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A Novel Method for Sleep-Stage Classification Based on Sonification of Sleep Electroencephalogram Signals Using Wavelet Transform and Recurrent Neural Network

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Keywords
Recurrent neural network · Electroencephalogram wavelet analysis · Sonification · Sleep

Abstract
Introduction: Visual sleep-stage scoring is a time-consuming technique that cannot extract the nonlinear characteristics of electroencephalogram (EEG). This article presents a novel method for sleep-stage differentiation based on sonification of sleep-EEG signals using wavelet transform and recurrent neural network (RNN). ***Methods:*** Two RNNs were designed and trained separately based on a database of classical guitar pieces and Kurdish tanbur Makams using a long short-term memory model. Moreover, discrete wavelet transform and wavelet packet decomposition were used to determine the association between the EEG signals and musical pitches. Continuous wavelet transform was applied to extract musical beat-based features from the EEG. Then, the pretrained RNN was used to generate music. To test the proposed model, 11 sleep EEGs were mapped onto the guitar and tanbur frequency intervals and presented to the pretrained RNN. Next, the generated music was randomly presented to 2 neurologists. ***Results:*** The proposed model classified the sleep stages with an accuracy of >81% for tanbur and more than 93% for guitar musical pieces. The inter-rater reliability measured by Cohen's kappa coefficient (κ) revealed good reliability for both tanbur ($\kappa = 0.64$, $p < 0.001$) and guitar musical pieces ($\kappa = 0.85$, $p < 0.001$). ***Conclusion:*** The present EEG sonification method leads to valid sleep staging by clinicians. The method could be used on various EEG databases for classification, differentiation, diagnosis, and treatment purposes. Real-time EEG sonification can be used as a feedback tool for replanning of neurophysiological functions for the management of many neurological and psychiatric disorders in the future.

Introduction

Visualization of brain neurophysiological activities has been widely used for the examination of the brain functions and disorders [1–3]. Almost all structural and functional brain mapping methods such as MRI, func-

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tional MRI [4], positron emission tomography scan, and electroencephalography (EEG) [5] use a type of visual output to reveal the brain data. Nevertheless, less attention has been paid to the transformation of brain neurophysiological activities into other sensory modalities than visual outputs. In this regard, using the human auditory system as the most sophisticated physiological equipment for precise sound identifiers and differentiators may be helpful [6, 7]. When the human visual system can response to only limited wavelengths of electromagnetic waves [8], the auditory system can accurately differentiate a wide range of sound frequencies and amplitudes [9]. EEGs contain many electrophysiological fine-tuned data, and instead of visualization, sonification of the output from the human auditory system may open new windows for future clinical use of EEG.

EEG signals contain a large amount of neuroelectrical data, which could be used for diagnostic and interventional purposes. One of the important fields which use EEG as a main diagnostic and research instrument is sleep medicine. In general, sleep stages are classified as rapid eye movement (REM) and non-REM. In REM sleep, the EEG signals contain mixed frequencies with low-voltage sawtooth waves. In non-REM sleep stage 1 (N1), eye movements become slow, and the brainwaves contain more theta waves (4–7 Hz). In non-REM sleep stage 2 (N2) which is recognized as light sleep, eye movements stop, and K-complex and sleep spindles (11–15 Hz) appear behind the theta waves. The slow wave sleep (SWS) contains high-amplitude EEG signals (>75 UV) with prominent delta waves (<4 Hz) [10]. Sleep-stage classification is a core component of sleep medicine for studying normal and disordered sleep. As visual sleep-stage scoring is a time-consuming method with poor reliability and disregard for nonlinear characteristics of EEG, different methods have been proposed for automatic sleep-stage classification. Analysis of sleep EEG based on time-frequency images (TFIs) has been used for the classification of sleep stages. Bajaj and Pachori [11] reached a 92.93% accuracy in sleep-stage classification using EEG signals. Histogram-based features have also been extracted from TFIs and classified by various techniques, such as the support vector machine [12], radial basis function [13], neural networks [14, 15], Mexican-hat wavelet analysis, and Morlet wavelet kernel function [16, 17]. Most of these studies have classified sleep stages mostly based on the nonlinear dynamics [18] and chaotic features of sleep-EEG signals [10, 19]. Methods such as Fourier-based spectral analysis extract frequency compositions in EEG signals but are unable to capture the underlying nonlinear dynamics of the EEG [19]. Decomposition of this nonlinearity by methods like wavelet transform can extract more informative data about brain oscillation. Ebrahimi et al. [20] have provided 93% accuracy in the classification of N2 and N3 using wavelet transform on single-channel sleep-EEG signal. However, their method failed to differentiate N1 and REM stages [20]. Another study achieved 94.80% accuracy for differentiating of N1, N2, N3, and REM stages based on single-channel sleep-EEG analysis using Tunable q-factor wavelet transform [21]. In another study, automatic sleep staging was performed with 90% accuracy using recurrence analysis on a single-channel sleep EEG, and the method could classify subjects with and without mental distress using biomarkers based on stage designation [22]. In a recent article, Zieleniewska et al. [23] describe a parametric description of EEG profiles for the assessment of sleep in disorders of consciousness.

In addition to sleep-stage classification, EEGs as a real-time brain mapping method with the most temporal resolution, can be used as a feedback tool for replanning and reprogramming of neurophysiological functions. This powerful feedback tool can be used for the management of many mental conditions such as attention deficit hyperactive disorder [24, 25] and anxiety [26–28]. Current methods usually convert brain oscillations to visual feedback. It seems that the transformation of EEG to polyphonic feelingful musical pieces may open a new window for neurofeedback and neuromodulation fields. The sonification of sleep EEG for sleep-stage classification has recently attracted the attention of researchers. In this regard, various methodologies such as real-time/offline sonification have been used for the differentiation of sleep stages [29], diagnosis of sleep disorders and sleep quality assessment [30], detection of anesthesia during surgery [31], epileptic seizure diagnosis [32, 33], brain control of musical instruments [34], and transformation of specific brain patterns into musical compositions [35]. Most of these methods have generated note sequences and chords based on the limited features of EEG signals. Adrian and Matthews (1934) used the amplitude of alpha EEG signals as a music generation source for the first time [36]. On the other hand, Miranda [35] trained a computer using augmented transition networks to detect and convert EEG patterns into musical structures [35]. In another study, a method was proposed for the segmentation and encoding of EEG frequency bands to monody musical rhythms, in which the musical tempo changes depending on the EEG signal fluctuations in different sleep stages. As a result, sleep stages were trans-

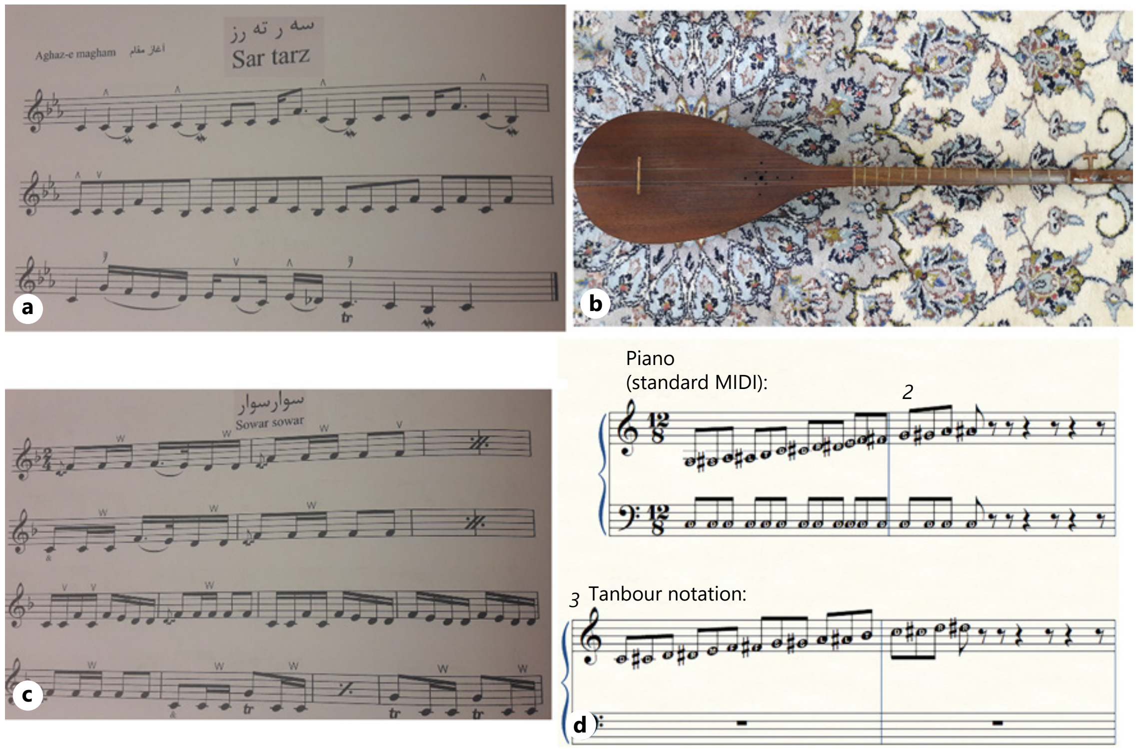


Fig. 1. a Measureless and dynamical ancient Makam. **b** Kurdish tanbur instrument. **c** Virtual Makam rationalized in terms of rhythm and interval. **d** Tanbur monody notation and standard polyphonic MIDI notation. MIDI, Musical Instruments Digital Interface.

formed into various melodies with a specific tempo, but the accuracy and reliability of this method for clinical applicability were not reported [29]. Olivan et al. [30] have mapped the amplitude and frequency of EEG into audible signals for the evaluation of sleep quality. This study proposed the transformation of signals into audio files as a complementary method to support visual interpretation of EEG [30].

An important challenge in EEG sonification is to generate the most informative and feelingful musical structure. In addition, the clinical application of sonified EEG is an important challenge that has not been investigated very well. Transformation of the detailed neuroelectrical information extracted from EEG into elegant, detailed musical pieces may reveal the neuropsychological features of the brain in various emotional, cognitive, and arousal states. In the present study, by using the performance recurrent neural network (RNN) model, we aimed to convert sleep-EEG signals to dynamical feelingful western (classical guitar) and eastern musical structures (Kurdish tanbur) by polyphonic EEG sonification for sleep-stage classification.

Materials and Methods

Proposed Methodology

First, musical databases of guitar and tanbur were created. Then, RNN was trained on the musical database. On the other hand, EEG signals were pre-processed and artifacts were removed by applying independent component analysis. In the next step, an optimal mother wavelet was identified using cross-correlation coefficient factor. After that, brainwaves and musical pitches were mapped by continuous wavelet transform (CWT), and the note duration of each musical pitch was specified by discrete wavelet transform (DWT). Finally, the musical beat-based feature was calculated, the derived notes and features were presented to the pre-trained RNN, and the clinical validation of the musical output was performed by 2 neurologists. All steps are presented in detail in the next sections.

