

A Study of Emotion-Aware Personalized Music Therapy and Adaptive Recommendation Systems

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Abstract. Existing studies indicate that music therapy has a positive effect on insomnia. However, the effectiveness of traditional music therapy is often limited by subjective evaluation and practical barriers. Therefore, it is necessary to provide a more reproducible, accessible home-based conceptual method to relieve insomnia. The well-established machine learning model will become the core of it. Instead of using therapists' subjective evaluation, objective data such as electroencephalogram (EEG), Electrocardiogram (ECG) and Photoplethysmography (PPG) are suitable to provide more consistent judgements. Additionally, the recent more reliable wearable EEG devices lay a favorable foundation for this concept. Methods of quantification of arousal (both sleep-related and emotional arousal) have been introduced, so that the time-series signals, after noises being filtered or avoided, are input to Long Short-Term Memory (LSTM) network continuously. After the initialization is finished with rule-based program, it will collect users' emotional feedback and predict users' reaction to music based on previous record of their feedback to the recommended music. It aims at improving sleep quality consequently. Reinforcement Learning (RL) will also be integrated to enable the algorithm adapt to users' preference repetitively after investigating the feedbacks.

Keywords: Music Therapy, Insomnia, Machine Learning

1. Introduction

Insomnia has become a universal issue in modern society. Music therapy is conventionally an important complementary therapy in psychotherapy. Music directly engages the brain's emotional centers, which produces significant psychological benefits. There was research that proved that listening to music before sleeping causes increase of Rapid Eye Movement (REM) stage duration [1]. And improvement of subjective sleeping quality of chronic insomnia patients is reported [1]. However, the result of traditional way of music therapy exhibits variability. It largely depends on therapists who always give subjective selections, which affects treatment fidelity and reproducibility [2]. Inconsistent interpretation and use of terminology also impede therapists to have interprofessional communication. The cost of implementing traditional music-based interventions may constitute a barrier to their wider adoption [3]. Hence, it is necessary to offer them a choice with better accessibility. The past few years witness rapid development of machine learning (ML)

model, which makes the combination of AI and affordable personalized music therapy more possible.

The development of portable, home-use monitor enables users to monitor their emotion. People's emotional states are reflected by change in electroencephalogram (EEG), Electrocardiogram (ECG), and Photoplethysmography (PPG), and can be recognized by emotional recognition model [4]. This method has shown high reliability with application of wearable devices [4].

This review aims at synthesizing existing progress in signal acquisition and relative algorithms, and proposing a framework to illustrate AI-based approach of relieving insomnia.

2. Biomedical signal acquisition methods and their characteristics

2.1. Roles of different biological signals in determining sleep disorder

EEG signal is an objective indicator for insomnia. Its relativity with insomnia has been proven the strongest among the three main signals. EEG acquired in different frequency band in both awake and asleep state can be used to determine if any hyperarousal is shown. Alpha, Delta and Theta wave are acquired by a new ML model, which is designed to output Wake Electroencephalographic Similarity Index (WESI) to quantify level of brain arousal [5].

Insomnia is often accompanied by negative emotions. Music can induce measurable changes in neural activity associated with emotional processing. And the research demonstrates that the data collected by EEG can detect interviewees' emotional change with an accuracy of $82.29\% \pm 3.06\%$ after being categorized with Support Vector Machine (SVM) [6]. Hence, except for determining if user has hyperarousal while sleeping, EEG can also be used to receive emotional feedback from users when they are listening to the music recommended by algorithm. So that the algorithm will take the feedback into account before next recommendation.

ECG detects alternation in autonomic cardiac regulation by receiving Heart rate variability (HRV). Although evidence regarding consistent HRV impairment remains mixed, it is considered as a correlate with insomnia [7].

PPG can be used as an auxiliary method to determine sleeping state, but it cannot be used as a direct method to diagnose insomnia [8]. The data acquired can be provided to trained model to infer which sleeping state is the user in. In order to compute a Wake Electroencephalographic Similarity Index, the ML model needs EEG data under different sleeping stages (N1, N2, etc.) [5]. Thus, the EEG data can be categorized in different sleeping stages in order to draw a more credible conclusion of level of hyperarousal. In spite of reliability of sleep staging that EEG devices provide, PPG offers complementary cardiovascular and autonomic information [9].

