

2) Approximate entropy

Approximate entropy (ApEn) is a statistical tool that measures the complexity and regularity of time series data and is used to quantify the complexity of signal sequences. The calculation of approximate entropy is based on the frequency of similar patterns in a sequence. Specifically, it calculates the difference between the number of approximate matches for m-dimensional vector patterns and the number of approximate matches for (m+1)-dimensional vector patterns under a given tolerance r. This difference reflects the degree of random variation in the sequence and can be used to distinguish stochastic from deterministic processes. Its calculation formula is:

$$\mathrm{ApEn}(\mathrm{m},\mathrm{r}) = \varphi\hat{}\mathrm{m}(\mathrm{r}) - \varphi\hat{}(\mathrm{m}+1)(\mathrm{r}) \tag{2}$$

Approximate entropy has several advantages, including being robust to noise, not requiring long data sequences, and suitable for the analysis of both stochastic and deterministic signals. However, it also has some limitations, such as calculation bias and dependence on the data length N.

3) Spectral entropy

Spectral entropy (SE) is calculated based on the concept of Shannon entropy and is calculated by analyzing the power spectral density of a signal. The size of spectral entropy can reflect the uniformity of the frequency component distribution of the signal, thereby providing an indicator of the complexity of the signal structure. Specifically, spectral entropy is defined by calculating the Shannon entropy of the signal power spectral density, and its mathematical expression is usually as:

$$\mathrm{SE} = -\sum_{\mathrm{f}=0}^{\mathrm{f_s}/2} \mathrm{P}(\mathrm{f}) \log_2 [\mathrm{P}(\mathrm{f})] \tag{3}$$

Where P(f) is the power spectral density at frequency f, and $\mathrm{f_s}$ is the sampling frequency of the signal. If P(f) is 0, define $\mathrm{P}(\mathrm{f}) \log_2 [\mathrm{P}(\mathrm{f})]$ to be 0. This summation is performed over the entire Nyquist frequency (i.e., $\mathrm{f_s}/2$), covering all frequency components of the signal.

4) Permutation entropy

Permutation entropy (PE) is a statistical tool used to measure the complexity of time series data. It calculates entropy based on the relative order of values in a time series, rather than specific numerical values, which is particularly suitable for analyzing signals with nonlinear and non-stationary characteristics. Permutation entropy can reveal the randomness and structural complexity of time series data, which is of great significance for analyzing and understanding the dynamic features of signals. The calculation formular is as:

$$H_{PE}(m) = -\sum_{i=1}^{N-(m-1)\lambda} P(i)\log_2 P(i) \quad (4)$$

Where P(i) is the probability of sorting, m is the embedding dimension, and λ is the time delay.

5) Number of zero-crossings

The number of zero crossings (ZCR) is a basic parameter used to describe signal characteristics in signal processing. It refers to the number of times the signal passes through the zero point (that is, the intersection point from positive to negative or from negative to positive) within a certain time range. The number of zero crossings can provide useful information for analyzing the frequency characteristics, waveform characteristics and approximate energy distribution of the signal.

6) Hjorth parameter

The Hjorth parameter includes two time domain features: Mobility and Complexity.

Mobility: Mobility is the square root of the ratio of the variance of the first derivative of the signal to the variance of the signal itself. Mobility reflects the "mobility" of the signal envelope, which can be understood as the "width" of the signal's frequency components or the "bandwidth" of the signal. It is defined as:

$$\text{Mobility} = \sqrt{\frac{\sigma^2(y')}{\sigma^2(y)}} = \frac{\sigma(y')}{\sigma(y)} \quad (5)$$

Where y is the original signal, y' is the first derivative of the signal, and σ represents the standard deviation.

Complexity: Complexity is the square root of the ratio of the variance of the second derivative of the signal to the variance of the first derivative of the signal, which reflects the nonlinear and non-periodic characteristics of the signal and is used to measure the similarity of the signal to a pure cosine wave. A high Complexity value indicates that the signal changes more complexly over its length of time. It is defined as:

$$\text{Complexity} = \sqrt{\frac{\sigma^2(y'')}{\sigma^2(y')}} = \frac{\sigma(y'')}{\sigma(y')} \quad (6)$$

Where y'' is the second derivative of the signal.