Classical Guitar and Kurdish Makam Database

The rationality of musical structures is critical to the development of informative musical pieces when artificial intelligence methods are recruited. The rationality that appears in musical intervals and rhythm implies the predictability of a musical structure [37]. Rational musical structures are far more predictable compared to emotional musical structures. Emotionality in a musical piece is expressed as microtones or "pitch bends" in a musical structure. In addition, if the pieces have a constant rhythm (i.e.,

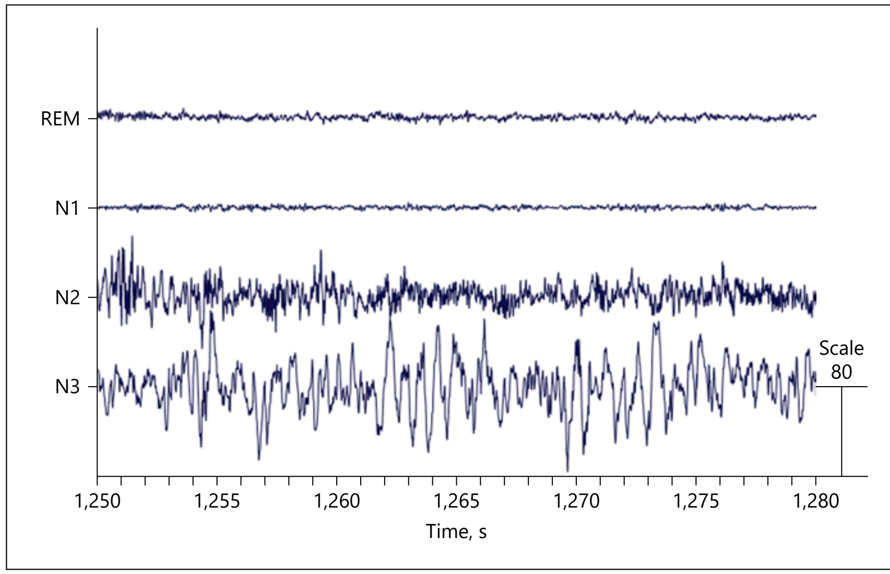


Fig. 2. EEG signals of sleep stages in epoch of 30 s. REM, rapid eye movement.

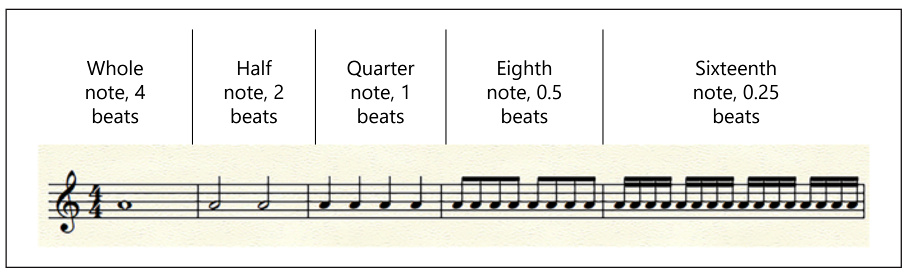


Fig. 3. Note durations and beats.

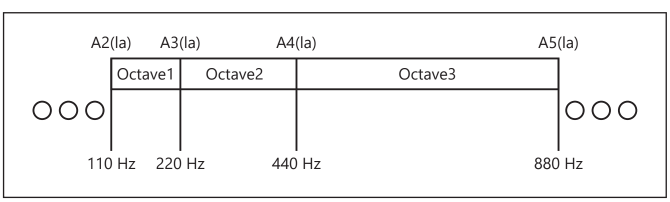


Fig. 4. Bandwidth of octaves.

metric structure), they are rhythmically rationalized. In the current research, 2 rational musical structures were applied, and since to the extent of the authors' knowledge, the training of an RNN on a measureless musical piece (rhythmically emotional) is not possible. Measureless music is an emotional musical structure with no rhythmic component, in which microtones may also be overlooked.

The first musical structure was a database of classical guitar pieces composed by a Spanish composer Francisco Tarrega (1852–1909), and the second structure was a database of the Kurdish Makams (tonalities), which are often played by tanbur. Guitar is a plucked-string instrument with rational intervals, and the classical guitar repertoire contains dynamic and rhythmically rationalized pieces.

Ancient Kurdish music is taught aurally to musicians and has a highly dynamic and emotional structure. Oral or aural tradition is a traditional approach to teaching the totality of the dynamics and emotions of music. It is impossible to write the entire dynamics on pieces of a music sheet, and the performance is extremely more complex than the notation. As the notation of ancient Makams is measureless (Fig. 1a), the recognition of the variational rhythm and dynamics is possible through the aural tradition. In the present study, the dynamics in the musical database was considered as far as possible.

Kurdish tanbur is an ancient plucked-string musical instrument with rational intervals (Fig. 1b). Tanbur Makams include ceremonial (ancient), Kalaam (Haghani), and virtual Makams (Majazi) [38]. Ceremonial or ancient Makams semantically consist of epic, romantic, mystical, and worldly states. These Makams are rational in interval but irrational in rhythm. In other words, the only way to comprehend the rhythm variations and performance with true dynamics is the aural tradition, while notation is significantly simpler than the performance. Figure 1a depicts a measureless notation for a ceremonial Makam (Sar-Tarz). Kalaam (Haghani) Makams are sacred voices and are measureless in terms of notation. Virtual (Majazi) Makams focus on the daily life of humans and are rationalized in terms of rhythm, while their rhythm remains constant throughout the entire piece. Figure 1c shows a sample of virtual Makam (Swar-Swaras) which represents the galloping of horses. In the present study, the tanbur database was

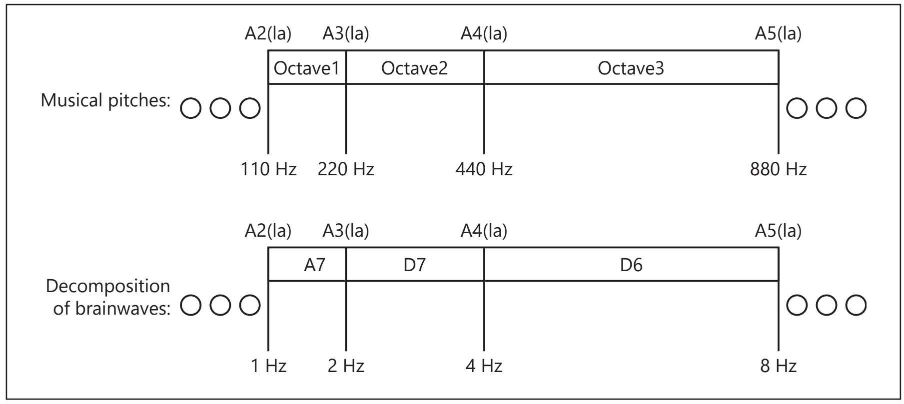


Fig. 5. Binary system dominating musical pitches and decomposed levels of EEG by DWT. DWT, discrete wavelet transform.

prepared for virtual Makams due to their constant rhythm and rationalized structure.

The notation of tanbur Makams is often carried out based on a simple agreement [38]. Figure 1d shows the simple monody notation and polyphonic method used in the present study for the development of the Musical Instruments Digital Interface database. The database was developed based on the actual frequencies of tanbur instead of the previously described method [38]. To this end, 5 virtual Makams, including Baya Baya, Janga Ra, Joloshahi-Sahari, first Joloshahi, and Khan Amiri, were arranged and provided as the musical database in a polyphonic manner. Previous sonification methodologies have mainly generated monody music [29]. Although classical Kurdish musical notation is monody (Fig. 1a, c), the performance is polyphonic in some repertoires.

Sleep-EEG Database

The Sleep Disorders Research Center in Kermanshah (Iran) has provided a polysomnography (PSG) database for normal individuals and patients with insomnia disorder [39]. The database includes EEG, electrocardiogram, electromyography, and electrooculography channels, with a sampling rate of 256 samples per second for approximately 7 h of sleep for each subject. In addition, the database contains power spectral features within a 30-s epoch. The PSG data of 11 normal sleepers aged 18–63 years were used for the present study. They were interviewed by a sleep clinician, and they did not have any psychiatric and neurological disorders or any other problems which may affect the sleep and EEG. They also did not have any sleep problems based on the interview and a whole night PSG.

In the present study, 1 frontal EEG channel (F3) was used for the sonification of the sleep-EEG data. Use of single-channel sleep-EEG signal was valuable for sleep staging [22, 40]. The second sleep cycle was selected from each participant to sleep-EEG analysis. Sleep stages were classified by the PSG equipment through the analysis of the PSG row data including EEG, electrocardiogram, electromyography, and electrooculography and confirmed by the sleep clinician who was a member of the research team.

Figure 2 depicts sleep-EEG signals at different stages. Prior to independent component analysis, a high-pass filter with the cutoff frequency of 1 Hz was used to filter the EEG frequencies for the removal of artifacts [41].

In the present study, wavelet packet transformation [42, 43] was used to decompose the signal and interpret associations between musical pitches and brainwaves in the proposed method. Wavelet packet transformation was performed on 6 levels with 1 approximation and 6 details. Moreover, CWT was employed for the detection of the dominant frequencies and extraction of the proper features to grade the sleep stage.

DWT and Mapping of the Brainwaves to the Musical Pitches

A musical scale is a sequence of discrete pitches, with each pitch corresponding to a specific frequency. In a rationalized musical structure, a musical scale known as an octave contains 13 notes with 12 equal intervals. In many cultures, musical intervals are not rationalized and contain a narrow distance between the adjusted tones known as pitch proximity or microtone.

Tonality, rhythm, and pitch proximity are derived from the built-in functional properties of the brain [44]. A binary system dominates musical structures; for instance, the note duration of tones (Fig. 3) includes the whole note (4 beats), half note (2 beats), quarter note (1 beat), and eighth note (0.5 beat). The frequency bandwidth of the octaves (Fig. 4) included A2–A3 (span: 110 Hz), A3–A4 (span: 220 Hz), and A4–A5 (span: 440 Hz). In addition, the binary form is a form of music that is usually used in the baroque period.

Brainwaves were decomposed into subbands using the DWT. A binary system dominated the frequency bandwidth of each DWT subband (Fig. 5). Therefore, the subbands in the 6-level DWT bandwidth were approximate 6 (span: 1 Hz), detail 6 (span: 2 Hz), detail 5 (span: 4 Hz), detail 4 (span: 8 Hz), detail 3 (span: 16 Hz), and detail 2 (span: 32 Hz).

EEG signals with the sampling frequency of 256 samples per second were decomposed by DWT which was applied by db5 wavelet in the 6 levels (Fig. 6). For choosing the optimal mother wavelet, the similarities between 24 mother wavelets (db 1–8, sym 1–10, coif 1–5, and haar) and sleep-EEG signals were analyzed by Pearson cross-correlation coefficient [45–47]. Results indicated that Daubechies-5 (db5) Mother wavelet [48] is the optimal one as it maximizes the normalized mean Pearson cross-correlation coefficient. Figure 7a depicts db5 wavelet, and Figure 7b shows that db5 is the optimal filter to analyze EEG signals of the database.

