Semantic-based Bayesian Network to Determine Correlation Between Binaural-beats Features and Entrainment Effects

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***Abstract*— In coping with hectic everyday lives, people have tried many different ways to reduce stress and depression. Such effort has also lead to meditation practice, which is believed and proven able to help. While meditation is beneficial, for some people, meditation is just hard to perform. These people may switch to other alternatives that give the same effects as meditation, such as through binaural beats entrainment. Many studies on brainwave entrainment have demonstrated that the brain responds by synchronizing its own electrical cycles to the same rhythm of the stimulating binaural-beats audio. The results of binaural beats entrainment towards the brainwave can be determined by monitoring the EEG readings, which can be analyzed to capture the altered brainwave patterns and qualities they exhibit. In relation to the monitoring process, our work focuses on capturing and analyzing the correlations between different binaural beats features to resulting EEG and perceived mental states. A general methodology is presented while detailing further on the proposed Semantic-based Bayesian Network Engine, which is the core mechanism employed in capturing the correlations. This novel approach is proposed firstly due to the well-known capability of Bayesian Network in modeling the elements of causal and effects. Secondly, with the introduction of semantic notion, the engine is enhanced even more for allowing dynamic-construction of Bayesian Network based on its semantics.**

***Keywords* — binaural beats, auditory, brainwave, entrainment, semantic, Bayesian Network**

I. INTRODUCTION

The purpose of finding the "mind serenity" for reducing stress and depression has lead to meditation practices by many. By performing meditation, the mind is found to be at its relaxing state. With respect to such practices, early scientific studies were performed to observe the effects of meditation and found that the calming effects are due to the hemispheric synchronization it produced [1]. For some people, meditation is hard to perform as it requires a good technique and frequent practices in reducing thoughts. Such people may switch to another easier and effortless alternative that gives the same effects as meditation, i.e. through binaural beats entrainment.

Binaural beats were first discovered in 1839 by Heinrich Wilhelm Dove, a professor of physics [2]. Binaural beats are perceived by presenting two coherent sounds of nearly similar frequencies, one to each ear, and the brain detects phase differences between these sounds [3]. This phenomenon is illustrated in Figure 1 [4], where a 24 Hz monaural beat is produced by mixing two separate tones with a 24 Hz difference between them.

The binaural-beat element of the process appears to be associated with an electroencephalographic (EEG) frequency-following response (FFR) in the brain [3]. Many studies have demonstrated the presence of a frequency-following response to auditory stimuli, in which the brain responds by synchronizing its own electrical cycles to the same rhythm.

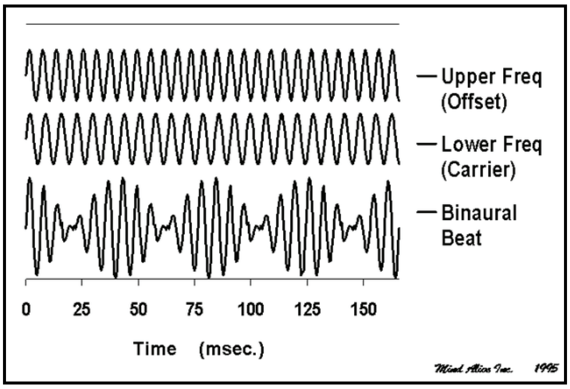

Figure 1. Vector summation of tones at two different frequencies produces binaural beats [4].

Brainwave patterns can be measured by placing sensors on the scalp for recording the Electroencephalography (EEG) readings. The sensors are in the form of electrodes that record electrical activity along the scalp [5]. Different brainwave patterns are associated with different mental states or consciousness. In this regards, brainwaves are normally categorized by five main power spectrums, namely delta, theta, alpha, beta and high beta. Table I summarizes the association between these different brainwave frequency-groups to the associated mental states.

Balanced brainwaves are found to be harmonically organized with alpha-wave being twice theta-wave and beta-wave being twice alpha-wave [6]. Such harmonic EEG-patterns are always found on healthy individuals, while abnormal EEG patterns either cause disease or reflect a disease state. In regards to this finding, having a means to alter the brainwave states of an individual allows new ways to be explored in order to create positive impacts to health condition due to changes in the brainwave patterns. This potential quality correlates with one major area for the use of binaural beat, i.e. alterations of brainwave states to create a positive effect in the physiological and psychological state of human subjects, by restoring 'normal' healthy brain wave patterns [7].

