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(54) **SYSTEM AND METHOD FOR ESTIMATING COGNITIVE TRAITS**

SYSTEM UND VERFAHREN ZUR BEURTEILUNG KOGNITIVER MERKMALE

SYSTÈME ET PROCÉDÉ D'ÉVALUATION DE CARACTÉRISTIQUES COGNITIVES

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Description**FIELD OF INVENTION**

[0001] The present invention relates to the field of perceptual cognitive traits, and more particularly to a system and method of estimating and improvising perceptual-cognitive traits of a subject.

BACKGROUND OF THE INVENTION

[0002] Cognitive load, in general, is defined by the amount of short term memory used by an individual for a given task and primarily depends on how an individual perceives, assimilates and responds to an external stimulus. Usually, the actions of an individual are mediated and influenced by external environment and ability of an individual to understand and effectively interact with the environment is dependent on the cognitive traits of an individual. Hence in order to achieve the best results and exhibit best performance, the cognitive load on the individual should be optimum since too much cognitive load might result in stress, anxiety, etc. On the other hand, very less cognitive load is actually a un-utilization of one's cognitive capacity and ability.

[0003] It will however be agreeable that optimum level of cognitive load may vary from one individual to another, and is basically dependent on inherent cognitive skills of an individual. Developing basic cognitive skills of an individual, however remains an ardent task, to which education has a supreme role to play. The process by which a person learns best is also different across different people.

[0004] Bloom's taxonomy of learning domains is known to promote higher forms of thinking in education such as analyzing and evaluating concepts, processes, procedures, and principles. It majorly defines six major categories of cognitive skills that are arranged according to the increasing order of cognitive maturity as knowledge, comprehension, application, analysis, synthesis and evaluation. There are usually two measures of cognitive load:

a) Subjective Measures of Cognitive Load- This domain has been well read by many to find that various instructional methods can be used to improve the short term memory operations

b) Objective Measures of Cognitive Load- This includes estimation using different physiological signals and in order to measure the cognitive skills of an individual, particularly in the field of education area is relatively a new area of search. To make it more accessible, the sensing mechanism needs to be low cost and commercially available.

[0005] Recently, there have been various works to analyze the cognitive load of an individual for a given task using commercial EEG devices. As part of the education psychology, the cognitive load is analyzed based on the continuous EEG signals during the learning from hypertext and multimedia contents. EEG signals are being used in diverse application areas like estimation of video quality, ease of reading texts, and scientific problem solving. Apart from EEG, other physiological parameters like eye tracking, skin conductance and heart-rate are also used to investigate the effect of stimulus on the mental stress. There has been an attempt in past to study the students' learning trajectories and teachers' effect on problem solving abilities, however there has been complete reliance on the students' outcomes and never used brain signals. Many have also used Elementary Cognitive Tasks (ECTs) to investigate how the level of complexity (low and high cognitive load) manifests in the EEG and various physiological parameters.

[0006] The Conference Proceedings article "Evaluation of Different Onscreen Keyboard Layouts Using EEG Signals" by Arijit Sinharay, Debatri Chatterjee, Aniruddha Sinha published in IEEE International Conference on Systems, Man, and Cybernetics, 13-16 Oct. 2013, p. 480-486, discloses a method and system for evaluating different onscreen keyboard layouts based on electroencephalogram signals. Document US2014242559 discloses a method and a system for determining a task for a subject based on EEG signals.

[0007] However, none of the above works objectively analyze the relationships between the various ECTs or focus on investigating the relationship between the ECTs and Bloom's categories.

OBJECTIVES OF THE INVENTION

[0008] In accordance with the present invention, the primary objective is to provide a system and method for analyzing elementary cognitive tasks with Bloom's Taxonomy using low cost commercial EEG device.

[0009] Another objective of the invention is to provide a system and method to objectively analyze the relationship among various ECTs and also between various elementary cognitive tasks (ECTs) and Bloom's categories.

[0010] Another objective of the invention is to provide a system and method to characterize an unknown stimulus and also derive various performance attributes of a subject.

[0011] Yet another objective of the invention is to provide a method and system for estimating or improvising perceptual-

cognitive traits of a subject by creating Electroencephalogram (EEG) models for the cognitive skills defined in the Bloom's taxonomy.

[0012] A further object of this disclosure is to evaluate cognitive behavior of an individual using cluster analysis of EEG features for different stimuli or tasks.

[0013] Other objects and advantages of the present invention will be more apparent from the following non-restrictive description of illustrative embodiments thereof, when read in conjunction with the accompanying figures, which are not intended to limit the scope of the present disclosure.

SUMMARY OF THE INVENTION

[0014] Before the present methods, systems, and hardware enablement are described, it is to be understood that this invention is not limited to the particular systems, and methodologies described, as there can be multiple possible embodiments of the present invention which are not expressly illustrated in the present disclosure. It is also to be understood that the terminology used in the description is for the purpose of describing the particular versions or embodiments only, and is not intended to limit the scope of the present invention which will be limited only by the appended claims.

[0015] Accordingly, in a preferred embodiment the disclosure provides a method for estimating or improvising perceptual-cognitive traits of a subject. The steps for estimating perceptual-cognitive traits of a subject comprise, firstly retrieving and pre-processing the data and associated metadata indicative of brainwave activity of the subject to obtain effect of a plurality of elementary cognitive tasks, followed by identification of cognitive categories within a cognitive domain of cognitive learning model. Next, plurality of elementary cognitive tasks to be performed by the subject are mapped with the identified cognitive categories and cluster analysis on each of the mapped elementary cognitive tasks is performed. Further, separation index values are determined from cluster analysis in relation to the identified cognitive categories and finally metrics are generated from the separation index values to estimate the perceptual-cognitive traits of a subject.

[0016] According to another embodiment of the disclosure, the data is electroencephalogram (EEG) signals captured using low resolution EEG devices.

[0017] In one significant embodiment of the present disclosure, the system for estimating and improvising perceptual-cognitive traits of a subject is disclosed. The system broadly comprises a processor, a data bus coupled to said processor; and a computer-usable medium embodying computer code, said computer-usable medium being coupled to said data bus, said computer program code comprising instructions executable by said processor and configured for:

retrieving and pre-processing data and associated metadata indicative of brainwave activity of the subject to obtain a plurality of elementary cognitive tasks;
identifying cognitive categories within a cognitive domain of cognitive learning model;
mapping plurality of elementary cognitive tasks to be performed by the subject with identified cognitive categories;
performing cluster analysis on each of the mapped elementary cognitive tasks and determining separation index values therefrom the cluster analysis in relation to the identified cognitive categories; and
generating metrics from the separation index values for estimation or improvisation of perceptual-cognitive traits of the subject.

BRIEF DESCRIPTION OF THE DRAWINGS

[0018] The foregoing summary, as well as the following detailed description of preferred embodiments, are better understood when read in conjunction with the appended drawings. For the purpose of illustrating the invention, there is shown in the drawings exemplary constructions of the invention; however, the invention is not limited to the specific methods and system disclosed. In the drawings:

Figure 1 of the present disclosure is a schematic functional block diagram of an exemplary architecture for the system, in accordance with one embodiment of present disclosure;

Figure 2 is a block diagram illustrating the flow of EEG signal processing, in accordance with one embodiment of present disclosure;

Figure 3 is a graph showing comparison of various feature components for F_{peak}^I F_{mean}^I in accordance with one preferred embodiment of present disclosure; and

Figure 4 is a graph showing result of Xie-Beni index variation among subjects for different feature combinations, in accordance with one embodiment of present disclosure.

DETAILED DESCRIPTION OF THE INVENTION

[0019] Some embodiments of this invention, illustrating all its features, will now be discussed in detail.

[0020] The words "comprising," "having," "containing," and "including," and other forms thereof, are intended to be equivalent in meaning and be open ended in that an item or items following any one of these words is not meant to be an exhaustive listing of such item or items, or meant to be limited to only the listed item or items.

[0021] It must also be noted that as used herein and in the appended claims, the singular forms "a," "an," and "the" include plural references unless the context clearly dictates otherwise. Although any systems and methods similar or equivalent to those described herein can be used in the practice or testing of embodiments of the present invention, the preferred, systems and methods are now described.

[0022] The disclosed embodiments are merely exemplary of the invention, which may be embodied in various forms.