The frequency of an octave of any pitch is twice that of the first pitch. Thus, an octave is a geometrical sequence (Equation 1). In this equation, the scale factor (a) is the frequency of the first pitch. The common ratio (q) could also be calculated for any octave to evaluate the frequency of any pitch based on a given frequency. For

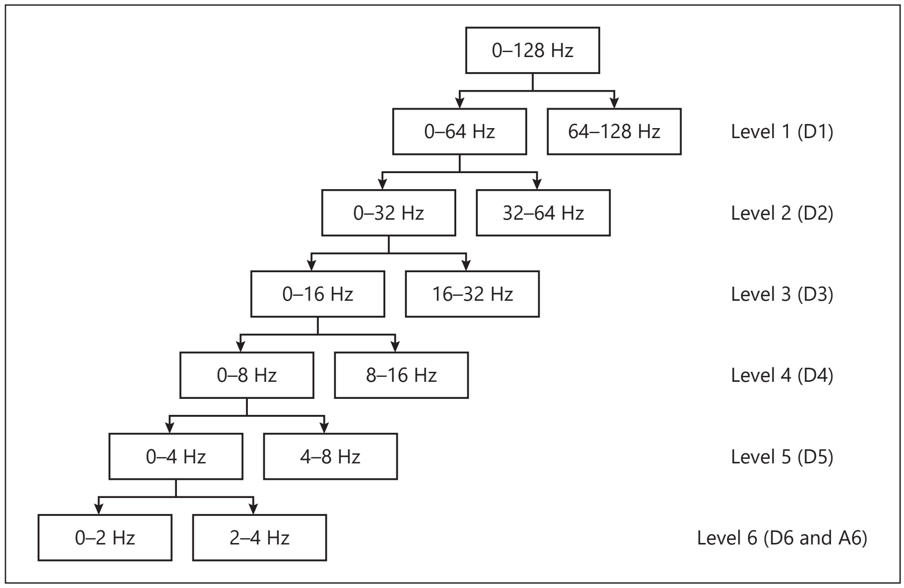


Fig. 6. Wavelet packet decomposition of EEG signals in 6 levels (sampling frequency: 256 samples/s).

Table 1. Mapping of decomposed EEG sub-bands to note durations

Frequency	DWT	Bands	Note duration
0–2, Hz	A6	Low delta	Whole note
2–4, Hz	D6	High delta	Half note
4–8, Hz	D5	Theta	Quarter note
8–16, Hz	D4	Alpha	Eight note
16–32, Hz	D3	Beta	Sixteenth note
32–64, Hz	D2	Gamma	–
64–128, Hz	D1	Noises	–

EEG, electroencephalography; DWT, discrete wavelet transform.

instance, the frequencies of the A2 (F_{A2}) and A3 (F_{A3}) notes was 110 and 220 Hz, and the common ratio of musical intervals was determined using the following equation:

$$a \times q^{(n-1)} = a_n \rightarrow (F_{A2}) \times (q^{12}) = (F_{A3}) \rightarrow q = \sqrt[12]{2}; \qquad (1)$$

In the present study, the common ratio (q) was also used for the brainwave subbands. The decomposed levels contained 12 rational segments that were mapped to the musical octaves and their rational musical intervals (Table 1). This is a new link between musical pitches and brainwaves, which is known as a kind of "Parameter Mapping Algorithm" [49]. In the present study, CWT was applied to extract the exact prominent frequency values of the EEG epochs, as it has better resolution than DWT in detecting the dominant frequency of continuous signals such as EEG. On other hand, DWT was used for signal decomposition, mapping of the brainwaves to the musical intervals, and mapping of the pitches to proper note durations.

Designing and Training of RNN for Music Generation

Deep-learning methods have been employed for music generation [50]. In the present study, RNN was employed to generate a time series of musical notes in the form of melodies and note sequences. RNNs are neural networks, in which a feedback generates input and output sequences within a specific time interval instead of receiving inputs, thereby generating outputs; as such, RNNs are able to learn both current and previous data. Use of back-propagation through time leads to an exploding gradient problem, so the long short-term memory (LSTM) architecture was proposed to train the RNNs and avoid repetitive multiplications. Moreover, the variational auto-encoder was applied along with the recurrent decoder for the natural sentences in order to impute the missing words [51].

The deep-learning methods used for automatic music generation (e.g., BachBot) often utilize LSTM to harmonize musical pieces [52, 53]. For instance, the DeepBach project uses the pseudo-Gibbs procedure to generate musical notes [54]. Furthermore, Magenta as an open-source project developed by the Google Brain Team has provided models such as drums RNN, melody RNN, polyphony RNN, piano roll RNN, neural autoregressive distributed estimator, and performance RNN in order to generate music [55].

Performance RNN can learn and produce feelingful musical structures without overlooking the dynamics [56]. It is differing from standard RNN in encoding the musical features as it encodes TIME-SHIFT and VELOCITY to generate dynamical music. Dynamics refers to the louder and quieter musical expressions that vary depending on the feelings of the musician.

In the present study, RNN was designed and trained on the dynamical musical databases. Performance RNN from the Google Brain Project was selected for training. The RNN contained a single hidden layer with 256 LSTM cells for tanbur Makams and 2 layers with 256 neurons for the classical guitar database. The features of the Musical Instruments Digital Interface database were

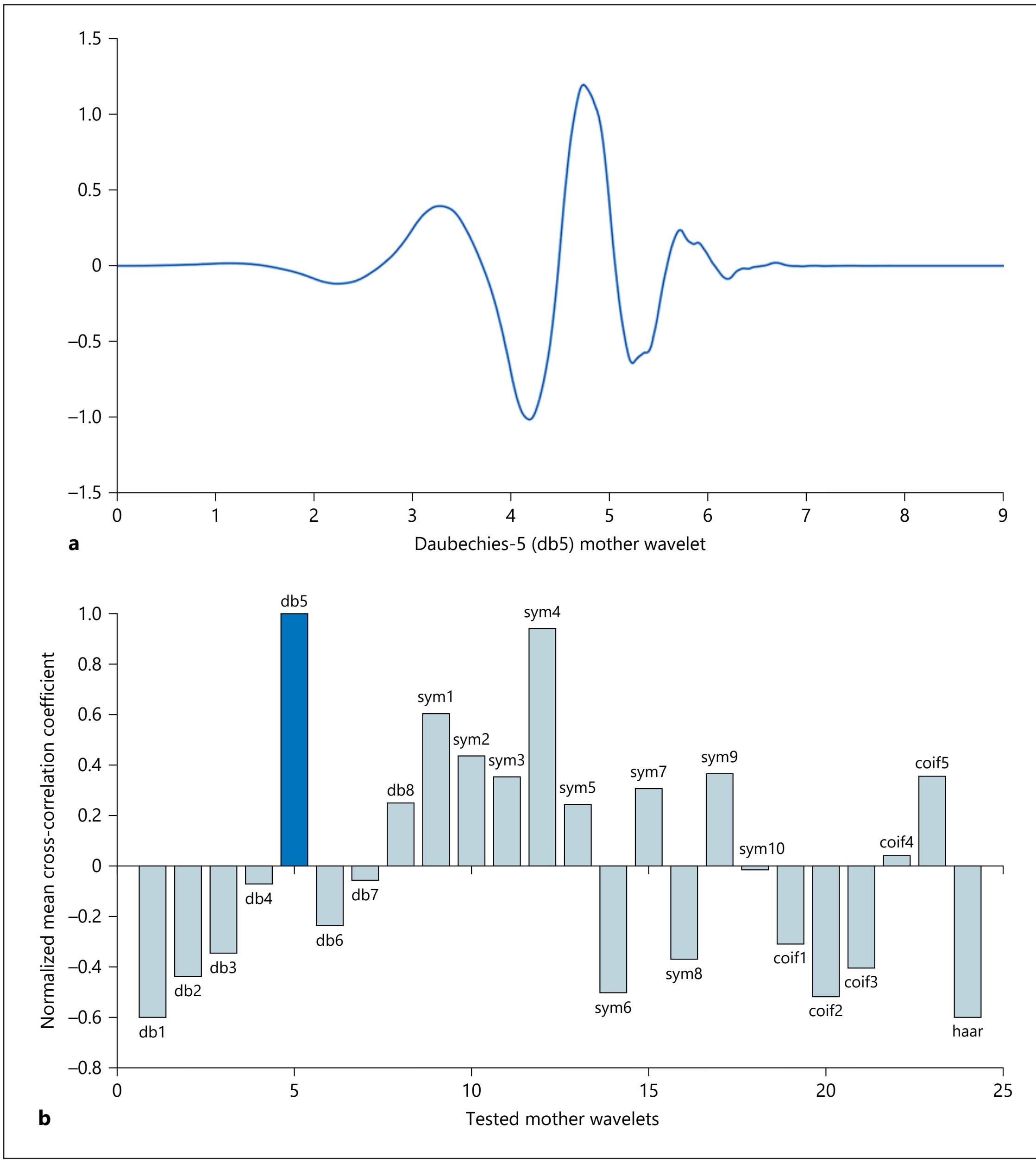


Fig. 7. a db5 mother wavelet. **b** Normalized mean cross-correlation of 24 mother wavelets. db5, Daubechies-5.

encoded in order to realize the note that had started or released, such as NOTE-ON (start note) and NOTE-OFF (release note).

The action mechanism of the performance RNN is to encode the TIME-SHIFT and VELOCITY events to learn and generate feelingful dynamic music. The default model of the performance RNN was used, which is a single 413 dimensional one-hot encoding vector of the features at each training stage. As RNN training by the teacher forcing method leads to better results with higher accuracy [57], the teacher forcing algorithm was applied during training to force the network to learn and generate proper outputs.

A previous study indicated that 32 steps of velocity are sufficient for the encoding classical piano music [56]. For the present method, 128 NOTE-OFF, 128 NOTE-ON, 125 TIME-SHIFT, and 32 VELOCITY events formed the 413 dimensional one-hot encode vector of the input (Fig. 8).

Figure 9 depicts the detailed structure of an LSTM cell. LSTM is able to add or remove information to the cell state by gates. These gates are composed of a sigmoid neural network and a point-wise multiplication function. The sigmoid outputs are within the range of 0–1, with the zero value preventing anything through, and the

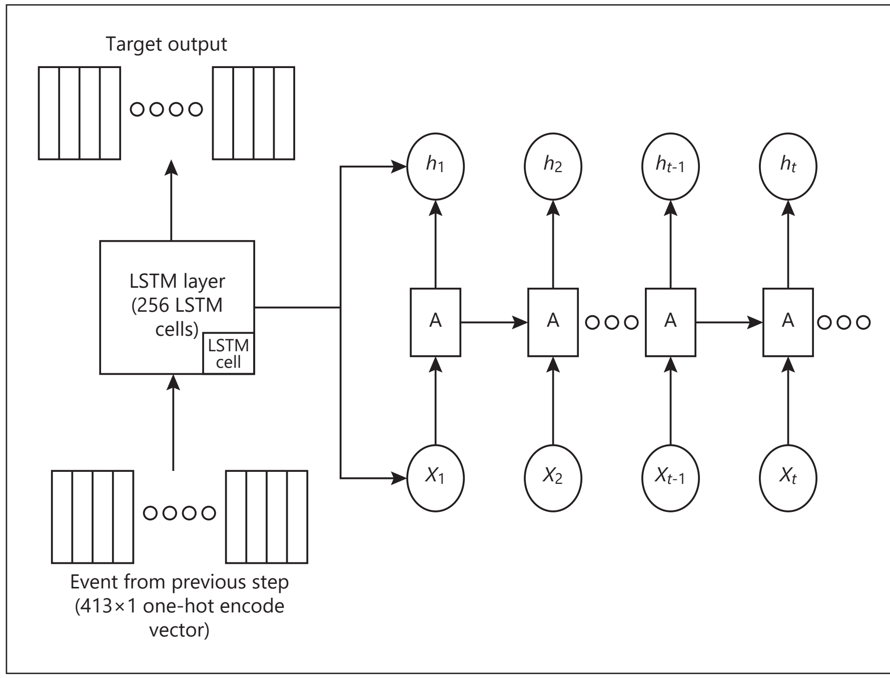


Fig. 8. Configuration of designed RNN and LSTM cells. LSTM, long short-term memory.