TABLE I.
BRAINWAVE FREQUENCIES ASSOCIATED WITH DIFFERENT MENTAL STATES [8]

Brainwave Frequency Range	Associated Mental States
Delta frequencies (1-4 Hz)	deep sleep
Theta frequencies (4-8 Hz)	light sleep creativity insight
Alpha frequencies (8-12 Hz)	a calm and peaceful yet alert state
Beta frequencies (13-21 Hz)	Thinking focusing state
High beta frequencies (20-32 Hz)	intensity or anxiety

This would be the general scope of our work, i.e. to employ binaural-beat entrainment for imposing positive impacts to the entrained individual's mental and health. In general, effective binaural beats should at least be able to entrain both hemispheres to the same frequency, which maximizes inter-hemispheric neural communication [9]. The results of a binaural beats entrainment towards an individual's brainwave can be determined by monitoring their EEG readings. Such readings should be analyzed to capture the altered brainwave patterns and qualities they exhibit; i.e. whether the desired beneficial states are achieved. In relation to the overall process, our work focuses on one particular aspect; i.e. capturing and analyzing the correlations between different binaural beats to resulting EEG and perceived mental states, which will be presented next.

II. THE METHODOLOGY

In defining the correlations between stimulating binaural-beats and the effects on an individual's EEG, we propose a general methodology as follow (see Figure 2). First of all, preliminary data, which include user profile and binaural-beat audio features, are captured. Profile information of a particular individual could be captured by e.g. asking the individual some questions or requesting them to fill in a form (step 1). This may include some queries to recognize the current mental state of the individual. Once this is done, features of the binaural-beat audio that has been selected for entrainment are recorded (step 2). The recorded features may include the audio carrier frequency to be played to one ear, the offset frequency to be played to another ear and the expected frequency of resulting vector summation of the two tones (waveform sum). Once this is done, the binaural-beat audio is then ready to be played with the motive of entraining the brainwave of the specific individual. Prior to the entrainment session (step 3), EEG electrodes are placed onto the individual's scalp.

Recording of EEG is then started upon initiation of the entrainment session, which could take about 20-60 minutes (step 4). This is assumed to be a sufficient amount of time to induce some alterations to the individual's brainwave and mental states. By the end of an entrainment session, the EEG recording is also concluded. After Step 4, a post-entrainment questionnaire may need to be filled in by the individual for capturing the perceived effects and altered mental states. The recorded user profile and binaural-beats features (captured in step 1 and step 2) together with the acquired EEG readings and post-entrainment feedback from the individual are then fed onto an analyzer component as the inputs. On reception of the inputs, the analyzer component starts to perform the processing and on completion, correlations between the binaural-beats features and the entrainment results; i.e. resulting EEG and perceived mental-states are recorded and produced as a result (step 5).

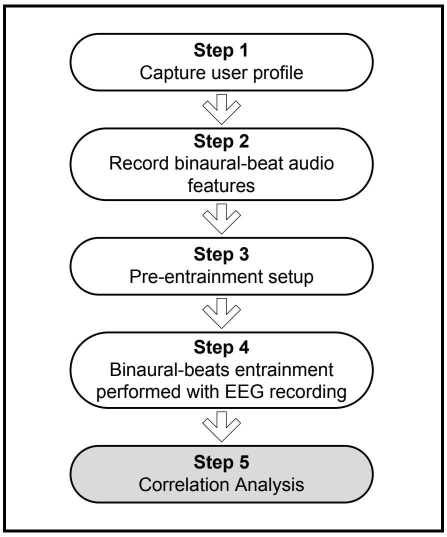

Figure 2. The general methodology applied in capturing correlations between binaural-beat audio features and outcomes of the brainwave entrainment

In describing the methodology illustrated in Fig. 2, the main focus of this paper is to highlight the procedures adopted in the Correlations Analysis (step 5), while detailing further the proposed Semantic-based Bayesian Network Engine that is the core mechanism, used to model the correlations between different binaural beat features and resulting EEG patterns and perceived mental states. Binaural-beats EEG Analyzer (BBEA) is the name given to the component employed in performing the said correlation analysis, which will be described next.