7) Singular value decomposition (SVD) entropy

SVD entropy is a feature extraction method based on singular value decomposition that is used to quantify the complexity or uncertainty of data. Singular values can decompose any matrix into the multiplication of three specific matrices: an orthogonal matrix, a diagonal matrix, and the transpose of another orthogonal matrix. Specifically, the calculation of SVD entropy usually involves the following steps:

a. Perform singular value decomposition on the data matrix to obtain a series of singular values σ_i.

b. Calculate the proportion of each singular value relative to the total energy as:

$$p_i = \frac{\sigma_i^2}{\sum_{j=1}^{N}\sigma_j^2} \quad (7)$$

Where p_i indicates the proportion of the i-th singular value.

c. Use these ratios to calculate the entropy value, the formula is:

$$H_{SVD} = -\sum_{i=1}^{N} p_i \log_2(p_i) \quad (8)$$

8) Lempel-Ziv complexity

Lempel-Ziv complexity (LZC) is a nonlinear dynamic measure of the complexity of time series data. The core idea is to count the number of different subsequences encountered when reading the data bit by bit. The step of calculating LZC usually include: intialization, pattern recognition, update separator, count.

2.4 Feature Selection and Classification

After the hybrid entropy feature extraction, the fusion feature is ultilized through concatenation of different entropy features. For the fused feature, we applied recursive feature selection (RFE) to perform the feature selection. RFE is a backward elimination feature selection method that determines the importance of features by recursively removing features and retraining the model.The basic idea of RFE is to start with a model containing all features and then gradually remove the least important features. This process is repeated until the required number of features or model complexity is reached. For classification model, the support vector

machine (SVM) (Sha'Abani et al., 2020) to train the data. Specifically, we used the linear core SVM combined with RFE to train the model. The flow chart is given in Fig. 3.