[0023] The elements illustrated in the Figures interoperate as explained in more detail below. Before setting forth the detailed explanation, however, it is noted that all of the discussion below, regardless of the particular implementation being described, is exemplary in nature, rather than limiting. For example, although selected aspects, features, or components of the implementations are depicted as being stored in memories, all or part of the systems and methods consistent with the attrition warning system and method may be stored on, distributed across, or read from other machine-readable media.

[0024] The techniques described above may be implemented in one or more computer programs executing on (or executable by) a programmable computer including any combination of any number of the following: a processor, a storage medium readable and/or writable by the processor (including, for example, volatile and non-volatile memory and/or storage elements), plurality of input units, and plurality of output devices. Program code may be applied to input entered using any of the plurality of input unit to perform the functions described and to generate an output displayed upon any of the plurality of output device.

[0025] Each computer program within the scope of the claims below may be implemented in any programming language, such as assembly language, machine language, a high-level procedural programming language, or an object-oriented programming language. The programming language may, for example, be a compiled or interpreted programming language. Each such computer program may be implemented in a computer program product tangibly embodied in a machine-readable storage device for execution by a computer processor.

[0026] Method steps of the invention may be performed by one or more computer processors executing a program tangibly embodied on a computer-readable medium to perform functions of the invention by operating on input and generating output. Suitable processors include, by way of example, both general and special purpose microprocessors. Generally, the processor receives (reads) instructions and data from a memory (such as a read-only memory and/or a random access memory) and writes (stores) instructions and data to the memory. Storage devices suitable for tangibly embodying computer program instructions and data include, for example, all forms of non-volatile memory, such as semiconductor memory devices, including EPROM, EEPROM, and flash memory devices; magnetic disks such as internal hard disks and removable disks; magneto-optical disks; and CD-ROMs. Any of the foregoing may be supplemented by, or incorporated in, specially-designed ASICs (application-specific integrated circuits) or FPGAs (Field-Programmable Gate Arrays). A computer can generally also receive (read) programs and data from, and write (store) programs and data to, a non-transitory computer-readable storage medium such as an internal disk (not shown) or a removable disk.

[0027] Any data disclosed herein may be implemented, for example, in one or more data structures tangibly stored on a non-transitory computer-readable medium. Embodiments of the invention may store such data in such data structure(s) and read such data from such data structure(s).

Definitions:

[0028] Bloom's Taxonomy: Bloom's Taxonomy is an essential model for promoting higher forms of thinking in an individual by providing appropriate learning conditions. Bloom's taxonomy classifies different learning objectives into three domains, namely, Cognitive, Affective and Psychomotor, and the element of discussion for present disclosure is Cognitive domain that involves knowledge, comprehension, application, analysis and evaluation of a particular topic.

[0029] Cognitive load primarily depends on how an individual perceives, assimilates and responds to an external stimulus. The present disclosure attempts to create Electroencephalogram (EEG) models for the cognitive skills defined in the Bloom's taxonomy using low cost, commercial EEG devices.

[0030] The present disclosure comprises a system for estimating and improvising perceptual-cognitive traits of a subject. The embodiments of the present disclosure may be applied in educational psychology to provide individual assistance according to one's learning style and traits, although it should be understood that the scope of the present invention is in no way limited to these applications.

[0031] In an embodiment of the present disclosure, as presented in Figure 1, the system 100 comprises a processor

104, a data bus 106 coupled to said processor 104, and a computer-usable medium like a memory 102 embodying computer code and coupled to a data bus 106, wherein the computer program code comprises instructions executable by said processor 104 and is configured to relate the brain signals generated by various cognitive tasks to different cognitive categories of Bloom's taxonomy. The actual modulations originating in brain are captured which in turn control the ultimate thinking process for each and every response/action, eventually enabling measurement of improvisation in cognitive skills of an individual.

[0032] While different techniques may be used for reading and analyzing brain function, most widely used ones being- Electroencephalogram (EEG), functional magnetic resonance imaging (fMRI), functional near infra-red spectroscopy (fNIRS), positron emission tomography (PET) etc. For the purposes of present disclosure, EEG has been selected as it is a non-invasive and relatively in-expensive method having excellent temporal resolution. More specifically, 14 lead EEG device from Emotiv has been used for capturing and analyzing brain signals.

[0033] A set of Elementary Cognitive Tasks (hereinafter referred to as ECTs) focusing on visual perceptions and cognitive speed is recognized and defined as the stimulus as ECTs are directly linked with general mental ability and intelligence of an individual. As a non-limiting example, the factors that are being considered for visual perception includes speed of closure and flexibility of closure.

[0034] In one exemplary embodiment, the stimulus is presented and EEG data and associated metadata is captured using python based capture tool. For EEG data collection a 14- lead Emotiv headset is used. The subject is presented with a set of questions that he is expected to answer using any of plurality of input devices 108 (referring to Figure 1)-a cursor control, such as a mouse, a trackball, or cursor direction keys for communicating information and command selections to processor. After completion of questionnaire and data collection process, the subject is evaluated in terms of response time and accuracy and the result is displayed on the commonly known output device 110 (shown in Figure 1).

[0035] The EEG signals and associated metadata are analyzed as depicted in Figure 2. The metadata may include the time stamps for the EEG signals; presentation time of the stimulus, instruction and fixation slides; time stamps and the entries of the user responses. The relation between the accuracy and the response time of the subjects for each stimulus are analyzed.

[0036] The raw EEG signal is preprocessed and segmented based on predefined markers and then analyzed in time-frequency domain for feature extraction and clustering as shown in Figure 2. First in the pre-processing step, the signal is normalized to zero mean and fed to a low pass filter of predefined frequency range, e.g. 35Hz to limit the signal to the frequency band of interest. EEG signal is vulnerable to different artifacts, the dominant of them being the eye blink related artifact.

[0037] One of the described embodiments of the present disclosure, Hilbert-Huang Transform (HHT) based approach is used to remove the artifact. After that the clean data is segmented into baseline and trial epochs. Then these epochs are partitioned in windows of N seconds with 50% overlap.

[0038] In one selected embodiment, N is selected to be 20 seconds for baseline epoch and 5 seconds for trial epochs. This is particularly done to examine multiple trial windows with a single baseline window. Both the trial and baseline windows are decomposed in the time-frequency domain using S-transform of N seconds with 50% overlap. From this decomposition the mean frequencies are computed using the following formula:

$$f(\omega) = \frac{\sum_{i=0}^{n-1} I_{\omega(i)} f_{\omega(i)}}{\sum_{i=0}^{n-1} I_{\omega(i)}} \quad (1)$$

Where ω is the frequency band under analysis, n is the number of frequency bins in ω , f_i is the frequency at bin i and I_i is the energy density of ω at frequency bin i.

[0039] In a single window, the maximum and average powers of all the mean frequencies are extracted for both trial and baseline. Finally the feature vector is computed with the peak and average energy shifts ($\Delta E_{\max}^i$, ΔE_{avg}^i), the corresponding frequency shifts ($\Delta f_{\max}^i$, Δf_{avg}^i) between the baseline and trial in the frequency band i for channel 1. Here both alpha (α) and theta (θ) bands are considered. The feature vectors used are given by (2), where F_{peak}^i and F_{mean}^i respectively denote the feature vectors comprising features computed from maximum and average powers of all the mean frequencies for channel 1.

$$\left. \begin{aligned} F_{\text{peak}}^l &= \{ \Delta E_{\text{max}}^{l,\alpha}, \Delta f_{\text{max}}^{l,\alpha}, \Delta E_{\text{max}}^{l,0}, \Delta f_{\text{max}}^{l,0}, L_{\text{max}}^l \} \\ F_{\text{mean}}^l &= \{ \Delta E_{\text{avg}}^{l,\alpha}, \Delta f_{\text{avg}}^{l,\alpha}, \Delta E_{\text{avg}}^{l,0}, \Delta f_{\text{avg}}^{l,0}, L_{\text{avg}}^l \} \end{aligned} \right\}, 1 \leq l \leq 14 \quad (2)$$

where L_{max}^l or L_{avg}^l is defined as the cognitive load, computed taking maximum or average powers respectively and $1 \leq l \leq 14$ denotes the 14 leads of the Emotiv EEG device. The final feature vectors F_{peak}^l and F_{mean}^l are obtained by concatenating the vectors F_{peak}^l or F_{mean}^l respectively for all l . Feature selection is performed to select a subset of the above EEG features. If f is the number of features per channel of EEG data then the feature vectors from all 14 channels are concatenated to form R^{14f} dimensional feature vector.