III. BINAURAL-BEATS EEG ANALYZER

In the first instance, upon acquiring the expected inputs, BBEA will perform signal processing and analysis on the acquired raw EEG data (captured in step 4) before they can be manipulated in the correlation analysis process. EEG data are normally recorded from multiple channels based on the readings captured by a number electrodes placed on the scalp. The more EEG channels being recorded means the more input data could be learnt and this may contribute to a more accurate correlation analysis. The overall process flow and architecture of BBEA is illustrated in Fig. 3.

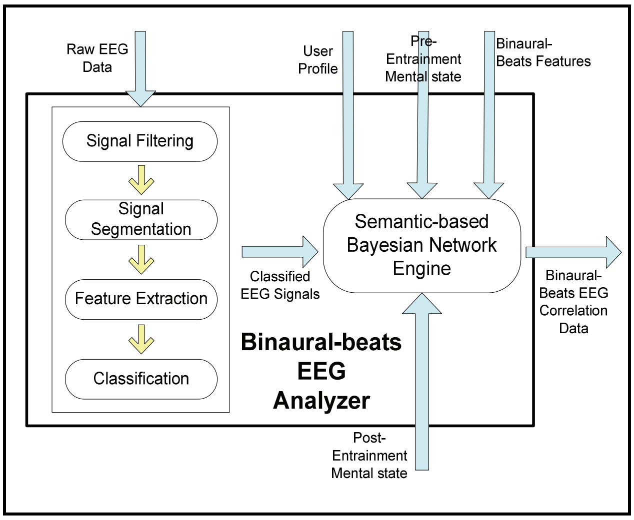

Figure 3. General architecture of Binaural-beats EEG Analyzer (BBEA)

As mentioned in Section I, EEG signal recorded on a single channel can be classified into 5 different main frequency bands based on its rhythmical activity. In our methodology, a single channel EEG data captured on the different frequency bands are first pre-processed using digital filters to remove noise, after which the filtered signals have to go through the segmentation process. This is then followed by the signal feature extraction process and subsequently the signal classification process (see Fig. 3). Numerical methods for instance discrete Fourier transform (DFT) or discrete wavelet transform (DWT) can be used in signal feature extraction process to represent the signal either in frequency domain or wavelet form. Further signal analysis can be performed by using various statistical methods or machine learning approach for e.g. self-organizing neural-network, which can be applied to classify signal segments into a given number of classes using segments features [10].

The specific techniques that will be used in the initial process of filtering up to classifying EEG signals are still not defined since further investigations are needed in this area. Such discussion is also beyond the scope of this paper since in this phase, we are focusing more on step 5 i.e. the correlation analysis between pre and post entrainment data. No matter what techniques to adopt, the expected outcomes from this initial process will be in the form of classified EEG signals, each class having its own distinct set of features and properties. In the context of our proposed architecture, such classified EEG signals are then fed onto the semantic-based Bayesian network that will be described next.

IV. SEMANTIC-BASED BAYESIAN NETWORK ENGINE

The Semantic-based Bayesian Network Engine is employed as one of the components of BBEA. Its main role is to dynamically construct the Bayesian Network that will generate the correlation analysis. A Bayesian Network (BN) is known as a graphical model that encodes probabilistic relationships among variables of interest [11]. To allow dynamic-construction of a BN, we enhance the approach further by extending the semantic factor, where the structure of the network itself and each of its node are labeled with their semantic or specific meaning.

A. *The Bayesian Network*

The main reason why we adopt BN is due to its capability of modeling the elements of causal and effects. The whole BN can actually be perceived as a general model that memorizes all identified related historical evidences and once matured, able to predict the future patterns. In a similar manner, each node of a BN focuses on learning the behavior of a particular observed element with respect to its causes and effects. There are other related works that adopt BN in analyzing EEG signals. Among others are [12,13,14] that adopt BN to particularly classify EEG signals. Our approach here is a little different where we employ BN in determining the correlations between pre and post entrainment data. Since this is just an initial phase of our work, the performance of this approach is not yet known and experiments will be conducted in order to compare this technique with other statistical or machine language techniques.