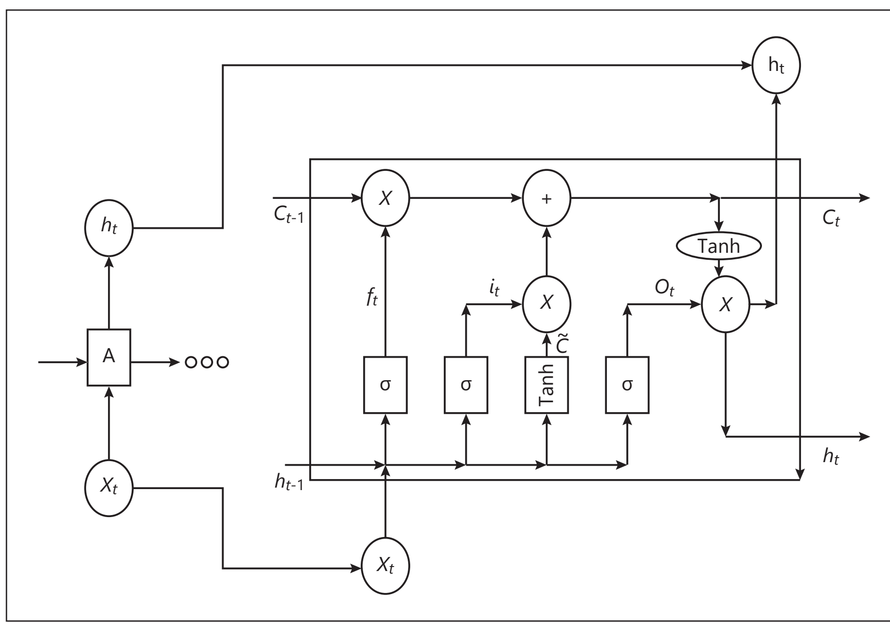


Fig. 9. LSTM cell. LSTM, long short-term memory.

value 1 is to let everything through. For designing an LSTM cell, the forget-gate layer was developed first. This layer looks at h_{t-1} and x_t to decide to accept or eliminate a value. A zero value in the sigmoid output means elimination, and value one means acceptance. Equation 2 shows f_t as the generated value by the forget gate. The second step is to store proper information into the cell state, which consists of 2 segments; the first segment is the sigmoid and an input-gate layer that updates the values. The second segment is the tanh layer, which generates the new candidate values that are added to the cell state (Equation 3). Following that, the old-cell state (C_{t-1}) has to be updated. The multiplication of f_t by the old state causes the previous cell state to be forgotten, which has been decided to be canceled. Equation 4 depicts the new candidate value for the new state. At the final stage, the cell state and the sigmoid function produce the output value between −1 and +1 that could set the output to the proper final values (Equation 5–7) [58].

$$f_t = \sigma(W_f . [h_{t-1}, X_t] + b_f); \tag{2}$$
$$i_t = \sigma(W_i . [h_{t-1}, X_t] + b_i); \tag{3}$$
$$\tilde{C}_t = \tanh(W_c . [h_{t-1}, X_t] + b_c); \tag{4}$$
$$C_t = f_t \times C_{t-1} + i_t \times \tilde{C}_t; \tag{5}$$
$$o_t = \tanh(W_o . [h_{t-1}, X_t] + b_o); \tag{6}$$
$$h_t = o_t \times \tan h(C_t); \tag{7}$$

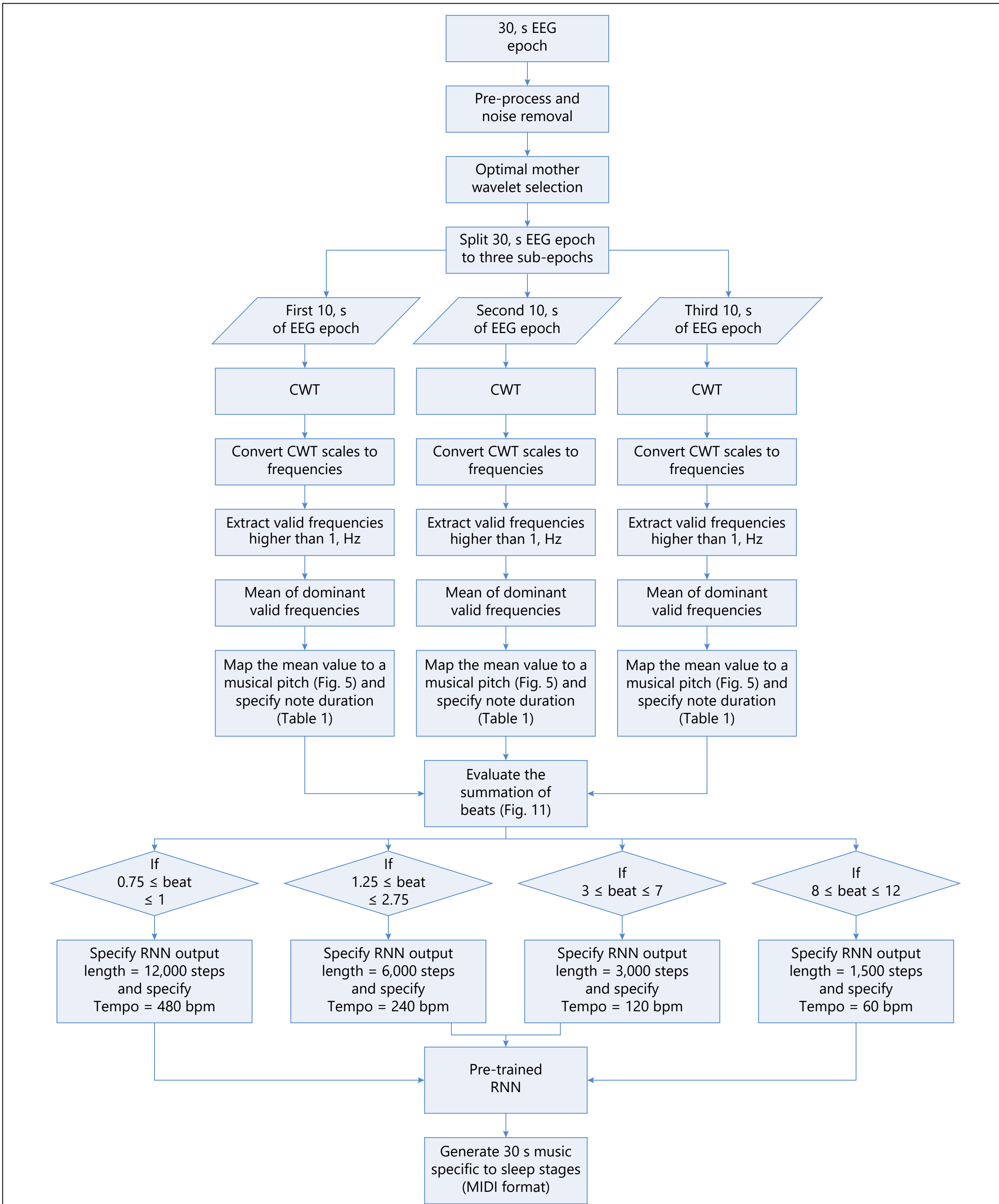


Fig. 10. Algorithm flowchart. EEG, electroencephalogram; CWT, continuous wavelet transform.

Color version available online

Fig. 11. Musical beat-based features (n = 29) specific to 30-s EEG epochs which represents frequency activity of brainwaves.

The Final Algorithm for Music Generation

DWT was applied to explain the mapping between the EEG frequency bands and musical pitches (Fig. 5, 6). For a 30-s EEG signal, the epoch was divided into 3 sections. CWT was applied to each section and 3 note durations (Table 1), and musical notes (Fig. 5) were mapped to the EEG epoch based on the mean dominant frequency. The summation of the note beats was the final feature used to classify the EEG-signal activity. In general, 29 musical beat-based features could describe the frequency content of a 30-s EEG epoch. In addition, 3 notes specific to the EEG epoch were generated as the RNN input, and the tempo of the generated music was also specified by the musical beat-based feature (Fig. 11). Accordingly, the higher musical beat-based feature was associated with the lower musical tempo.

Figure 10 is a flowchart that represents the entire algorithm. For the sleep-EEG signals, 29 categories were reduced to 4, representing 4 sleep stages. Moreover, the control of the output tempo was carried out based on the beat-based feature. At the default tempo of 120 bpm, each step-in time led to the generation of 10-ms musical pieces, and the increased step resulted in the increased length of the generated music. As indicated in Figures 10 and 11, the step value and tempo changed depending on the musical beat-based feature for the generation of 30-s music.

Validity and Reliability of Music Pieces for Sleep-Stage Differentiation

The generated music (see online suppl. files; for all online suppl. material, see www.karger.com/doi/10.1159/000511306) was randomly presented by a computer and headphone to 2 neurologists who were blinded to the participants and EEG signals. They had no specialized musical education. Both the order of participants and the order of sleep stages in each participant were arranged for presentation randomly. For the first neurologist, the tanbur Makams were presented first, then the guitar pieces. However, for the second neurologist, the order of presentation was reversed, the guitar pieces were presented first, and then the tanbur Makams. These specialists were asked to classify each musical piece as REM, N1, N2, and SWS. For each participant, eight 30-s music pieces, including 4 tanbur and 4 guitar music pieces, each piece representing one of the sleep stages (N1, N2, SWS, and REM), were selected. Validity of sleep staging based on generated music was calculated and presented as percent of correct answers. Inter-rater agreement was measured by Cohen's kappa coefficient (κ) using Statistical Package for the Social Sciences version 26.