[0040] The ECT or stimulus is categorized according to Bloom's categories; Table 1 below depicts mapping of stimulus or ECTs to identified Bloom's categories, namely Understand, Remember and Analyze. However, it has to be understood that the identification of three given Bloom's categories is only for exemplary purposes. Similar mapping can be done for Bloom's six categories namely remember, understand, apply, analyze, evaluate and create.

Stimulus	Task details	Measure	Relationship to Bloom's category
1. Scattered X's (SX)	Find number of times 'X' appears on screen.	Perceptual speed	Understand & Remember
2. Finding A (FA)	Count words containing 'a' from a page full of words.	Perceptual speed	Analyze & Remember
3. Hidden pattern (HP)	Find a target pattern from a list of five complex patterns	Flexibility of closure	Analyze
4. Visual pursuit (VP)	Count the number of occurrences of a target image from an array of multiple complex images.	Perceptual speed	Understand & Remember
5. Finding number (FN)	Count the non-matching number pairs from a list of number pairs.	Perceptual speed	Understand & Remember
6. Gestalt closure test (GC)	Look at an incomplete image and identify the object.	Speed of closure	Understand

Table 1. Mapping Stimuli to Bloom's Categories

[0041] The EEG signals are first cleaned from various artifacts and then analyzed using standard machine learning techniques. Having also identified the cognitive categories within the Bloom's taxonomy and mapped plurality of ECTs with identified cognitive domains of Bloom's taxonomy, a cluster analysis is performed on the features of EEG signals using K-means algorithm. An unsupervised approach has been adapted to objectively measure the effects of various ECTs on individual subjects.

[0042] An optimum number of clusters for an individual are identified by performing K means based clustering on the EEG features. Referring to afore-given non limiting description of illustrative embodiment wherein 6ECTs have been identified, the K is varied from 2 to 10. The value of K that generates compact clusters and also separates the clusters well, is determined using the minimum Xie-Beni index, in accordance with one exemplary embodiment of present disclosure. Further, relationships between the clusters in terms of distance between the centroids and the insights with the Bloom's categories are determined. It should however be noted that the scope of the invention is in no way limited to this example, and alternative variations of this task or given ECTs are possible and included within the scope of the invention.

[0043] Let, referring to above example, the maximum number of minimum time response is obtained in the task "Finding A" (FA) and maximum number of maximum time response is obtained in "Visual Pursuit" (VP) task. Similarly let maximum

accuracy is achieved in FA and minimum accuracy is achieved for "Hidden Pattern" (HP). Thus FA provides maximum accuracy at minimum response time.

[0044] For exemplary purposes, all the tasks are of comparable load with a slight variation in their spread. As all the ECTs impart similar levels of cognitive load upon the subjects, the choice for the stimuli is justified.

[0045] Next, a feature selection is performed on the total feature list given in equation (2) above. Maximal Information Co-efficient (MIC) is used to choose the most appropriate feature subset among F_{peak}^I and F_{mean}^I . The MIC score of the corresponding peak (F_{peak}^I) and mean (F_{mean}^I) feature ratios in logarithmic unit is shown in Figure 3. The positive values indicate that F_{peak}^I is a better subset. Here individual features' MIC values are averaged across all 14 channels and then summed over all the participants.

[0046] While performing the cluster analysis, firstly the effects of taking peak energy and frequency shifts, average energy and frequency shifts or both in the feature vector are analyzed. This is illustrated in Figure 4. It can be observed that taking a five dimensional feature vector F_{peak} gives the best clustering performance (in terms of smaller Xie Beni Indices) compared to F_{mean} or a ten dimensional feature vector F_{both} , where $F_{both} = \{F_{peak}, F_{mean}\}$. Hence all further analyses are carried out using only F_{peak} as feature.

[0047] As can be seen from Table II below, results obtained from clustering analysis in terms of Xie - Beni indices have been summarized.

TABLE II. XIE BENI INDEX FOR DIFFERENT SUBJECTS AND FEATURES

Subject (K_{min})	Features						
	F_1	F_2	F_3	F_4	F_5	F_6	F_7
S1 (6)	1.9786	1.0073	2.2869	0.9156	1.0671	0.8103	0.8366
S2 (6)	1.7380	0.7125	0.8235	0.8935	0.7652	0.6745	0.6413
S3 (6)	1.7120	0.6637	1.1722	0.8462	1.2651	0.9040	0.7244
S4 (6)	1.3938	0.3777	1.2208	0.4630	1.2085	0.5866	0.3305
S5 (6)	1.3834	0.7948	0.9361	0.5566	1.6100	0.6423	0.5830
S6 (6)	2.3961	1.0465	0.9508	0.7961	2.4843	0.9268	0.7878
S7 (2)	0.8770	0.1607	1.2089	0.1583	0.9118	0.6000	0.1648
S8 (6)	1.0398	0.4943	1.1652	0.8390	1.0400	0.7440	0.6183
S9 (6)	1.2961	0.9185	1.5184	0.9483	0.8828	0.7383	0.8391
S10(6)	1.7442	0.6232	1.5616	0.6209	0.8355	0.7891	0.5216

[0048] Here F_1 to F_5 , denote the following features:

$$F_1 = L_{\max}^1, F_2 = \Delta E_{\max}^{1,\alpha}, F_3 = \Delta f_{\max}^{1,\alpha}, F_4 = \Delta E_{\max}^{1,\theta}, F_5 = \Delta f_{\max}^{1,\theta}$$

F_6 is a combination of the F_1 through F_5 while F_7 is a combination of F_2 and F_4 . It is found that 9 subjects show the best performance i.e. lowest Xie-Beni index for $K=6$ while only one shows better results with $K=2$. These are reported as K_{min} in Table II. Also it is found that compared to using the F_6 , only F_2 for subjects S3, S4, S8 and S10; or only F_4 for subjects S5, S6 and S7 gives better results. Thus feature F_7 is selected as it gives a better performance compared to F_6 for eight out of ten subjects.

[0049] Next the distance between cluster centroids for each ECTs is computed. Let, say that for K number of clusters, $K C_2$ different combinations of distances between clusters are obtained. From the given number of combinations, the cluster centers having minimum and maximum distance for each individual are identified. A study on these distance pairs with respect to relation with Bloom's categories is presented in Table III. Here the attempt is to group subjects with similar relative cognitive skills. As for example, it can be seen from the Table III that it can be inferred for S1, S2 and S3 the FN-HP pair is having minimum distance i.e. maximum similarity. Here, S7 is neglected as number of clusters with minimum Xie-Beni index is 2 which is different from all the remaining subjects.

Table III. Cluster centers with minimum and maximum distances

Subjects	Pair with min/max distance between centroids	Remarks
S1	Min: FN-HP Max: SX-VP	Min: Though they are from separate categories, the subject treats number as a pattern.

(continued)

Subjects	Pair with min/max distance between centroids	Remarks
		<u>Max</u> : Though both are in same category, the alphabets and shapes are treated differently.
S2	Min: FN-HP Max: FN-GC	<u>Min</u> : Though they are from separate categories, the subject treats number as a pattern. <u>Max</u> : Same categories but FN needs remembering also.
S3	Min: FN-HP Max: FN-GC	<u>Min</u> : Though are from separate categories, the subject treats number as a pattern. <u>Max</u> : Same categories but FN needs remembering also
S4	Min: FA-SX Max: FN-GC	<u>Min</u> : Different category but, searching "A" (in FA) is similar to searching "X" (in SX). <u>Max</u> : Same categories but FN needs remembering also
S5	Min: GC-VP Max: FN-VP	<u>Min</u> : They are from same category and are treated similarly as both are related to patterns. <u>Max</u> : Same category but the numbers and patterns are treated differently.
S6	Min: GC-VP Max: GC-HP	<u>Min</u> : They are from same category and are treated similarly as both are related to patterns. <u>Max</u> : Separate categories.
S8	Min: FN-VP Max: GC-HP	<u>Min</u> : Same category - numbers and patterns are treated similarly. <u>Max</u> : Separate categories.
S9	Min: FN-SX Max: FN-HP	<u>Min</u> : Same category - numbers and patterns are treated similarly. <u>Max</u> : Separate categories.
S10	Min: SX-VP Max: SX-GC	<u>Min</u> : Same category - the "X" (in SX) is treated as a pattern as in VP. <u>Max</u> : Same category but for SX, user needs to remember as well.