In the scope of our work, BN is used to model data that are collected from previously performed binaural-beats entrainment sessions on many individuals. Based on such data, BN can be used to predict the best suitable binaural-beat features to alter the mental states of a user given a set of input values such as user profile data, pre-entrainment mental states and expected value, i.e. post-entrainment mental states. Just like any other machine learning techniques, a BN has to be trained in order to reach its equilibrium state, at which stage all inferences performed are able to produce consistent and stable results.

A sample of the BN design is illustrated in Figure 4. As we can see from the figure, nodes with arrows pointing out to the other nodes are defined as the direct causes of the pointed nodes. For brevity, this network is purposely designed to be straightforward and simplified. The user-profile data, (e.g. gender and age-group), pre-entrainment mental-state and binaural-beat features (e.g. waveform sum) nodes are defined as the causal nodes, which directly give impacts to the nodes representing the classified EEG signals (recorded from a particular channel within a particular frequency band). Being an intermediary node, the latter is also the direct cause of a node representing the post-entrainment perceived mental state.

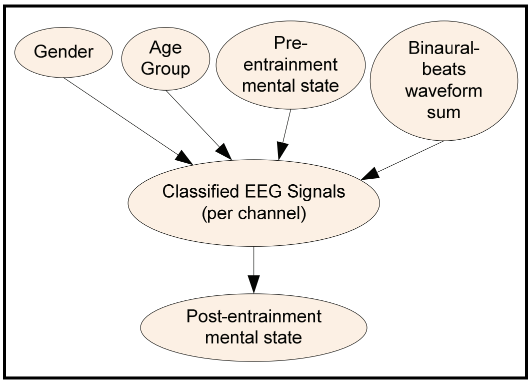

Figure 4. A sample of Bayesian network to model correlations between different binaural beats features and resulting EEG and mental state

In the proposed system, the structure of such BN is stored in a semantic-store, where the nodes are identified based on their types, i.e. causal or effect. On top of that, the causality relationships between the nodes are also semantically defined in the same store. Each BN node holds a conditional probability table (CPT), which comprises of multiple states representing values of the node. Some sample CPT states for the given BN are shown in Figure 5.

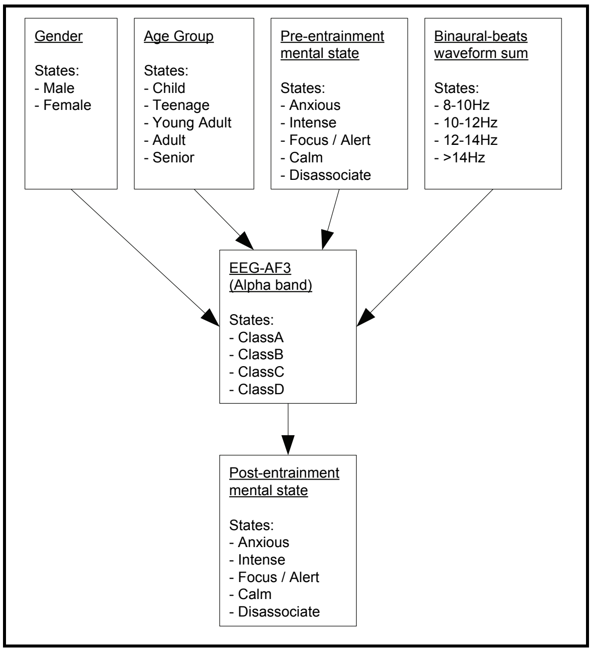

Figure 5. Sample CPT states of each BN node

B. Dynamic Construction of Bayesian Network

Based on the stored BN structure, a semantic-engine dynamically constructs the whole BN on the fly as needed. Firstly the nodes and their relationships are generated, after which CPT states of each node are populated from the semantic-store. This is followed by a process that pumps in the conditional or unconditional probability values for each state being defined in the CPTs from a standard relational database. The rationale of having the CPT states being populated from the semantic-store is mainly due to the advantages of having each state defined semantically in relation to the node that holds the CPT. For example the term "Anxious" can be recognized as a CPT state either for the "Pre-entrainment mental state" node or "Post-entrainment mental state" node. Another advantage offered by this approach is that it allows the semantic store to evolve to accommodate more CPT states (e.g. acquired from a newly imported ontology), allowing the CPT to expand and represent a more comprehensive set of applicable states.