Results

Generation of Music

The relationship between musical pitches and sleep-EEG brainwaves was defined by a parameter mapping algorithm. This mapping algorithm provided a set of musical notes as inputs to the RNN for the transformation of

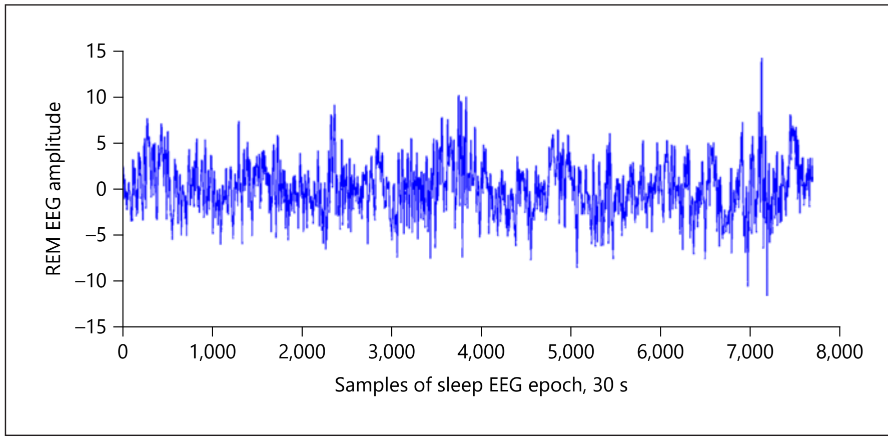


Fig. 12. EEG epoch of REM sleep stage. EEG, electroencephalogram; REM, rapid eye movement.

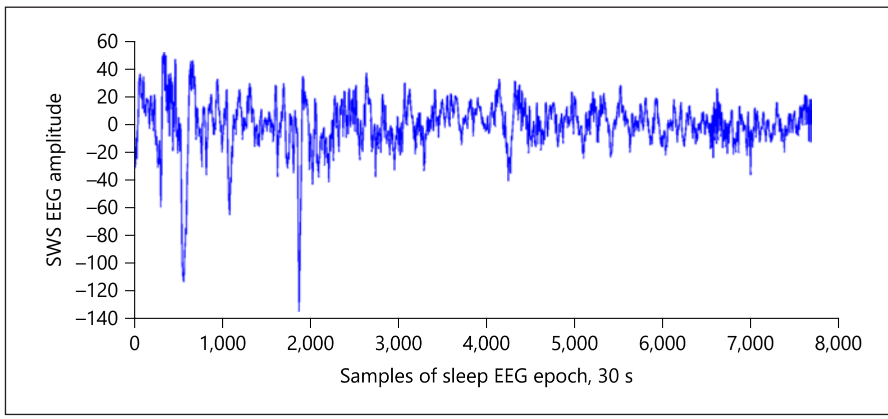


Fig. 13. EEG epoch of SWS sleep stage. EEG, electroencephalogram; SWS, slow wave sleep.

EEG signals into pleasant musical structures. Here, we present the process for REM and SWS. Figures 12 and 13 show two 30-s epochs of the EEG data for SWS and REM stages. The 30-s EEG epoch was divided into 3 parts, and CWT was applied to each part (Fig. 14, 15). The dominant frequency and mean value of each part were extracted (Fig. 16, 17). Then, the mean values of the dominant frequencies were mapped to the musical pitches (Fig. 5), and the time duration was selected for each dominant frequency (Table 1). The summation of all beats (musical beat-based feature) showed the frequency content of EEG. Overall, 29 scores were extracted which reduced to fewer categories of the EEG databases. Finally, 4 categories were considered for sleep-EEG classification based on the American Academy of Sleep Medicine standards [59].

The musical beat-based feature was calculated for various sleep stage's EEG epochs. As is observed in Figure 18, the N1 musical beat-based feature was often within the range of 0.75–1. In the REM stage, the beat values were determined within the range of 1.25–2.5, and the values were within the range of 4–8 in N2. The beat values of 6–12 belonged to the SWS sleep stage. According to this classification, 4 values were selected for the musical tempo that was generated by the RNN (Table 2).

The beat values were overlapped in some of the EEG epochs because of various reliability of sleep staging. For instance, the EEG epoch of N2 with the reliability of <35% and SWS EEG with the reliability of higher than 70% may have equal beat values. At any rate, 29 scores were presented to demonstrate the activity level of EEG, and the final results were matched to the American Academy of Sleep Medicine standards, thereby resulting in the generation of music with 4 different tempos (Table 2).

Validity and Reliability

All 30-s musical pieces comprising 44 tanbur and 44 guitar pieces (online suppl. material), including 4 musical pieces for each instrument for each participant, were randomly presented to 2 neurologist co-authors. They had not any musical knowledge but described the generated music as pleasant tonalities. They also introduced the REM musical representations as full-of-dream tones and SWS as calming sounds and slower than the other 3 stag-

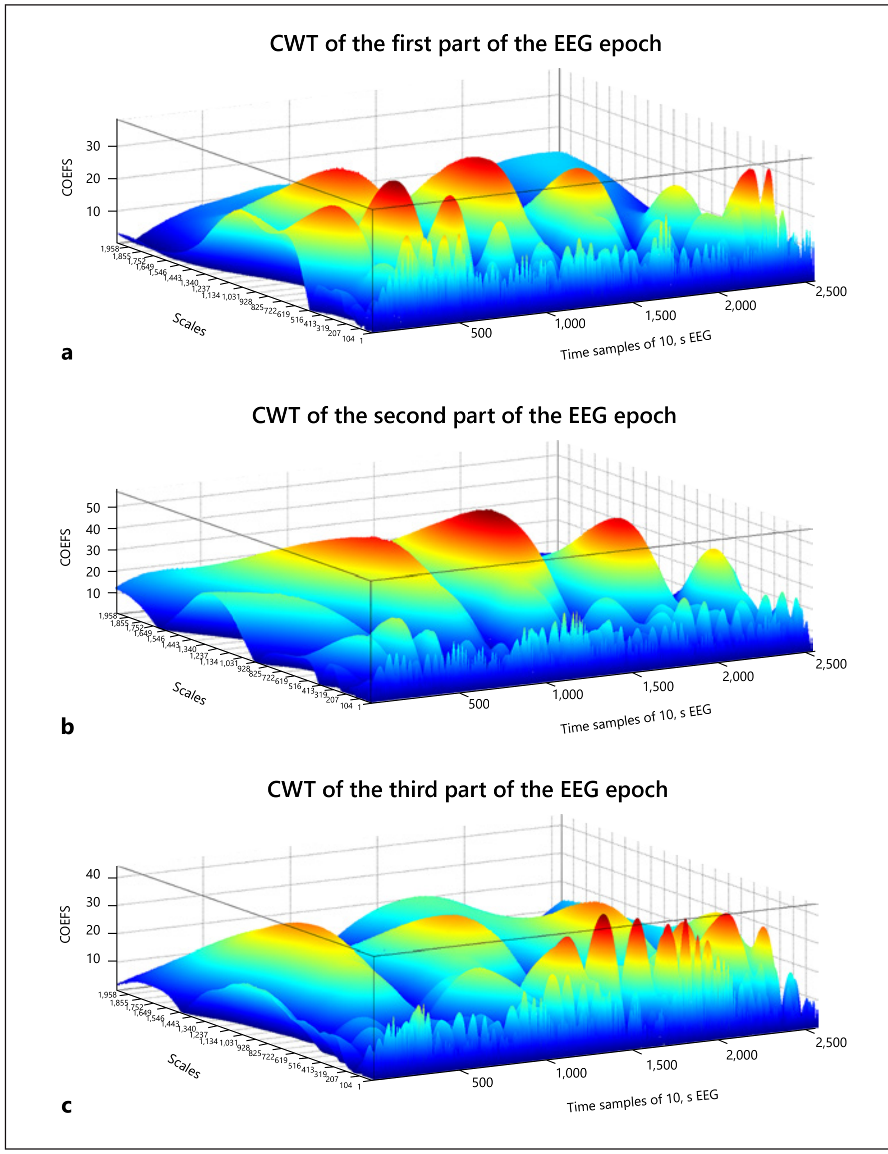


Fig. 14. CWT of first EEG sub-epoch (**a**), second EEG sub-epoch (**b**), and third EEG sub-epoch in REM sleep stage (**c**). EEG, electroencephalogram; CWT, continuous wavelet transform; REM, rapid eye movement.

Table 2. AASM sleep classification standard and final musical tempos specific to each sleep stage

Sleep stage	REM	N1	N2	SWS
Musical tempo, bpm	240	480	120	60

N1, nonrapid eye movement stage 1; N2, nonrapid eye movement stage 2; AASM, American Academy of Sleep Medicine; SWS, slow wave sleep; REM, rapid eye movement.

es. Validity was measured as the percent of correct identification of sleep stages and calculated for each tanbur and guitar instrument separately (Table 3). According to the result, sleep-stage identification based on sonified sleep EEG by the method introduced in the present research has a good validity. The result revealed higher validity for sleep staging based on guitar musical pieces than tanbur musical pieces.

The inter-rater reliability of the method was measured by Cohen's kappa coefficient (κ). According to the result, the method was reliable for both tanbur ($\kappa = 0.64$, $p < 0.001$) and guitar musical pieces ($\kappa = 0.85$, $p < 0.001$). Similar to validity, the reliability of the method was high-

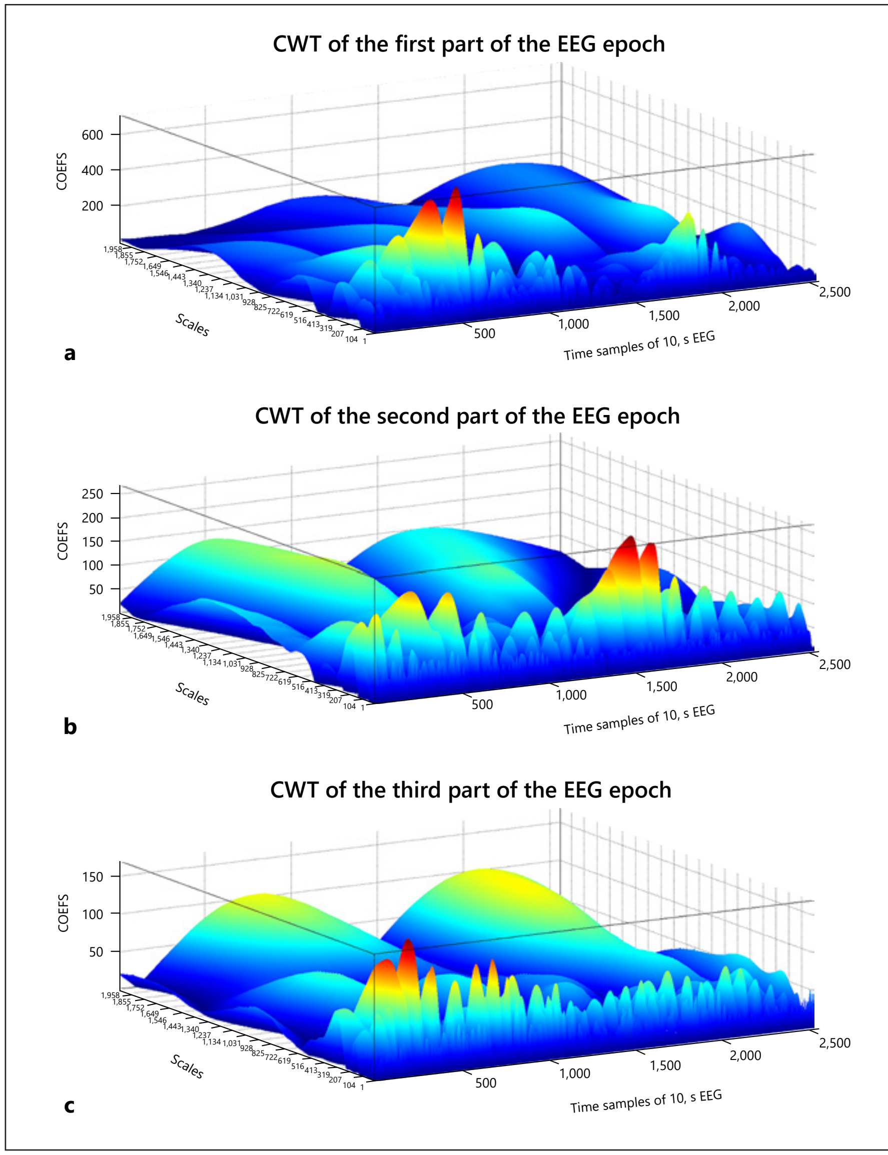


Fig. 15. CWT of first EEG sub-epoch (**a**), second EEG sub-epoch (**b**), and third EEG sub-epoch in SWS sleep stage (**c**). EEG, electroencephalogram; CWT, continuous wavelet transform; SWS, slow wave sleep.

er with guitar musical pieces than tanbur. Detailed sleep-stage identifications for both identifiers in both musical repertoires are presented inTable 4.