2.2. Devices with improved portability and accessibility

Although traditional polysomnography (PSG) devices are reference standards of sleeping quality, their complexity of using impedes users' daily use. In order to monitor in long term, Wearable EEG monitor devices are more suitable. In recent research, wearable devices are featured with wireless signal transfer and dry electrodes which does not need conductor gel [10]. This makes long-term monitor during sleeping possible in home-based scenario achievable. Although they somehow sacrifice signal fidelity, ear-centered EEG still shows stable signal acquisition [10] and they met the technical requirements for clinical EEG recordings established by the International Federation of Clinical Neurophysiology (IFCN) [11]. The Pearson correlation of wearable devices and research-grade EEG is 0.93 [11]. Hence, compared with professional devices, wearable EEG devices are

reliable enough to make credible conclusions about users' sleep quality. In addition, the cost of EEG device has become particularly low (compared with unaffordable cost for therapist). The Table 1 below illustrates the price of several common wearable products in market [12]. As the Table 1 illustrates, the price of those devices with limited amounts of channels is quite reasonable.

Wearable ECG devices have diverse forms. The main-stream choices are patched ECG, smartwatch ECG and garment ECG [13]. They enable overnight tracing of HRV, which is appropriate for long-term sleep monitoring [13].

Table 1. The price of some wearable EEG devices in the market

Device	Channels	Price
NeuroSky MindWave	1	\$99.99
Muse v1/v2	4	\$200
Emotiv Insight	5	\$299
OpenBCI	8	\$500
Emotiv EPOC	14	\$799
OpenBCI 16-channel	16	\$949

2.3. Possible issue when portable devices are applied for daily use

In daily care monitoring, bio-signal rarely remains stable on the zero-voltage line [14]. In other word, baseline wandering is a critical interference. Any physiological movement would be a source of interference, which cause the signal baseline fluctuating over time. Consequently, it causes false-positive heart rate trigger or neglect of important events in EEG or ECG detection. This problem would be even more significant in portable devices since the unnoticed movements in daily scenario are unavoidable. The common solution for it is high-pass filtering with RC network [14]. A more notable source of noise is Radio Frequency (RF) signal in domestic scenario. Presence of domestic electrical household especially the wireless access points emit RF signal, making human body acts as antennas [14]. The signal captured by monitor devices is mixed with noises inevitably. Proper printed circuit board (PCB) design is an important factor to eliminate such noise [14]. Such devices should be carefully designed to avoid any ground loops and unacceptably long ground traces [14].

3. AI-based personalized music therapy systems

3.1. Data to be used

Before the recommendation, the favored music recommendation model is expected to be input with the WESI value to determine if the user is in the state of hyperarousal, which conjectures sleep-related arousal since WESI value reflects the similarity between users' EEG and typical hyperarousal EEG [5]. This will not only inform the diagnosis of insomnia, but also be saved to compare with following WESI values after several recommendations. Apart from the sleep related arousal, emotional arousal is also important to make an initial recommendation. In this stage, SVM will output the most possible emotions in this state.

3.2. Closed-loop adaptive music therapy

People have different preferences on music. People react differently to any specific music genre. Therefore, there is no fixed answers for the music appropriate for relieving insomnia. Algorithm should be adaptive to different users' preferences. Hence, ML model is to be introduced to produce apt recommendation to diverse users in this scenario.

There are huge differences on the model to apply when initiating this algorithm since there are not yet any records about users' preference. So, there is no material available for machine learning. In other word, users' aesthetic preference is unknown. In this case, a simple algorithm to recommend a few pieces of music is favorable to test users' preference. These keywords that describe emotions will become the input of a traditional rule-based model together with WESI value. The program below is an example written in pseudocode.

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IF WESI > threshold
→ recommend calming music
IF WESI decreases after music
→ continue similar music
IF WESI increases
→ try another type of music
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After the initialization is completed, there are a set of data that indicates change of sleep-related arousal and emotional arousal. A preferred model to be used is Long Short-Term Memory (LSTM) network, which produce results based on time-series data, which enables the algorithm to predict users' reaction to different music. Fortunately, there was example that utilize this model to recommend music [15]. This example aimed to improve emotional issues by recommending the music that is most helpful to the situation (instead of the most matched) [15]. This feature makes it suitable for the algorithm since this LSTM model learned to lead to an improved psychological state. However, the original model is not typically a model that can update the recommendation strategy iteratively based on users' reaction. Hence, Reinforcement Learning (RL) is to be integrated with the original algorithm. As the figure 1 shows, the algorithm contains three main processes, and the last two, which are personalization and closed-loop optimization, constitute an iterative learning loop.