Adopting semantic notion in defining BN nodes and their CPT states allows for dynamic alteration of BN structure. For instance, when an additional ontology is incorporated into the semantic store, new nodes or CPT states are made available and can easily be extended onto the existing BN. Such flexibility is lacking in conventional methods of BN construction, which relies more on static BN composition hardcoded by the programmer.

Architecture of the proposed Semantic-based Bayesian Network Engine is illustrated in Figure 6. The semantic engine reads the data required for dynamic construction of the Bayesian Network from two storages namely the semantic store and a relational database. Besides that, the semantic engine also receives 5 external inputs, namely i) the classified EEG signals, ii) user profile data, iii) pre-entrainment mental state, iv) binaural-beats features and v) post-entrainment mental state. These inputs can be used both to further enhance the probability value and to supply the evidence value to the BN node prior to an entrainment session. By supplying the evidence value, the outcome of the entrainment could be predicted.

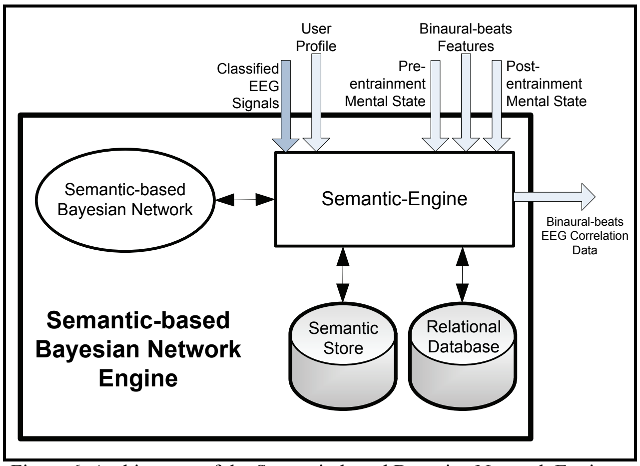

Figure 6. Architecture of the Semantic-based Bayesian Network Engine

As an example, before the entrainment session is initiated, the semantic-engine can be supplied with the pre-entrainment inputs, e.g. the user profile data defined as an adult woman with her pre-entrainment mental state perceived as "Intense". By setting the entrainment waveform sum tuned at 10-12Hz, outcome of the entrainment could be predicted e.g. mental state is believed, i.e. with some confidence level; will be altered to "Calm" state. Such prediction can be performed when the BN has been trained from previously recorded entrainment sessions. To enable faster analysis, such predictions are also captured as rules (with belief values) in the semantic-store. By having this knowledge handy, the semantic-engine will be able to act as an expert system that could predict an outcome of an entrainment session given a set of pre-entrainment inputs.

C. The Ontology

The main skeleton of a semantic store is an ontology, which is defined as a specification of a conceptualization [15], normally specific to a particular domain. Before data population could be performed onto a semantic-store, the main ontology for the store should be designed, just like designing entities and relationships for a relational database. In the context of our work, the ontology that holds up the semantic store is an ontology that defines the semantics of the proposed Bayesian Network (see Section IV-A). Figure 7 shows a graph demonstrating the semantic taxonomy of terms representing the nodes defined for the BN. The semantic is described in regards to the membership of each term using the rdf:subClassOf property. For example, AgeGroup and Gender classes are defined as members of UserProfile class. Thus AgeGroup and Gender can be constructed as nodes in the BN to represent UserProfile.