[0050] Following the unsupervised cluster analysis on the EEG features for segregating the cognitive categories, one or more metrics are introduced for EEG based identification of the Traits of Cognitive Perception (TCP) among different individuals. In one aspect of the disclosure, if C_i and C_j be the centers of the i^{th} and the j^{th} clusters respectively for a particular subject, the separation Index ($SI_{i,j}$) between these two clusters is given as (3), where $\|\cdot\|$ denotes the Euclidean Distance between them.

$$SI_{i,j} = \|C_i - C_j\| \quad (3)$$

If, say there are N number of clusters formed, NC_2 pair-wise $SI_{i,j}$ values are obtained. Next, search is made for the pair of clusters that lead to the maximum and minimum separation index values $SI_{\min}$ and $SI_{\max}$ for each subject. Further, the ratio S_r of $SI_{\min}$ upon $SI_{\max}$ is computed as can be seen in equations. (4), (5) and (6) below.

$$SI_{\min} = \text{minimum}(SI_{i,j}) \quad (4)$$

$$SI_{\max} = \text{maximum}(SI_{i,j}) \quad (5)$$

$$S_r = SI_{\min} / SI_{\max} \quad (6)$$

[0051] The above obtained $SI_{\min}$, $SI_{\max}$ and S_r values are used as metrics to identify the TCP of a particular subject. While, it is obvious that $SI_{\min}$ (or $SI_{\max}$) determines the how similarly (or dissimilarly) a subject treats the pair of tasks, S_r determines the spread of cognitive perception. A value of S_r close to 1 indicates almost similar interpretation of all tasks by the subject. This pertains to the subject wise study of TCPs. Now, depending on the $SI_{\min}$, $SI_{\max}$ and S_r values across all subjects, they are grouped into different categories of TCPs. This amounts to the stimulus-wise study of TCPs across all subjects.

[0052] Likewise, a similar approach can be used to analyze a new task (say T_{new}). In such a scenario a set of subjects are considered who belong to the same group of TCP. Then the EEG signal is captured by presenting the new task. The EEG signals are analyzed to understand the relative structure with respect to the C_j . Assuming that there are N ECTs, then $1 \leq i \leq N$. The centroid of the EEG features for the T_{new} is C_{new} . Then the weight of each ECT present in the new task is given by equation (7) as follows.

$$W_i = 1 - \frac{C_i - C_{new}}{\sum_{i=1}^N (C_i - C_{new})} \quad (7)$$

[0053] In the interest of clarity, not all of the routine features of the implementations of the perceptual-cognitive-system and method are shown and described. It will, of course, be appreciated that in the development of any such actual implementation of the perceptual-cognitive system and method, numerous implementation-specific decisions may need to be made in order to achieve the system specific goals, and that these specific goals will vary from one implementation to another and from one application area to another.

[0054] It is to be understood that the invention is not limited in its application to the details of construction and parts illustrated in the accompanying drawings and described herein-above. The invention is capable of other embodiments and of being practiced in various ways. It is also to be understood that the phraseology or terminology used herein is for the purpose of description and not limitation. Hence, although the present invention has been described hereinabove by way of illustrative embodiments thereof, it can be modified at will, within the scope of the appended claims, without departing from the scope of the subject invention.

Claims

1. A method for estimating or improvising perceptual-cognitive traits of a subject, comprising processor (104) implemented steps of:

retrieving and pre-processing data and associated metadata indicative of brainwave activity of the subject to obtain effect of a plurality of elementary cognitive tasks, the data being electroencephalogram (EEG) signals; the method being **characterized in that** it further comprises the following processor implemented steps of:

identifying cognitive categories within a cognitive domain of cognitive learning model;
mapping plurality of elementary cognitive tasks to be performed by the subject with identified cognitive categories;
performing cluster analysis on each of the mapped elementary cognitive tasks and determining separation index values therefrom the cluster analysis in relation to the identified cognitive categories; and
generating metrics from the separation index values for estimation or improvisation of perceptual-cognitive traits of the subject.

2. The method of claim 1, wherein the elementary cognitive tasks are representative of stimulus directly linked with cognitive perception of the subject.
3. The method of claim 1, wherein the electroencephalogram (EEG) signals are captured using low resolution EEG devices and the associated metadata includes time stamps for EEG signals, presentation time of the stimulus, instruction and fixation slides; time stamps and the entries of the subject responses.
4. The method of claim 1, wherein the cognitive learning model is Bloom's taxonomy.

5. The method of claim 4, wherein the identified cognitive categories of Bloom's taxonomy comprises analyze, remember, apply, evaluate, create and understand.

6. The method of claim 1, wherein the pre-processing of EEG signals involve steps of:

removing voltage offset from received EEG signals;
normalizing the EEG signals to zero mean;
filtering means to restrict normalized signals within a predefined frequency range; and
removing ocular artifacts using Hilbert Huang Transform technique.

7. The method of claim 1, wherein the pre-processed EEG signals are further analyzed in steps of:

partitioning the processed EEG signals into plurality of baseline and trial epochs;
analyzing the baseline and trial epochs in time frequency domain using S-transform; and computing mean frequencies of the baseline and trial epochs to derive peak and average power shifts and corresponding frequency shifts thereof; and
concatenating the peak powers and peak frequency shifts or average powers and average frequency shifts or a combination thereof to determine characterizing feature vectors between the baseline and trial epochs obtained from different frequency bands.

8. The method of claim 7, wherein the frequency bands are selected from alpha and theta frequency bands and maximal information coefficient is used to determine if the peak powers and peak frequency shifts or average powers and average frequency shifts or a combination thereof is selected for determining the feature vectors.

9. The method of claim 1, wherein cluster analysis is performed on the feature vectors of EEG signals obtained from different frequency bands using K-means model, optimum number of clusters to be formed being derived from Xie-Beni index.

10. The method of claim 1, wherein the separation index between various clusters for each elementary cognitive task is based on standardized Euclidean distance there between and the separation index values include determining maximum and minimum values of separation index between the plurality of clusters for each of the elementary cognitive tasks, and a ratio of minimum values against the maximum values to finally generate the metrics for cognitive traits.

11. The method of claim 1, wherein for each new elementary cognitive task to be performed by the subject:

iteratively analyzing the EEG signals in response to the stimulus presented and receiving results representative therefrom;
deriving the separation index values with respect to previously formed clusters; and accordingly categorizing the subject based on perceptual-cognitive traits into corresponding cluster.

12. A system (100) for estimating and improvising perceptual-cognitive traits of a subject, comprising:

a processor (104);
a data bus (106) coupled to said processor (104); and
a computer-usable medium (102) embodying computer code, said computer-usable medium (102) being coupled to said data bus (106), said computer program code comprising instructions executable by said processor (104) and configured for:

retrieving and pre-processing data and associated metadata indicative of brainwave activity of the subject to obtain a plurality of elementary cognitive tasks, the data being electroencephalogram (EEG) signals;
characterized in that the instructions are further configured for:

identifying cognitive categories within a cognitive domain of cognitive learning model;
mapping plurality of elementary cognitive tasks to be performed by the subject with identified cognitive categories;
performing cluster analysis on each of the mapped elementary cognitive tasks and determining separation index values therefrom the cluster analysis in relation to the identified cognitive categories; and

generating metrics from the separation index values for estimation or improvisation of perceptual-cognitive traits of the subject.

13. The system of claim 12, wherein the pre-processing of EEG signals involve steps of:

removing voltage offset from received EEG signals;
normalizing the EEG signals to zero mean;
filtering means to restrict normalized signals within a predefined frequency range; and
removing ocular artifacts using Hilbert Huang Transform technique.

14. The system of claim 12, wherein the associated metadata includes time stamps for EEG signals, presentation time of the stimulus, instruction and fixation slides; time stamps and the entries of the subject responses.