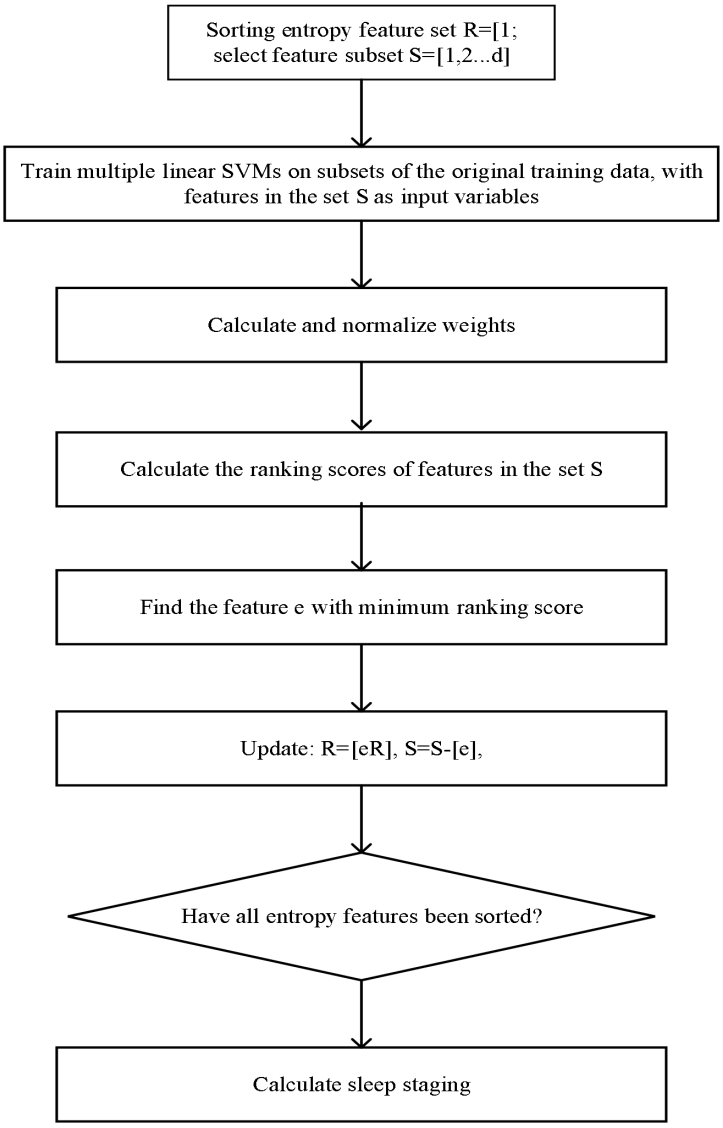

Figure 3. SVM-REF training procedure

Results and Discussion

3.1 Calculation Results of Hybrid Entropy Features

Entropy features can distinguish sleep stages mainly because they can quantify the complexity and randomness of EEG signals, which are closely related to physiological changes in sleep stages.

Observing Table 2, we can find that in W stage, brain activity is the most complex, and complexity metrics such as approximate entropy, and sample entropy in this period tend to reach the highest. As the individual enters sleep, these index values begin to gradually decrease, reflecting the decrease in the complexity of brain activity as sleep progresses. These metrics typically reach their lowest point during deep sleep, indicating that brain activity is most regular and least complex.

However, during the REM phase, the values of these indicators will increase, but are usually still lower than the level of the awake phase, showing that the complexity of brain activity in the REM phase is between that of light sleep and between two stages.

Table 2. Mean entropy features for each sleep stage

Entropy	W	N1	N2	N3	REM
SampEn	0.51	0.39	0.34	0.41	0.48
ApEn	0.78	0.65	0.69	0.67	0.90
SE	0.43	0.32	0.28	0.29	0.43
PE	0.78	0.68	0.68	0.68	.078
ZCR	0.98	0.89	0.76	0.90	0.95
Hjorth	0.82	0.68	0.72	0.71	0.88
SVD	0.53	0.53	0.53	0.53	0.54
LZC	0.47	0.45	0.35	0.47	0.45

3.2 Results of Sleep Stages Classication

The results from our method is shown in Table 3, which include the accuracy (ACC) and F1-score indicators.

Table 3. Results of Sleep Stages Classification

	ACC (%)					F1
	W	N1	N2	N3	REM	(%)
n3	91.9	77.3	85.4	93.4	83.6	86.9
n5	22.0	88.1	86.2	89.2	93.2	88.1
n10	94.5	73.2	89.1	94.7	94.2	92.7
nfle1	32.5	62.9	89.9	91.4	93.6	83.8
nfle2	93.9	61.1	85.0	87.1	61.2	79.4
nfle3	82.9	86.2	90.3	91.8	91.5	90.9

3.3 Visualization of results

The Visualization of results can be used to compare the entropy results between the sleep expert's annatation.The Fig. 4 shows one typical health subject (n3) and a patient (nfle1). We can see (shown in Fig. 4(a)) that during the wake st EEG signals usually appear as low-amplitude, high-frequency activity. The zero rate is higher. In the N1 stage, theta waves begin to appear in the EEG signal, and the zero-crossing rate decreases. In N2 stage, EEG Sleep spindles and K complex waves can be observed and the zero-crossing rate fluctuates greatly. In N3 stage, delta waves is dominant, and the zero-crossing rate is low. During REM sleep, EEG signals show desynchronization, similar to the wake stage, the zero-crossing rate increased. This phenomenon is most pronounced in the parietal brain region where Channel 9 is located. From Fig. 4(b), we can see that in the N1, N2 and N3 stages of NREM sleep, as the sleep depth increases, the frequency components of the EEG signal change, and these changes can be quantified by spectral entropy. The full-band spectral entropy decreases the most in the N2 sleep stage. This suggests that changes in spectral entropy are related to the depth of sleep stages and the coordination of brain electrical activity. Usually, the EEG signal in the N1 stage is dominated by theta waves, sleep spindles appear in the N2 stage, and the N3 stage is dominated by delta waves. The value of spectral entropy changes as these frequency components change, distinguishing different sleep stages. This phenomenon is most significant in the parietal brain area where Channel 9 is located.