Discussion

The transformation of biosignals into visible outputs has wide application in medicine. However, less attention has been paid to the transformation of brain neurophysiological activities into auditory stimulus and specifically musical tonalities. Human auditory system is the most sophisticated physiological equipment with a good differ-

Table 3. Validity of sleep staging based on sonification of sleep EEG to tanbur and guitar musical pieces

	Tanbur	Guitar
Rater 1, %	81.80	95.50
Rater 2, %	84.10	93.20

EEG, electroencephalogram.

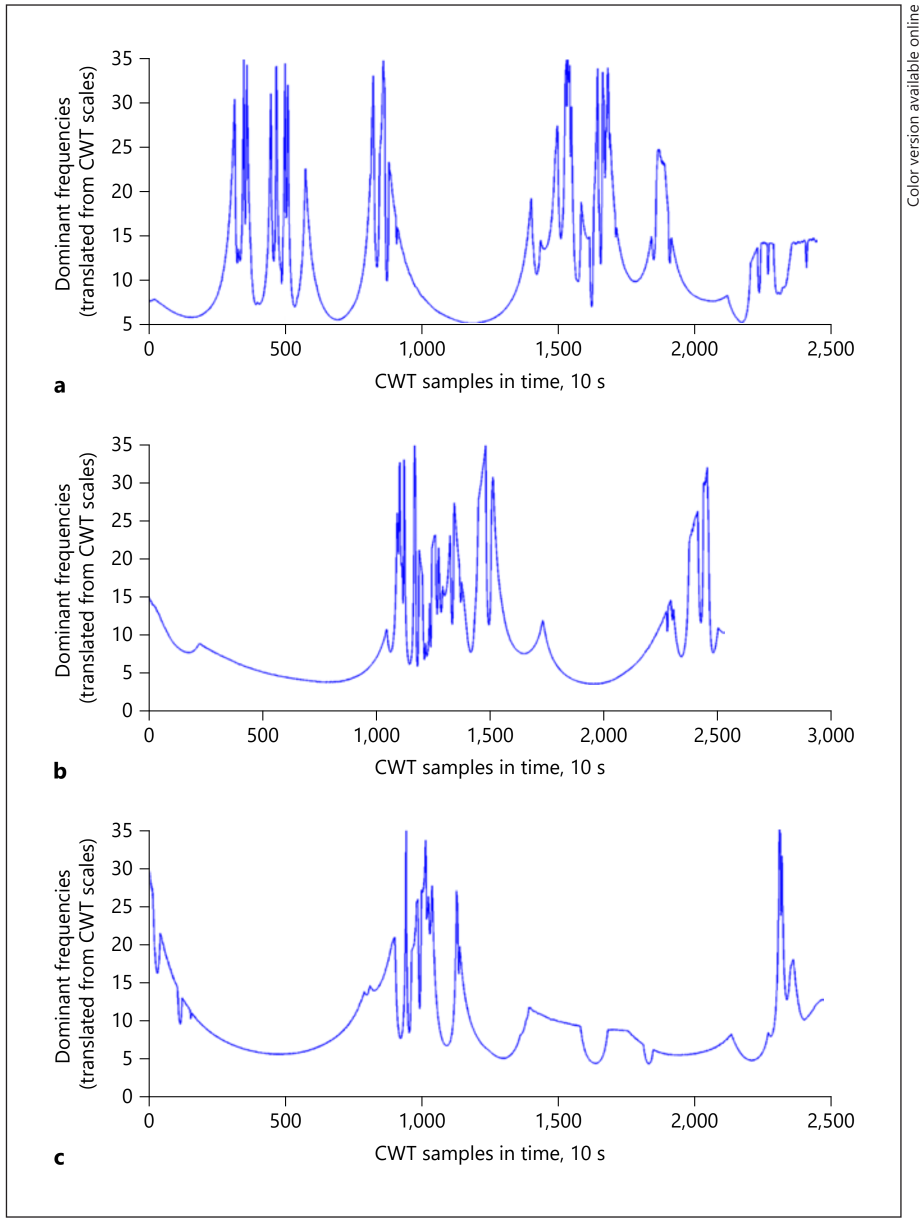


Fig. 16. Dominant frequencies of Figure 14a (mean value: 11.62 Hz) (**a**), dominant frequencies of Figure 14b (mean value: 9.36 Hz) (**b**), and dominant frequencies of Figure 14c (mean value: 9.58 Hz) (**c**). CWT, continuous wavelet transform.

ence threshold for precise sound differentiation. When the human visual system can response to only limited wavelengths of electromagnetic waves [8], the auditory system can accurately differentiate a wide range of sound frequencies and amplitudes. Human auditory system has a great 2 frequency/intensity discrimination [9]. This ability makes the auditory system a good tool for medical diagnosis historically. Auscultation as an act of listening to body sounds for diagnostic purposes has been used from ancient Egypt.

In the present study, sleep-EEG signals were converted into a Kurdish tanbur Makam and classical guitar musical pieces for sleep-stage classification by neurologists. Due to the changes in the sleep ultradian rhythm, the musical tempo was also altered, and the RNN generated polyphonic pleasant tonalities without overlooking musical dynamics and feelings. In the present study, the binary feature of the musical pitches was used to find a mapping between the musical notes and brainwaves. The brainwaves were mapped into musical pitches with proper note durations by CWT and DWT. The 30-s EEG epochs

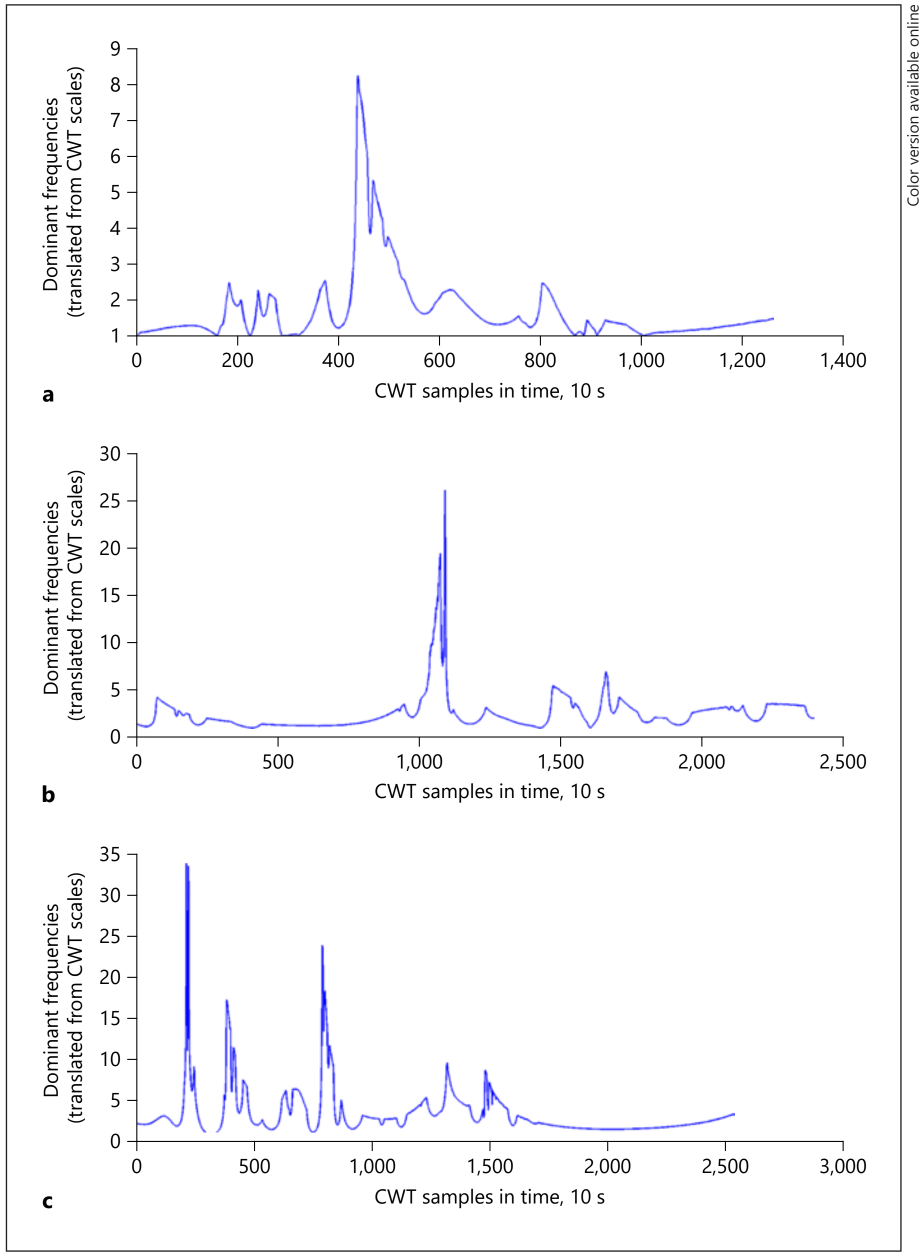
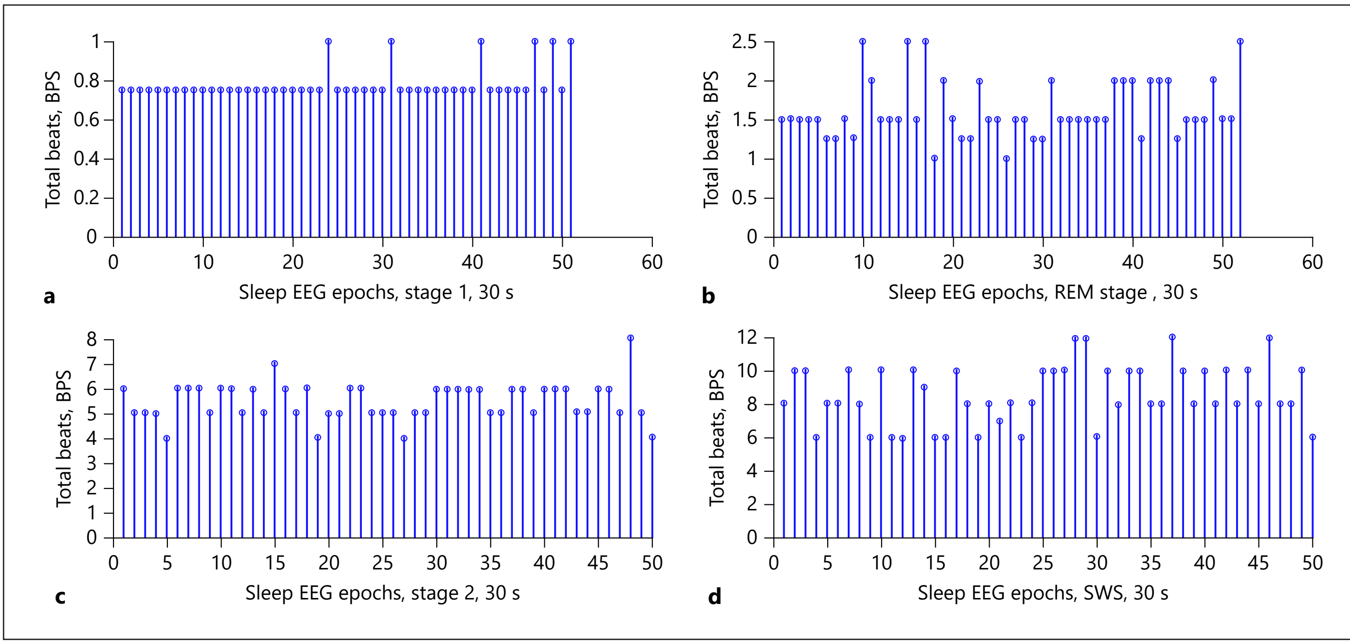