15. The system of claim 12, wherein the cognitive learning model is Bloom's taxonomy and identified cognitive categories of Bloom's taxonomy comprise analyze, remember, apply, evaluate, create and understand.

16. The system of claim 12, wherein the pre-processed EEG signals are further analyzed in steps of:

partitioning the processed EEG signals into plurality of baseline and trial epochs;
analyzing the baseline and trial epochs in time frequency domain using S-transform; and computing mean frequencies of the baseline and trial epochs to derive peak and average power shifts and corresponding frequency shifts thereof; and
concatenating the peak powers and peak frequency shifts or average powers and average frequency shifts or a combination thereof to determine characterizing feature vectors between the baseline and trial epochs obtained from different frequency bands.

17. The system of claim 16, wherein maximal information coefficient is used to determine if the peak powers and peak frequency shifts or average powers and average frequency shifts or a combination thereof is selected for determining the feature vectors.

18. The system of claim 12, wherein the cluster analysis is performed on the feature vectors of EEG signals obtained from different frequency bands using K-means model, optimum number of clusters to be formed being derived from Xie-Beni index.

19. The system of claim 12, wherein the separation index between various clusters for each elementary cognitive task is based on standardized Euclidean distance there between and the separation index values include determining maximum and minimum values of separation index between the plurality of clusters for each of the elementary cognitive tasks, and a ratio of minimum values against the maximum values to finally generate the metrics.

20. The system of claim 12, wherein for each new elementary cognitive task to be performed by the subject, the processor is configured to:

iteratively analyze the EEG signals in response to the stimulus presented and receiving results representative therefrom;
derive the separation index values with respect to previously formed clusters; and accordingly categorize the subject based on perceptual-cognitive traits into corresponding cluster.

Patentansprüche

1. Verfahren zum Schätzen oder Improvisieren von wahrnehmungskognitiven Eigenschaften eines Probanden, umfassend Prozessor (104)-implementierte Schritte von:
Abrufen und Vorverarbeiten von Daten und zugehörigen Metadaten, die die Hirnwellenaktivität des Probanden anzeigen, um die Wirkung einer Vielzahl elementarer kognitiver Aufgaben zu erhalten, wobei die Daten Elektroenzephalogramm-(EEG)-Signale sind; wobei das Verfahren **dadurch gekennzeichnet ist, dass** es ferner die folgenden prozessorimplementierten Schritte umfasst:

Identifizieren von kognitiven Kategorien innerhalb einer kognitiven Domäne des Modells des kognitiven Lernens;

Abbilden einer Vielzahl von elementaren kognitiven Aufgaben, die von dem Probanden auszuführen sind, mit identifizierten kognitiven Kategorien;
Durchführen einer Clusteranalyse an jeder der abgebildeten elementaren kognitiven Aufgaben und Bestimmen von Separationsindexwerten daraus der Clusteranalyse in Bezug auf die identifizierten kognitiven Kategorien;
und
Erzeugen von Metriken aus den Separationsindexwerten zur Schätzung oder Verbesserung von wahrnehmungskognitiven Eigenschaften des Probanden.

2. Verfahren nach Anspruch 1, wobei die elementaren kognitiven Aufgaben repräsentativ für Reize sind, die direkt mit der kognitiven Wahrnehmung des Probanden verbunden sind.

3. Verfahren nach Anspruch 1, wobei die Elektroenzephalogramm-(EEG)-Signale unter Verwendung von EEG-Vorrichtungen mit niedriger Auflösung erfasst werden und die zugehörigen Metadaten Zeitstempel für EEG-Signale, Präsentationszeit des Reizes, Anweisungs- und Fixationsfolien, Zeitstempel und die Einträge der Probandenantworten beinhalten.

4. Verfahren nach Anspruch 1, wobei das kognitive Lernmodell die Bloom-Taxonomie ist.

5. Verfahren nach Anspruch 4, wobei die identifizierten kognitiven Kategorien der Bloom-Taxonomie Analyse, Erinnerung, Anwendung, Bewertung, Erstellung und Verständnis umfassen.

6. Verfahren nach Anspruch 1, wobei die Vorverarbeitung von EEG-Signalen die Schritte von:

Entfernen des Spannungsoffsets von empfangenen EEG-Signalen;
Normierung der EEG-Signale auf den Mittelwert Null;
Filtermittel zum Einschränken normierter Signale innerhalb eines vordefinierten Frequenzbereichs; und
Entfernen von Augenartefakten mit der Hilbert-I-Tuang-Transformationstechnik.

7. Verfahren nach Anspruch 1, wobei die vorverarbeiteten EEG-Signale weiter analysiert werden in Schritten von:

Aufteilen der verarbeiteten EEG-Signale in eine Vielzahl von Baseline und Probeepochen;
Analysieren der Baseline und der Probeepochen im Zeitfrequenzbereich mittels S-Transformation; und
Berechnen der mittleren Frequenzen der Basis- und Probeepochen, um Spitzen- und Durchschnittsleistungsschwankungen und entsprechende Frequenzverschiebungen derselben abzuleiten; und
Verketten der Spitzenleistungen und Spitzenfrequenzverschiebungen oder der Durchschnittsleistungen und der Durchschnittsfrequenzverschiebungen oder einer Kombination davon, um charakterisierende Merkmalsvektoren zwischen der Baseline und den Versuchsepochen aus verschiedenen Frequenzbändern zu bestimmen.

8. Verfahren nach Anspruch 7, wobei die Frequenzbänder aus Alpha- und Theta-Frequenzbändern ausgewählt sind und der maximale Informationskoeffizient verwendet wird, um zu bestimmen, ob die Spitzenleistungen und Spitzenfrequenzverschiebungen oder Durchschnittsleistungen und Durchschnittsfrequenzverschiebungen oder eine Kombination davon zum Bestimmen der Merkmalsvektoren ausgewählt wird.

9. Verfahren nach Anspruch 1, wobei eine Clusteranalyse an den Merkmalsvektoren von EEG-Signalen durchgeführt wird, die aus verschiedenen Frequenzbändern unter Verwendung des K-Means-Modells erhalten werden, wobei die optimale Anzahl der zu bildenden Cluster aus dem Xie-Beni-Index abgeleitet wird.

10. Verfahren nach Anspruch 1, wobei der Separationsindex zwischen verschiedenen Clustern für jede elementare kognitive Aufgabe auf einem standardisierten euklidischen Abstand dort zwischen basiert und die Separationsindexwerte das Bestimmen von Maximal- und Minimalwerten des Separationsindex zwischen der Vielzahl von Clustern für jede der elementaren kognitiven Aufgaben und ein Verhältnis von Minimalwerten zu den Maximalwerten beinhalten, um schließlich die Metriken für kognitive Eigenschaften zu erzeugen.

11. Verfahren nach Anspruch 1, wobei für jede neue elementare kognitive Aufgabe, die von dem Probanden auszuführen ist:

iteratives Analysieren der EEG-Signale als Reaktion auf den dargestellten Stimulus und Empfangen von reprä-

sentativen Ergebnissen;

Ableiten der Separationsindexwerte in Bezug auf zuvor gebildete Cluster; und dementsprechend Kategorisieren des Probanden basierend auf wahrnehmungskognitiven Eigenschaften in entsprechende Cluster.

- 5 **12.** System (100) zum Schätzen und Improvisieren von wahrnehmungskognitive Eigenschaften eines Probanden, umfassend:

einen Prozessor (104);

einen Datenbus (106), der mit dem Prozessor (104) gekoppelt ist; und

- 10 ein computerverwendbares Medium (102), das Computercode beinhaltet, wobei das computerverwendbare Medium (102) mit dem Datenbus (106) gekoppelt ist, wobei der Computerprogrammcode Anweisungen umfasst, die von dem Prozessor (104) ausführbar und konfiguriert sind für:

- 15 Abrufen und Vorverarbeiten von Daten und zugehörigen Metadaten, die die Hirnwellenaktivität des Probanden anzeigen, um eine Vielzahl von elementaren kognitiven Aufgaben zu erhalten, wobei die Daten Elektroenzephalogramm-(EEG)-Signale sind;

dadurch gekennzeichnet, dass die Anweisungen ferner konfiguriert sind für:

- 20 Identifizieren von kognitiven Kategorien innerhalb einer kognitiven Domäne des Modells des kognitiven Lernens;

Abbilden einer Vielzahl von elementaren kognitiven Aufgaben, die von der Person auszuführen sind, mit identifizierten kognitiven Kategorien;

- 25 Durchführen einer Clusteranalyse an jeder der abgebildeten elementaren kognitiven Aufgaben und Bestimmen von Separationsindexwerten daraus der Clusteranalyse in Bezug auf die identifizierten kognitiven Kategorien; und

Erzeugen von Metriken aus den Werten des Separationsindexes zur Schätzung oder Verbesserung von wahrnehmungskognitiven Eigenschaften des Probanden.