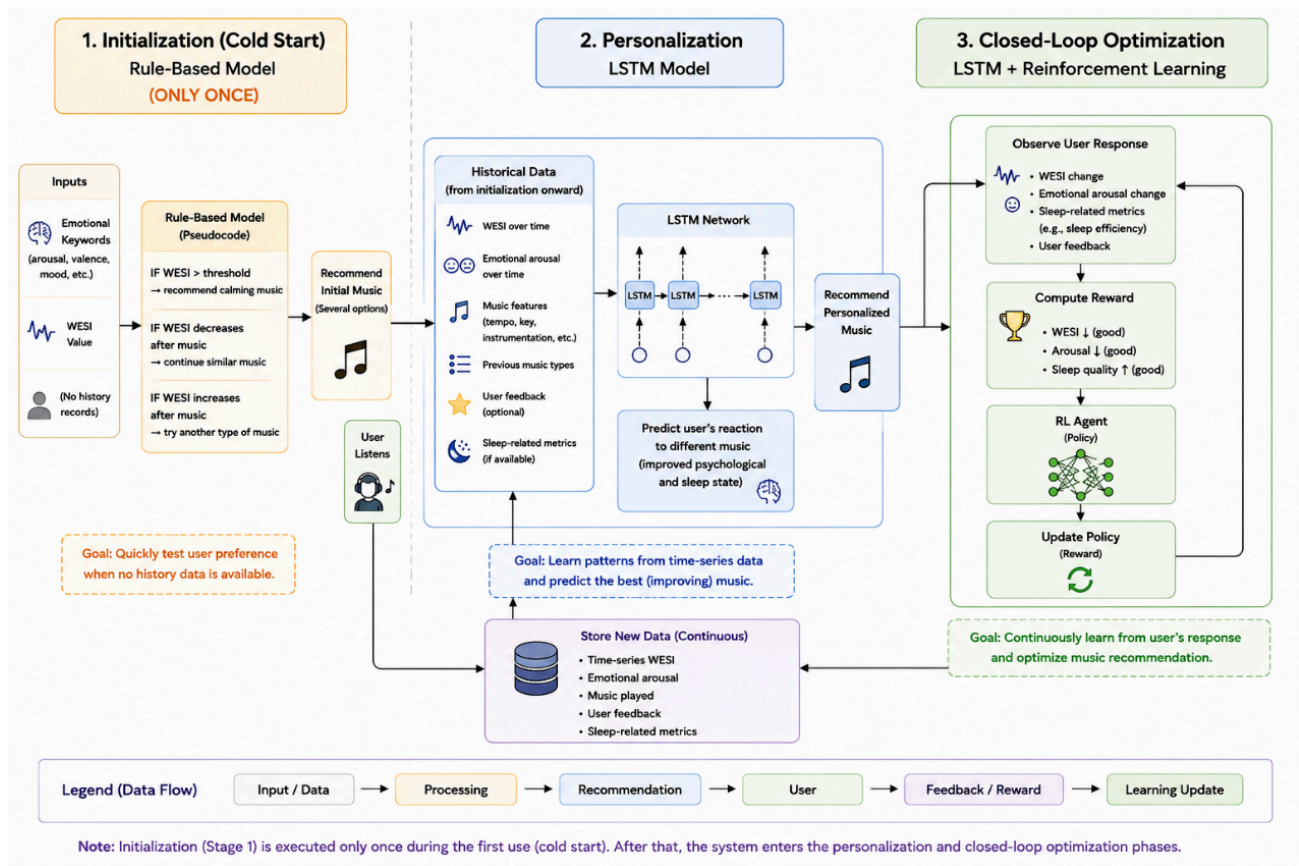


Figure 1. Procedure diagram of the algorithm

4. Conclusion

In conclusion, the concept drafts a possible prospective image of solving insomnia with biomedical signal and algorithms, while objective physiological measurements can provide a more consistent way to evaluate changes in sleep-related and emotional states. If this method is realized, a more accessible choice to relieve insomnia and secure working efficiency will be provided to those who cannot afford fee for a therapist. The value of this model also lies on the continuous overnight sleep monitor, which receive objective long-term signal to make a comprehensive knowledge of users' sleeping.

However, the concept remains theoretical. The proposed AI framework has not been clinically validated. Hence, related further study is necessary to put this conceptual model into practice.

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