Fig. 17. Dominant frequencies of Figure 15a (mean value: 1.69 Hz) (**a**), dominant frequencies of Figure 15b (mean value: 2.53 Hz) (**b**), and dominant frequencies of Figure 15c (mean value: 3.54 Hz) (**c**). CWT, continuous wavelet transform.

were divided into 3 10-s sub-epochs. Then, the frequency bands of each sub-epoch were decomposed by DWT, and the dominant frequency was extracted in each 10-s sub-epoch by CWT. In addition, 3 musical pitches with specific time duration were extracted for each sub-epoch. Each dominant frequency was mapped to the corresponding musical notes by the parameter mapping algorithm. The time duration of the notes was selected based on the dominant frequency level which was decomposed by DWT. Note duration represented the musical beat, and the summation of these beats made the musical beat-based feature. The musical beat-based feature was derived in order to categorize the activity of the EEG signals, and 29 different scores were calculated. The musical beat-based features and musical notes of each epoch were fed to pretrained RNN for the generation of music. The higher the frequency of EEG activity, the higher the musical tempo. Generated musical pieces were presented to 2 neurologists for sleep-stage classification; then, validity and inter-rater reliability were measured. According to



Color version available online

Fig. 18. Musical beat-based feature of sleep stage 1 (**a**), musical beat-based feature of REM sleep stage (**b**), musical beat-based feature of sleep stage 2 (**c**), and musical beat-based feature of SWS sleep stage (**d**). EEG, electroencephalogram; REM, rapid eye movement; SWS, slow wave sleep.

the result, the neurologists classified sleep stages based on the generated musical pieces with good accuracy (above 81% for tanbur and 93% for guitar pieces). In addition, the method had a significant inter-rater reliability for both tanbur ($\kappa = 0.64$, $p < 0.001$) and guitar musical pieces ($\kappa = 0.85$, $p < 0.001$). Results for guitar musical pieces had higher validity and reliability than tanbur musical tones. This condition may result from the higher rhythmicity of tanbur Majazi Makam than guitar musical pieces. Differentiating close tempo in higher rhythmical conditions is more difficult and prone to error. Our neurologist's co-authors mistook REM and N2 or N1. REM contains more alpha waves (8–12 Hz) which are located between N1 (4–7 Hz) and N2 (11–15 Hz) frequencies and more closed to N2. Therefore, it may be displaced with N2 more than N1.

Various methods have been used for automatic sleep-stage classification based on sleep-EEG signals (Acharya et al. [10]). Ebrahimi et al. [20] had provided 93% accuracy in the classification of N2 and N3, but their method failed to differentiate N1 and REM stages using wavelet transform on bipolar (Pz-Oz) channel sleep-EEG signals [20]. Another study had 94.80% accuracy for differentiating N1, N2, N3, and REM stages based on single-channel sleep-EEG analysis using tunable Q-factor wavelet transform [21]. Based on the TFI of EEG, Bajaj and Pachori [11] reached 92.93% accuracy in sleep-stage classification from EEG signals [11]. In another study, automatic sleep staging was performed with 90% accuracy using recurrence analysis on a single-channel sleep EEG, and the method could classify subjects with and without mental distress using biomarkers based on stage designation [22]. Results of the present study in the guitar section are as accurate as or better than the previous automatic sleep-classification methods.

Sonification of sleep EEG or other PSG signals is a new field. Early studies proposed the transformation of the signals to audio files as a complementary method to support visual interpretation of EEG [30], but in the present study, the sleep stages were classified accurately based on sonified EEG signals. Fernandes et al. [29] encoded EEG frequencies to musical tempo for sleep-EEG sonification, but they did not report any accuracy and reliability for clinical application of the method. They used a monody strategy for EEG sonification [29], but in the present study, a polyphonic strategy was used that led to the generation of pleasant musical pieces. Methods such as Fourier-based spectral analysis extract frequency compositions in EEG signals, but they were unable to capture the underlying nonlinear dynamics of the EEG [19]. Decomposition of this nonlinearity by methods like wavelet transform could extract more informative data about brain oscillation. Therefore, the present method extracted and converted more detailed informative data that led to more detailed tonalities.

Brain process which is recalled during auditive presentation of EEG signals essentially differs from brain mechanism which is recruited during visual interpretation of EEG. Human auditory system has been evolved for precise fine differentiation of sound frequencies and can amazingly differentiate sounds that are very similar. When this ability is compared to the visual system, the auditory system is more proficient than the visual system to detect small differences of stimulus. EEG contains huge fine-tuned neuroelectrical data, and instead of visualization, the sonification of the output may open the new windows for future clinical use of EEG. Neuroelectrical data which exist in EEG contain detailed information such as frequency, duration, amplitude, and inter-electrode changes in signal features. These characteristics are very dynamic and change dramatically by time. So, sonification of this signal instead of visualization may help us convert more detailed EEG information to auditory stimuli.

An important challenge in EEG sonification is to generate the most informative and feelingful musical structure. The present method results in the production of pleasant feelingful music. The clinicians described the REM music as full-of-dream tones and SWS as calming sounds. In addition to sleep-stage classification, EEGs as real-time brain-mapping method with most temporal resolution have been used as a feedback tool for replanning and reprogramming of neurophysiological functions. This strong feedback tool can be used for management of many mental conditions such as attention deficits and anxiety [26–28]. The present study converted EEG to polyphonic feelingful musical pieces and may open a new window for neurofeedback fields.

Although the present method generated musical tonalities with good validity and reliability for sleep staging, some limitations should be mentioned. Association between EEG and musical dynamicity was created using tempo and frequency changes in EEG signals, and the method did not focus on other EEG characteristics such as amplitude. Because REM contains frequency waves which was located between N1 (4–7 Hz) and N2 (11–15 Hz), the results for REM and N2 or N1 were similar and led to errors in stage classification. Using other EEG parameters may improve the reliability and validity of the method and lead to better differentiation of REM with N1

Table 4. Detailed sleep-stage identifications for neurologists in both musical instruments; light gray colors classified correctly, but dark gray colors classified wrongly

Participants	Sleep stages	Tanbur		Guitar	
		rater 1	rater 2	rater 1	rater 2
1	N1	N1	REM	N1	REM
	N2	N2	N2	N2	N1
	SWS	SWS	SWS	SWS	SWS
	REM	REM	N1	REM	N2
2	N1	N1	N1	N1	N1
	N2	REM	N2	N2	N2
	SWS	SWS	SWS	SWS	SWS
	REM	N2	REM	REM	REM
3	N1	N1	N1	N1	N1
	N2	REM	N2	N2	N2
	SWS	SWS	SWS	SWS	SWS
	REM	N2	REM	REM	REM
4	N1	REM	N2	N1	N1
	N2	N2	REM	N2	N2
	SWS	SWS	SWS	SWS	SWS
	REM	N1	N1	REM	REM
5	N1	N1	N1	N1	N1
	N2	N2	N2	N2	N2
	SWS	SWS	SWS	SWS	SWS
	REM	REM	REM	REM	REM
6	N1	N1	N1	N1	N1
	N2	N2	N2	N2	N2
	SWS	SWS	SWS	SWS	SWS
	REM	REM	REM	REM	REM
7	N1	N1	N1	REM	N1
	N2	N2	N2	N2	N2
	SWS	SWS	SWS	SWS	SWS
	REM	REM	REM	N1	REM
8	N1	N1	N1	N1	N1
	N2	N2	REM	N2	N2
	SWS	SWS	SWS	SWS	SWS
	REM	REM	N2	REM	REM
9	N1	REM	N1	N1	N1
	N2	N2	N2	N2	N2
	SWS	SWS	SWS	SWS	SWS
	REM	N1	REM	REM	REM
10	N1	N1	N1	N1	N1
	N2	N2	N2	N2	N2
	SWS	SWS	SWS	SWS	SWS
	REM	REM	REM	REM	REM
11	N1	N1	N1	N1	N1
	N2	N2	N2	N2	N2
	SWS	SWS	SWS	SWS	SWS
	REM	REM	REM	REM	REM

N1, nonrapid eye movement stage 1; N2, nonrapid eye movement stage 2; SWS, slow wave sleep; REM, rapid eye movement.

and N2. In addition, because RNN would not be able to learn microtones, the present method is unable to transform EEG to nonrational musical instruments.

Conclusion

In the present study, a new method was proposed for sleep-EEG sonification which leads to valid sleep staging by clinicians. Future studies may focus on the reliability of the method to differentiate normal sleepers from those with sleep disorders. The proposed sonification method could be used on various EEG databases for classification, differentiation, diagnosis, and treatment purposes. The method may be developed further to design a neurofeedback task in the future. Musical tempo, modality, and tonality affect the arousal and neuropsychological states of the brain, and cultural constraints may also influence musical perception and cognition. These considerations may result in an effective neurofeedback task through music. In addition, brain-based music therapy by real-time EEG sonification can be used as a feedback tool for replanning and reprogramming of neurophysiological functions. This powerful feedback tool can be used for the management of many neurological and psychiatric disorders.

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Statement of Ethics

This study was conducted in accordance with the World Medical Association Declaration of Helsinki, and it was approved by the ethics board of Kermanshah University of Medical Sciences (IR.KUMS.REC.1397.957). Subjects signed written-informed consent forms.

Conflict of Interest Statement

The authors have no conflicts of interest to declare.