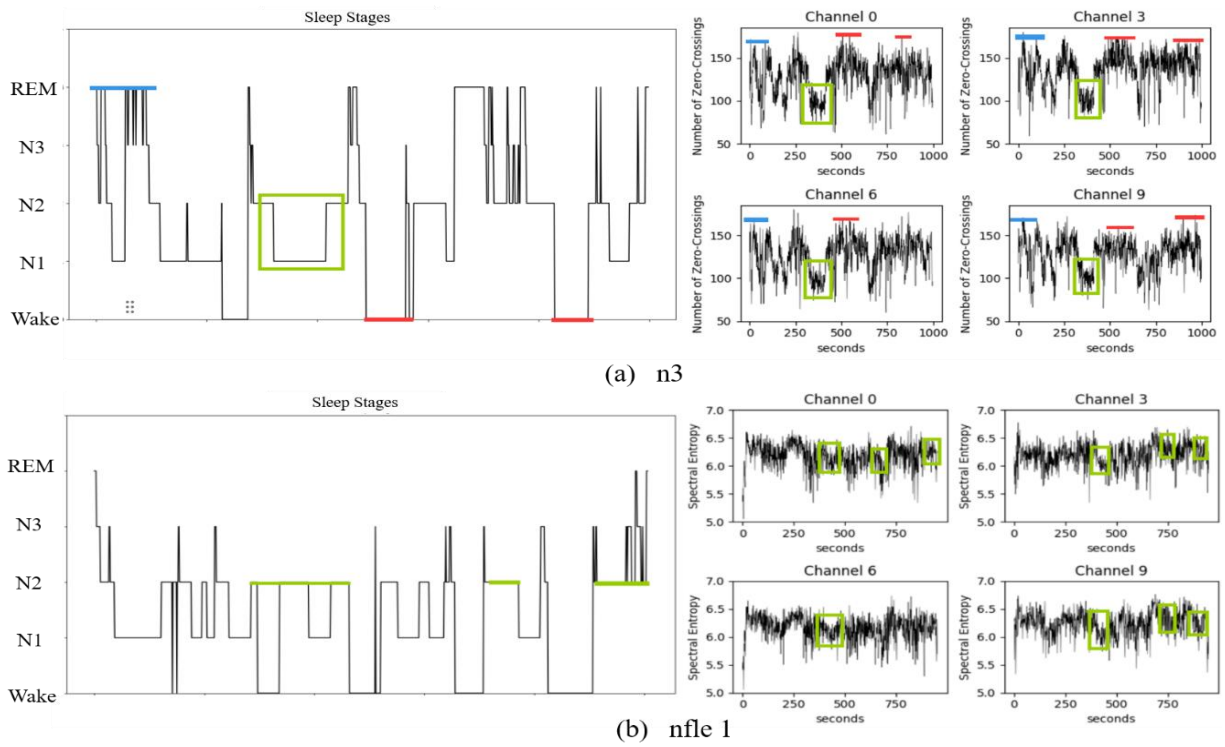

Fig. 4 Comparison between entropy results and experts' annotation

Conclusions

In this paper, we propose an EEG-based sleep staging method based on hybrid entropy computation measures, including preprocessing, hybrid EEG entropy feature extraction, feature selection and classification modules. In preprocessing, we combined ICA with wavelt decomposition methods to reconstruct the denosied sleep EEG. In hybrid EEG entropy feature extraction, eight entropy measures have been calculated covering the structural and dynamic types. For feature selection, we used the REF to select the more important features. Finally, in the classification module, the SVM is used to classify the sleep stages. Results show that the value of entropy feature descreased with the depth of sleep and the average accruacy is 91.3%.

In summary, entropy is one of the neurodynamics measures, which indicates the degree of signal orderliness. In the future, it is a method can be considered into practical system development to assist the clinical auxiliary diagnosis.

Data Availability (excluding Review articles)

The data used in this paper can be downloaded in the website of 'Public Archive: db553715ecbe1f3ac66c1dc569826eef (ku.dk)'.

Conflicts of Interest

All authors of this paper have no conflicts of Interest.

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