- 30 **13.** System nach Anspruch 12, wobei die Vorverarbeitung von EEG-Signalen die Schritte von:

Entfernen des Spannungsoffsets von empfangenen EEG-Signalen;

Normierung der EEG-Signale auf den Mittelwert Null;

Filtermittel zum Einschränken normierter Signale innerhalb eines vor definierten Frequenzbereichs; und

- 35 Entfernen von okulären Artefakten mit der Hilbert Huang Transform Technik.

- 14.** System nach Anspruch 12, wobei die zugehörigen Metadaten Zeitstempel für EEG-Signale, Präsentationszeit des Reizes, Anweisungs- und Fixationsfolien beinhalten; Zeitstempel und die Einträge der Probandenantworten.

- 40 **15.** System nach Anspruch 12, wobei das kognitive Lernmodell die Bloom-Taxonomie ist und die identifizierten kognitiven Kategorien der Bloom-Taxonomie Analyse, Erinnerung, Anwendung, Bewertung, Erstellung und Verständnis umfassen.

- 45 **16.** System nach Anspruch 12, wobei die vorverarbeiteten EEG-Signale weiter in Schritten von:

Aufteilen der verarbeiteten EEG-Signale in eine Vielzahl von Baseline und Probeepochen;

Analysieren der Baseline und der Probeepochen im Zeitfrequenzbereich mittels S-Transformation; und

- 50 Berechnen der mittleren Frequenzen der Basis- und Versuchsepochen, um Spitzen- und Durchschnittsleistungsschwankungen und entsprechende Frequenzverschiebungen derselben abzuleiten; und

Verketteten der Spitzenleistungen und Spitzenfrequenzverschiebungen oder der Durchschnittsleistungen und der Durchschnittsfrequenzverschiebungen oder einer Kombination davon, um charakterisierende Merkmalsvektoren zwischen der Baseline und den Versuchsepochen aus verschiedenen Frequenzbändern zu bestimmen.

- 55 **17.** System nach Anspruch 16, wobei der maximale Informationskoeffizient verwendet wird, um zu bestimmen, ob die Spitzenleistungen und Spitzenfrequenzverschiebungen oder Durchschnittsleistungen und Durchschnittsfrequenzverschiebungen oder eine Kombination davon zum Bestimmen der Merkmalsvektoren ausgewählt werden.

18. System nach Anspruch 12, wobei die Clusteranalyse an den Merkmalsvektoren von EEG-Signalen durchgeführt wird, die aus verschiedenen Frequenzbändern unter Verwendung des K-Mittelwert-Modells erhalten werden, wobei die optimale Anzahl der zu bildenden Cluster vom Xie-Beni-Index abgeleitet wird.

19. System nach Anspruch 12, wobei der Separationsindex zwischen verschiedenen Clustern für jede elementare kognitive Aufgabe auf einem standardisierten euklidischen Abstand dort zwischen basiert und die Separationsindexwerte das Bestimmen von Maximal- und Minimalwerten des Separationsindex zwischen der Vielzahl von Clustern für jede der elementaren kognitiven Aufgaben und ein Verhältnis von Minimalwerten zu den Maximalwerten beinhalten, um schließlich die Kennzahlen zu erzeugen.

20. System nach Anspruch 12, wobei der Prozessor für jede neue elementare kognitive Aufgabe, die von dem Probanden auszuführen ist, konfiguriert ist, um: die EEG-Signale als Reaktion auf den dargestellten Stimulus iterativ zu analysieren und daraus repräsentative Ergebnisse zu erhalten; Ableiten der Separationsindexwerte in Bezug auf zuvor gebildete Cluster; und entsprechendes Einteilen des Probanden basierend auf wahrnehmungskognitiven Merkmalen in entsprechende Cluster.

Revendications

1. Procédé d'estimation ou d'improvisation de caractéristiques perceptuelles et cognitives d'un sujet, comprenant les étapes ci-dessous, mises en oeuvre par processeur (104), consistant à :

récupérer et prétraiter des données et des métadonnées associées indicatives d'une activité d'ondes cérébrales du sujet, en vue d'obtenir l'effet d'une pluralité de tâches cognitives élémentaires, les données étant des signaux d'électroencéphalogramme (EEG) ;
le procédé étant **caractérisé en ce qu'il** comprend en outre les étapes, mises en oeuvre par processeur, ci-après consistant à :

identifier des catégories cognitives au sein d'un domaine cognitif d'un modèle d'apprentissage cognitif ;
mettre en correspondance la pluralité de tâches cognitives élémentaires devant être mises en oeuvre par le sujet avec des catégories cognitives identifiées ;
mettre en oeuvre une analyse de grappes sur chacune des tâches cognitives élémentaires mises en correspondance, et déterminer des valeurs d'indices de séparation à partir de l'analyse de grappes par rapport aux catégories cognitives identifiées ; et
générer des métriques à partir des valeurs d'indices de séparation pour l'estimation ou l'improvisation de caractéristiques perceptuelles et cognitives du sujet.

2. Procédé selon la revendication 1, dans lequel les tâches cognitives élémentaires sont représentatives d'un stimulus directement lié à la perception cognitive du sujet.

3. Procédé selon la revendication 1, dans lequel les signaux d'électroencéphalogramme (EEG) sont capturés en utilisant des dispositifs EEG à basse résolution, et les métadonnées associées incluent des estampilles temporelles pour les signaux EEG, un temps de présentation du stimulus, des lames de fixation et instructions ; des estampilles temporelles et les entrées des réponses du sujet.

4. Procédé selon la revendication 1, dans lequel le modèle d'apprentissage cognitif est la taxonomie de Bloom.

5. Procédé selon la revendication 4, dans lequel les catégories cognitives identifiées de la taxonomie de Bloom comprennent l'analyse, la mémorisation, l'application, l'évaluation, la création et la compréhension.

6. Procédé selon la revendication 1, dans lequel le prétraitement des signaux EEG implique les étapes ci-dessous consistant à :

supprimer un décalage de tension des signaux EEG reçus ;
normaliser les signaux EEG à une moyenne zéro ;
utiliser un moyen de filtrage pour limiter des signaux normalisés au sein d'une plage de fréquences prédéfinie ; et
supprimer des artefacts oculaires en faisant appel à la technique de transformée de Hilbert Huang.

7. Procédé selon la revendication 1, dans lequel les signaux EEG prétraités sont analysés en outre dans les étapes ci-dessous consistant à :

partitionner les signaux EEG traités en une pluralité de périodes de référence et d'essai ;
analyser les périodes de référence et d'essai dans le domaine temporel et fréquentiel en utilisant une transformée S ; et
calculer des fréquences moyennes des périodes de référence et d'essai en vue de dériver des décalages de puissances de crête et puissances moyennes et des décalages de fréquences correspondants connexes ; et
concaténer les puissances de crête et décalages de fréquences de crête, ou les puissances moyennes et décalages de fréquences moyennes, ou une combinaison connexe, en vue de déterminer des vecteurs caractéristiques de caractérisation entre les périodes de référence et d'essai obtenus à partir de différentes bandes de fréquences.

8. Procédé selon la revendication 7, dans lequel les bandes de fréquences sont sélectionnées parmi les bandes de fréquences « alpha » et « thêta » ; et un coefficient d'information maximal est utilisé en vue de déterminer si les puissances de crête et les décalages de fréquences de crête, ou les puissances moyennes et les décalages de fréquences moyennes, ou une combinaison connexe, sont sélectionnés pour déterminer les vecteurs caractéristiques.

9. Procédé selon la revendication 1, dans lequel l'analyse de grappes est mise en oeuvre sur les vecteurs caractéristiques de signaux EEG obtenus à partir de différentes bandes de fréquences, en utilisant un modèle des K centroïdes, un nombre optimal de grappes à former étant dérivé de l'indice Xie-Beni.