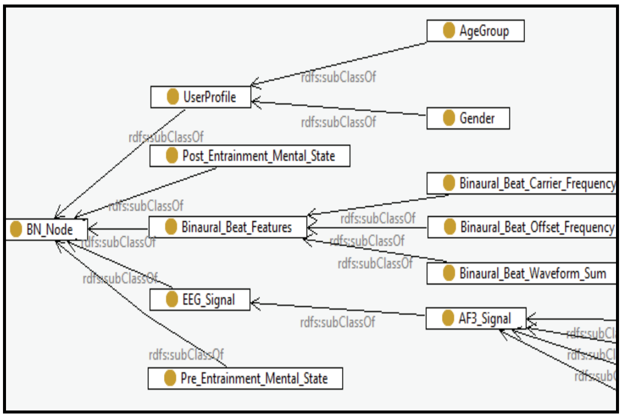

Figure 7. Semantic taxonomy of the employed BN Nodes

To define the CPT states of each node, each state is created as an ontology instance, which is defined as having the type of the node that holds the CPT. The rdf:type property is used to describe such relationship. For an example, the CPT states of the Pre-entrainment mental state node, e.g. "Anxious", "Intense", "Focus" and etc. are defined as the ontology instances of type Pre_Entrainment_Mental_State class (see Figure 8).

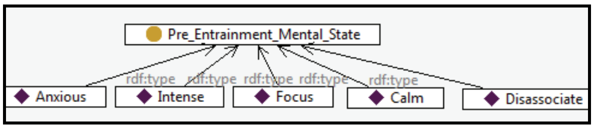

Figure 8. Defining CPT states in the ontology

The causality relationships are defined in the ontology in order to describe which nodes are affecting other nodes and which nodes get affected by other nodes. Such knowledge is encoded in the ontology by using the "affects" property. This is illustrated in Figure 9, where each of the top ontology classes, e.g. "AgeGroup", "Gender" and etc., affects the AF3_Alpha_Band node, which affects the Post_Entrainment_Mental_State node.

Based on the illustrations given, we can say that the main idea of having an ontology is to capture the main structure of the BN to be deployed. Due to space constraints, detailed design of the ontology is omitted from this paper. Note that a careful consideration should be imposed on the construction of ontology since it will be the driving factor ensuring the correctness of BN to be constructed. In this context, the ontology can be regarded as a dynamic entity that holds up the BN structure. Construction of BN becomes more dynamic since the structure is directly following the ontology. In this sense, testing out different BN structures based on different ontology versions can easily be performed. Such practice may be required to identify the significant sets of factors (i.e. nodes and CPT states) in determining the correlation between pre and post entrainment data.

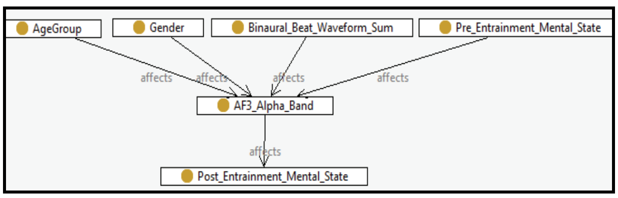

Figure 9. Defining CPT states in the ontology

V. Implementation

A high-level design of the system was proposed and presented in the previous sections. Our next step is to come out with the low-level design, followed by the implementation of the system. Java will be adopted as the main programming language, while Jena [16] and Weka [17] are the potential frameworks to be employed in the development. Jena is a Java-based semantic framework that provides API to construct ontology or to capture knowledge from the ontology. While Weka is a workbench, that contains machine learning algorithms for data analysis and predictive modeling. The latter will be used in building the virtual BN.

VI. Conclusion and Future Work

In this paper, we presented a general methodology adopted in capturing and analyzing data to identify the correlations between features of stimulating binaural-beats audio and the outcomes of the entrainment, specifically the resulting EEG patterns and perceived mental state subsequent to entrainment sessions. The paper focuses on describing a novel mechanism proposed to perform the correlation analysis, i.e. a semantic-based Bayesian Network engine, which learns from the experimental data captured from many binaural-beat entrainment sessions, in order to predict the trend of outcomes for future binaural-beats entrainment sessions. As mentioned earlier, our next step would be to proceed with the system development and this will be followed by experiments to assess the system capability and performance.

Acknowledgment

This research is funded by the Exploratory Research Grants Scheme Research, Ministry of Higher Education Malaysia.

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