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Author Contributions

Foad Moradi did the EEG analysis, designing algorithms, and transformation process. Hiwa Mohammadi introduced the main idea and contributed to the conception of the study, study design, validation process, data analysis, and preparing the first draft of the manuscript. Mohammad Rezaei did the EEG analysis and study design. Payam Sariaslani and Nazanin Razazian contributed to the conception of the study and validation process. Habibolah Khazaei contributed to the validation of visual sleep staging and study design. Hojjat Adeli contributed to designing algorithms and transformation process. In addition, he critically revised the manuscript. All authors reviewed and approved the final draft of the manuscript.

References

1 Schmidt C, Piper D, Pester B, Mierau A, Witte H. Tracking the reorganization of module structure in time-varying weighted brain functional connectivity networks. Int J Neural Syst. 2018;28(4):1750051.
2 Hua C, Wang H, Wang H, Lu S, Liu C, Khalid SM. A novel method of building functional brain network using deep learning algorithm with application in proficiency detection. Int J Neural Syst. 2019;29(1):1850015.
3 Ortiz A, Munilla J, Martínez-Murcia FJ, Górriz JM, Ramírez J. Empirical functional PCA for 3D image feature extraction through fractal sampling. Int J Neural Syst. 2019;29(2):1850040.
4 Cheng L, Zhu Y, Sun J, Deng L, He N, Yang Y, et al. Principal states of dynamic functional connectivity reveal the link between resting-state and task-state brain: an fMRI study. Int J Neural Syst. 2018;28(7):1850002.
5 Martínez-Rodrigo A, García-Martínez B, Alcaraz R, González P, Fernández-Caballero A. Multiscale entropy analysis for recognition of visually elicited negative stress from EEG recordings. Int J Neur Syst. 2019;29(2):1850038.
6 Dovgialo M, Chabuda A, Duszyk A, Zielewiewska M, Pietrzak M, Różański P, et al. Assessment of statistically significant command-following in pediatric patients with idsorders of consciousness, based on visual, auditory and tactile event-related potentials. Int J Neural Syst. 2019;29(3):1850048.
7 Kaminski M, Brzezicka A, Kaminski J, Blinowska KJ. Coupling between brain structures during visual and auditory working memory tasks. Int J Neural Syst. 2019;29(3):1850046.
8 Zhaoping L, Geisler WS, May KA. Human wavelength discrimination of monochromatic light explained by optimal wavelength decoding of light of unknown intensity. PLoS One. 2011;6(5):e19248–48.
9 Moore JK. Maturation of human auditory cortex: implications for speech perception. Ann Otol Rhinol Laryngol Suppl. 2002 May;189(5 Suppl):7–10.
10 Acharya UR, Bhat S, Faust O, Adeli H, Chua EC, Lim WJ, et al. Nonlinear dynamics measures for automated EEG-based sleep stage detection. Eur Neurol. 2015;74(5–6):268–87.

11 Bajaj V, Pachori RB. Automatic classification of sleep stages based on the time-frequency image of EEG signals. Comput Methods Programs Biomed. 2013;112(3):320–8.
12 Li D, Xu L, Goodman ED, Xu Y, Wu Y. Integrating a statistical background-foreground extraction algorithm and SVM classifier for pedestrian detection and tracking. Integr Comput Aided Eng. 2013 May 30;20(3):201–16.
13 Smolik M, Skala V. Large scattered data interpolation with radial basis functions and space subdivision. Integr Comput Aided Eng. 2018;25(1):49–62.
14 Zhou L, Yan G, Ou J. Response surface method based on radial basis functions for modeling large-scale structures in model updating. Computer-Aided Civ Infrastruct Eng. 2012 Dec 19;28(3):210–26.
15 Alexandridis A. Evolving RBF neural networks for adaptive soft-sensor design. Int J Neural Syst. 2013 Dec;23(6):1350029.
16 Adeli H, Zhou Z, Dadmehr N. Analysis of EEG records in an epileptic patient using wavelet transform. J Neurosci Methods. 2003/02;123(1):69–87.
17 Faust O, Acharya UR, Adeli H, Adeli A. Wavelet-based EEG processing for computer-aided seizure detection and epilepsy diagnosis. Seizure. 2015 Mar;26:56–64.
18 Plakias S, Boutalis YS. Lyapunov theory-based fusion neural networks for the identification of dynamic nonlinear systems. Int J Neural Syst. 2019;29(9):1950015.
19 Ma Y, Shi W, Peng CK, Yang AC. Nonlinear dynamical analysis of sleep electroencephalography using fractal and entropy approaches. Sleep Med Rev. 2018 Feb;37:85–93.
20 Ebrahimi F, Mikaeili M, Estrada E, Nazeran H. Automatic sleep stage classification based on EEG signals by using neural networks and wavelet packet coefficients. 2008 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE; 2008.
21 Hassan AR, Bhuiyan MI. A decision support system for automatic sleep staging from EEG signals using tunable Q-factor wavelet transform and spectral features. J Neurosci Methods. 2016 Sep 15;271:107–18.
22 Frilot C, McCarty DE, Marino AA. An original method for staging sleep based on dynamical analysis of a single EEG signal. J Neurosci Methods. 2018/10;308:135–41.
23 Zieleniewska M, Duszyk A, Różański P, Pietrzak M, Bogotko M, Durka P. Parametric description of EEG profiles for assessment of sleep architecture in disorders of consciousness. Int J Neural Syst. 2019;29(3):1850049.
24 Ahmadlou M, Adeli H, Adeli A. Graph theoretical analysis of organization of functional brain networks in ADHD. Clin EEG Neurosci. 2012;43(1):5–13.
25 Sridhar C, Bhat S, Acharya UR, Adeli H, Bairy GM. Diagnosis of attention deficit hyperactivity disorder using imaging and signal processing techniques. Comput Biol Med. 2017;88:93–9.
26 Hammond DC. Neurofeedback with anxiety and affective disorders. Child Adolesc Psychiatr Clin N Am. 2005 Jan;14(1):105–23.
27 Mennella R, Patron E, Palomba D. Frontal alpha asymmetry neurofeedback for the reduction of negative affect and anxiety. Behav Res Ther. 2017;92:32–40.
28 Enriquez-Geppert S, Smit D, Pimenta MG, Arns M. Neurofeedback as a treatment intervention in ADHD: current evidence and practice. Curr Psychiatry Rep. 2019;21(6):46.
29 Fernandes CM, Migotina D, Rosa AC. Brain's Night Symphony (BraiNSy): a methodology for EEG sonification. IEEE Trans Affect Comput. 2018.
30 Olivan J, Kemp B, Roessen M. Easy listening to sleep recordings: tools and examples. Sleep Med. 2004;5(6):601–3.
31 Glen J. Use of audio signals derived from electroencephalographic recordings as a novel 'depth of anaesthesia' monitor. Med Hypotheses. 2010;75(6):547–9.
32 Khamis H, Mohamed A, Simpson S, McEwan A. Detection of temporal lobe seizures and identification of lateralisation from audified EEG. Clin Neurophysiol. 2012;123(9):1714–20.
33 Frassineti L, Barba C, Melani F, Piras F, Guerrini R, Manfredi C. Automatic detection and sonification of nonmotor generalized onset epileptic seizures: preliminary results. Brain Res. 2019;1721:146341.
34 Arslan B, Brouse A, Castet J, Filatriau JJ, Lehembre R, Noirhomme Q, et al. Biologically-driven musical instrument. eINTERFACE'05-Summer Workshop on Multimodal Interfaces. 2005.
35 Miranda ER. Brain-computer music interface for generative music. ICDVRAT 2006. 2006.
36 Adrian ED, Matthews BHC. The Berger rhythm: potential changes from the occipital lobes in man. Brain. 1934;57(4):355–85.
37 Weber M. Rational and social foundations of music. The Routledge Reader on the Sociology of Music. Routledge; 2015. p. 59–64.
38 Aliakbar M, Heydar K. Row Tanbour Music, Majlesi and Majazi Maqams. 2018.
39 Rezaei M, Mohammadi H, Khazaie H. EEG/EOG/EMG data from a cross sectional study on psychophysiological insomnia and normal sleep subjects. Data Brief. 2017 Sep 21;15:314–9.
40 Su BL, Luo Y, Hong CY, Nagurka ML, Yen CW. Detecting slow wave sleep using a single EEG signal channel. J Neurosci Methods. 2015 Mar 30;243:47–52.
41 Delorme A, Makeig S. EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. J Neurosci Methods. 2004;134(1):9–21.
42 Pérez G, Conci A, Moreno AB, Hernandez-Tamames JA. Rician noise attenuation in the wavelet packet transformed domain for brain MRI. Integr Comput-Aided Eng. 2014 Mar 1;21(2):163–75.
43 Su WC, Huang CS, Chen CH, Liu CY, Huang HC, Le QT. Identifying the modal parameters of a structure from ambient vibration data via the stationary wavelet packet. Computer-Aided Civ Infrastruct Eng. 2014 Oct 16;29(10):738–57.
44 McDermott J, Hauser M. The origins of music: innateness, uniqueness, and evolution. Music Percept. 2005;23(1):29–59.
45 Singh BN, Tiwari AK. Optimal selection of wavelet basis function applied to ECG signal denoising. Digit Signal Process. 2006;16(3):275–87.
46 Benesty J, Chen J, Huang Y, Cohen I. Pearson correlation coefficient. Noise reduction in speech processing. Springer; 2009. p. 1–4.
47 Al-Qazzaz NK, Bin Mohd Ali SH, Ahmad SA, Islam MS, Escudero J. Selection of mother wavelet functions for multi-channel EEG signal analysis during a working memory task. Sensors. 2015;15(11):29015–35.
48 Daubechies I. The wavelet transform, time-frequency localization and signal analysis. IEEE Trans Inform Theory. 1990;36(5):961–1005.
49 Grond F, Berger J. Parameter mapping sonification. The sonification handbook. 2011.
50 García JC, Serrano E. Automatic music generation by deep learning. International symposium on distributed computing and artificial intelligence. Springer; 2018. p. 284–91.
51 Bowman SR, Vilnis L, Vinyals O, Dai AM, Jozefowicz R, Bengio S. Generating sentences from a continuous space. 2015.
52 Liang F. Bachbot: automatic composition in the style of bach chorales. University of Cambridge; 2016. Vol. 8; p. 19–48.
53 Liang F. Bachbot: automatic composition in the style of bach chorales. Masters thesis, University of Cambridge; 2016.
54 Hadjeres G.
55 Simon I, Oore S. Performance RNN: generating music with expressive timing and dynamics. 2017.
56 Oore S, Simon I, Dieleman S, Eck D, Simonyan K. This time with feeling: learning expressive musical performance. Neural Comput Appl. 2018:1–13.
57 Williams RJ, Zipser D. A learning algorithm for continually running fully recurrent neural networks. Neural Comput. 1989;1(2):270–80.
58 Hochreiter S, Schmidhuber J. Long short-term memory. Neural Comput. 1997;9(8):1735–80.
59 Berry RB, Brooks R, Gamaldo CE, Harding SM, Marcus C, Vaughn BV. The AASM manual for the scoring of sleep and associated events. Rules, terminology and technical specifications, Darien, Illinois. Am Acad Sleep Med. 2012;176:2012.