10. Procédé selon la revendication 1, dans lequel l'indice de séparation entre diverses grappes pour chaque tâche cognitive élémentaire est basé sur la distance euclidienne normalisée entre elles, et les valeurs d'indices de séparation incluent la détermination de valeurs maximales et minimales de l'indice de séparation entre la pluralité de grappes pour chacune des tâches cognitives élémentaires, et d'un rapport entre valeurs minimales et valeurs maximales pour générer finalement les métriques pour des caractéristiques cognitives.

11. Procédé selon la revendication 1, dans lequel, pour chaque nouvelle tâche cognitive élémentaire devant être mise en oeuvre par le sujet, le procédé comprend les étapes ci-dessous consistant à :

analyser itérativement les signaux EEG en réponse au stimulus présenté, et recevoir de résultats représentatifs à partir de cela ;
dériver les valeurs d'indices de séparation par rapport à des grappes formées précédemment ; et en conséquence, catégoriser le sujet sur la base de caractéristiques perceptuelles et cognitives, au sein d'une grappe correspondante.

12. Système (100) destiné à estimer et improviser des caractéristiques perceptuelles et cognitives d'un sujet, comprenant :

un processeur (104) ;
un bus de données (106) couplé audit processeur (104) ; et
un support utilisable par ordinateur (102) incorporant un code de programme informatique, ledit support utilisable par ordinateur (102) étant couplé audit bus de données (106), ledit code de programme informatique comprenant des instructions exécutables par ledit processeur (104) et configurées de manière à :

recupérer et prétraiter des données et des métadonnées associées indicatives d'une activité d'ondes cérébrales du sujet, en vue d'obtenir une pluralité de tâches cognitives élémentaires, les données étant des signaux d'électroencéphalogramme (EEG) ; **caractérisé en ce que** les instructions sont en outre configurées de manière à :

identifier des catégories cognitives au sein d'un domaine cognitif d'un modèle d'apprentissage cognitif ;
mettre en correspondance la pluralité de tâches cognitives élémentaires devant être mises en oeuvre par le sujet avec des catégories cognitives identifiées ;

mettre en oeuvre une analyse de grappes sur chacune des tâches cognitives élémentaires mises en correspondance, et déterminer des valeurs d'indices de séparation à partir de l'analyse de grappes par rapport aux catégories cognitives identifiées ; et

générer des métriques à partir des valeurs d'indices de séparation pour l'estimation ou l'improvisation de

caractéristiques perceptuelles et cognitives du sujet.

13. Système selon la revendication 12, dans lequel le prétraitement des signaux EEG implique les étapes ci-dessous consistant à :

supprimer un décalage de tension des signaux EEG reçus ;
normaliser les signaux EEG à une moyenne zéro ;
utiliser un moyen de filtrage pour limiter des signaux normalisés au sein d'une plage de fréquences prédéfinie ; et
supprimer des artefacts oculaires en faisant appel à la technique de transformée de Hilbert Huang.

14. Système selon la revendication 12, dans lequel les métadonnées associées incluent des estampilles temporelles pour les signaux EEG, un temps de présentation du stimulus, des lames de fixation et instructions ; des estampilles temporelles et les entrées des réponses du sujet.

15. Système selon la revendication 12, dans lequel le modèle d'apprentissage cognitif est la taxonomie de Bloom, et dans lequel les catégories cognitives identifiées de la taxonomie de Bloom comprennent l'analyse, la mémorisation, l'application, l'évaluation, la création et la compréhension.

16. Système selon la revendication 12, dans lequel les signaux EEG prétraités sont en outre analysés dans les étapes ci-dessous consistant à :

partitionner les signaux EEG traités en une pluralité de périodes de référence et d'essai ;
analyser les périodes de référence et d'essai dans le domaine temporel et fréquentiel en utilisant une transformée S ; et

calculer des fréquences moyennes des périodes de référence et d'essai en vue de dériver des décalages de puissances de crête et puissances moyennes et des décalages de fréquences correspondants connexes ; et
concaténer les puissances de crête et décalages de fréquences de crête, ou les puissances moyennes et décalages de fréquences moyennes, ou une combinaison connexe, en vue de déterminer des vecteurs caractéristiques de caractérisation entre les périodes de référence et d'essai obtenus à partir de différentes bandes de fréquences.

17. Système selon la revendication 16, dans lequel un coefficient d'information maximal est utilisé en vue de déterminer si les puissances de crête et les décalages de fréquences de crête, ou les puissances moyennes et les décalages de fréquences moyennes, ou une combinaison connexe, sont sélectionnés pour déterminer les vecteurs caractéristiques.

18. Système selon la revendication 12, dans lequel l'analyse de grappes est mise en oeuvre sur les vecteurs caractéristiques de signaux EEG obtenus à partir de différentes bandes de fréquences, en utilisant un modèle des K centroïdes, un nombre optimal de grappes à former étant dérivé de l'indice Xie-Beni.

19. Système selon la revendication 12, dans lequel l'indice de séparation entre diverses grappes pour chaque tâche cognitive élémentaire est basé sur la distance euclidienne normalisée entre elles, et les valeurs d'indices de séparation incluent la détermination de valeurs maximales et minimales de l'indice de séparation entre la pluralité de grappes pour chacune des tâches cognitives élémentaires, et d'un rapport entre valeurs minimales et valeurs maximales pour générer finalement les métriques pour des caractéristiques cognitives.

20. Système selon la revendication 12, dans lequel, pour chaque nouvelle tâche cognitive élémentaire devant être mise en oeuvre par le sujet, le processeur est configuré de manière à :

analyser itérativement les signaux EEG en réponse au stimulus présenté, et recevoir de résultats représentatifs à partir de cela ;
dériver les valeurs d'indices de séparation par rapport à des grappes formées précédemment ; et en conséquence, catégoriser le sujet sur la base de caractéristiques perceptuelles et cognitives, au sein d'une grappe correspondante.

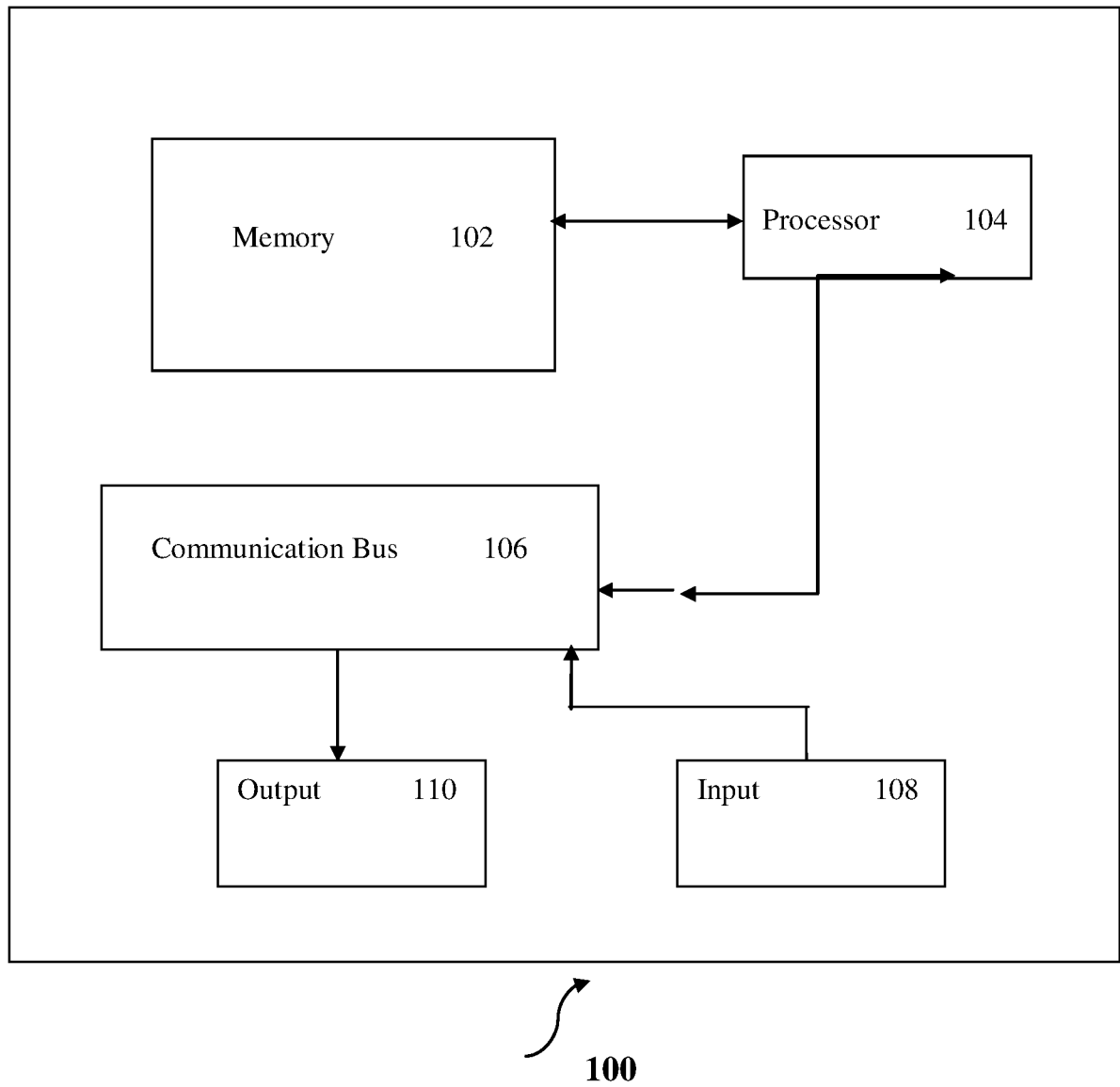
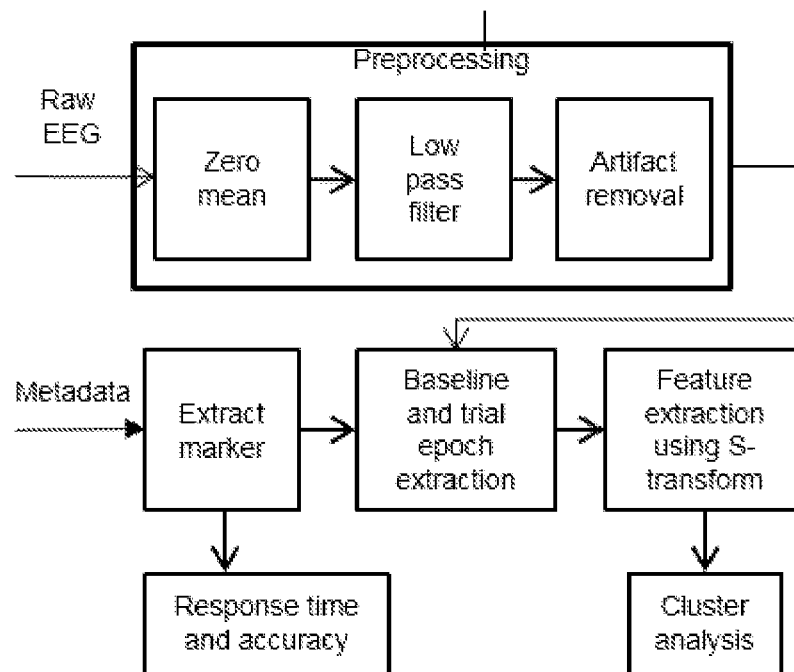


Figure 1

**Figure 2**

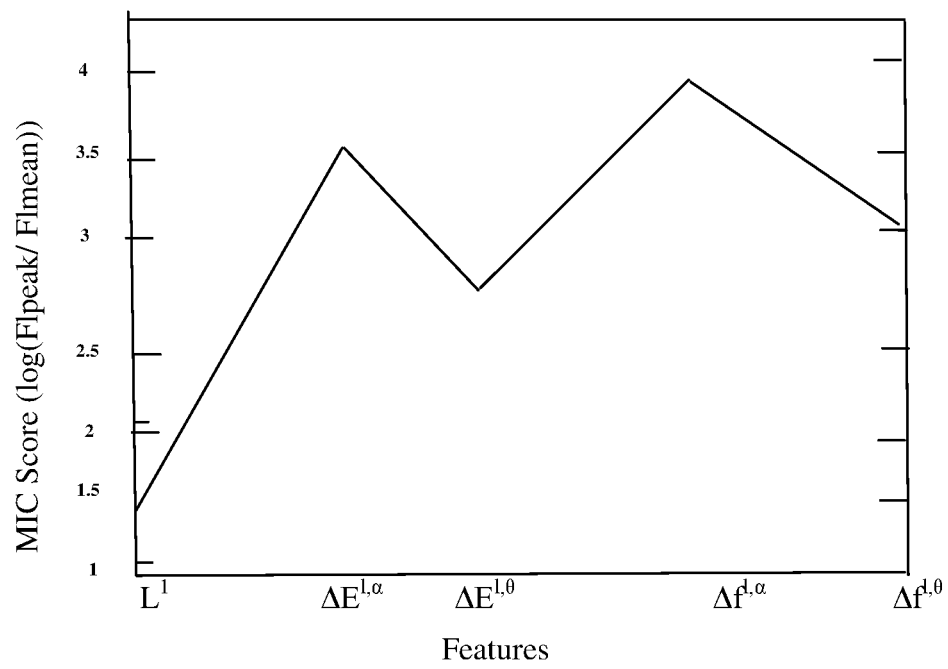


Figure 3

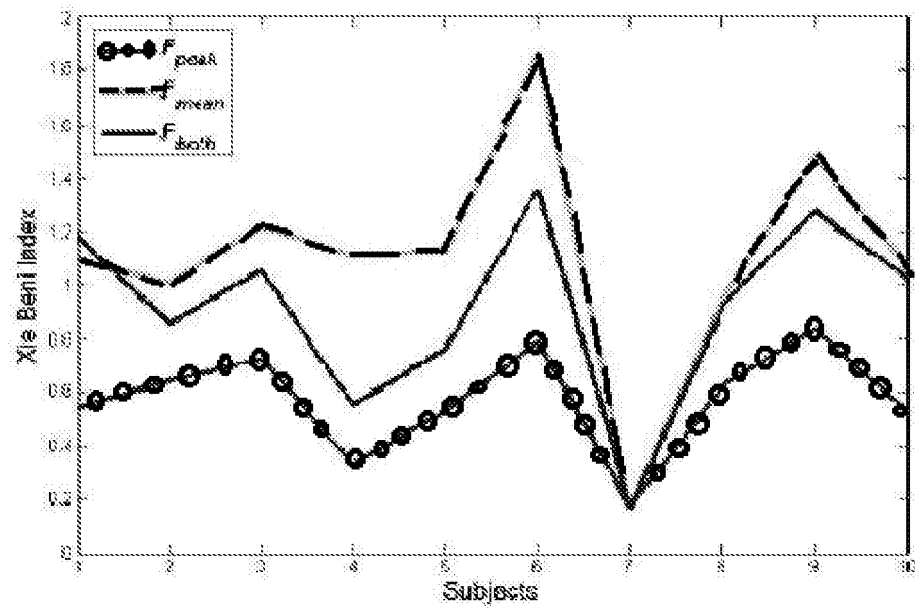


Figure 4

REFERENCES CITED IN THE DESCRIPTION

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Patent documents cited in the description

- US 2014242559 A [0006]

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- **ARIJIT SINHARAY ; DEBATRI CHATTERJEE ; ANIRUDDHA SINHA.** Evaluation of Different On-screen Keyboard Layouts Using EEG Signals. *IEEE International Conference on Systems, Man, and Cybernetics*, 13 October 2013, 480-486 [0006]

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摘要(译)

本公开设想了一种计算机实现的系统和方法，以通过脑电图（EEG）分析来推导基本认知任务（ECT）与个体的潜在认知技能之间的关系。目的是评估或改善受试者的感知认知特征，包括将给定任务分解为基本任务，然后将该基本任务映射到确定的Bloom分类法认知类别，然后进行聚类分析。之后，集群之间的分离指数确定了个人具有不同的思维过程，这是该主题的特征。

$$f(\omega) = \frac{\sum_{k=0}^{N-1} I_{\omega}(k) f(\omega_k)}{\sum_{k=0}^{N-1} I_{\omega}(k)}$$

(1)