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(54) **NEURAL MODEL-BASED CONTROLLER**

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(52) **U.S. Cl.**

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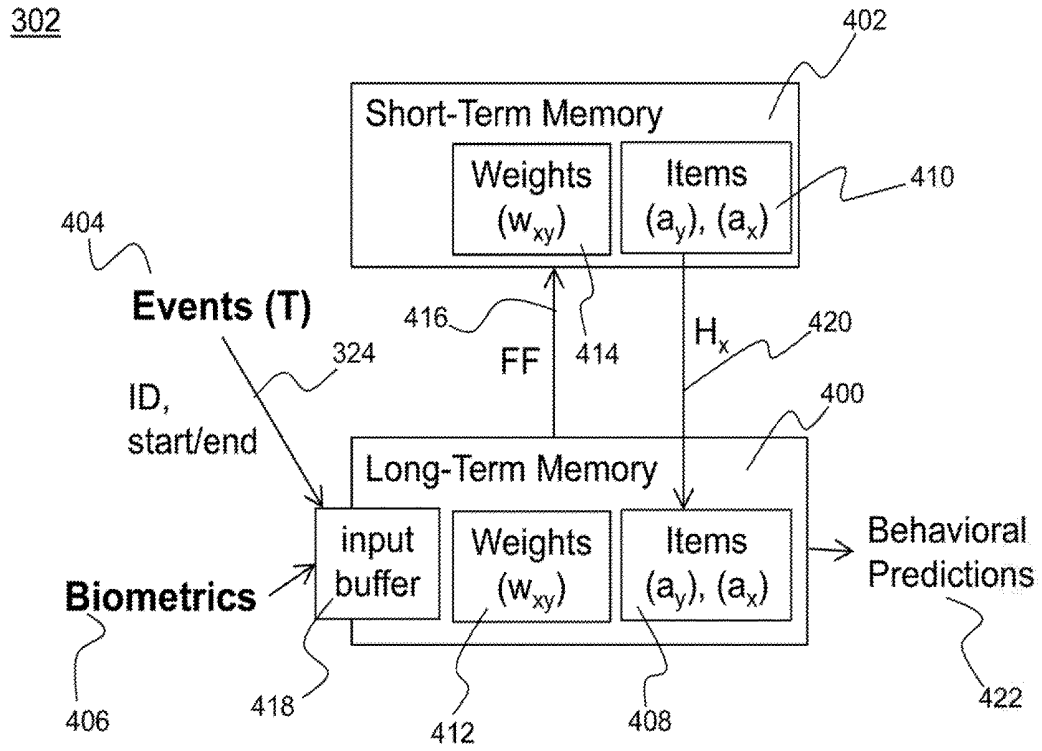
(57) **ABSTRACT**

Described is a system for memory improvement intervention. Based on both real-time EEG data and a neural model, the system simulates replay of a person's specific memory during a sleep state. Using the neural model, a prediction of behavioral performance of the replay of the specific memory is generated. If the prediction is below a first threshold, then using a memory enhancement intervention system, the system applies an intervention during the sleep state to improve consolidation of the specific memory. If the prediction is below a second threshold, the system reduces the intervention performed using the memory enhancement intervention system.



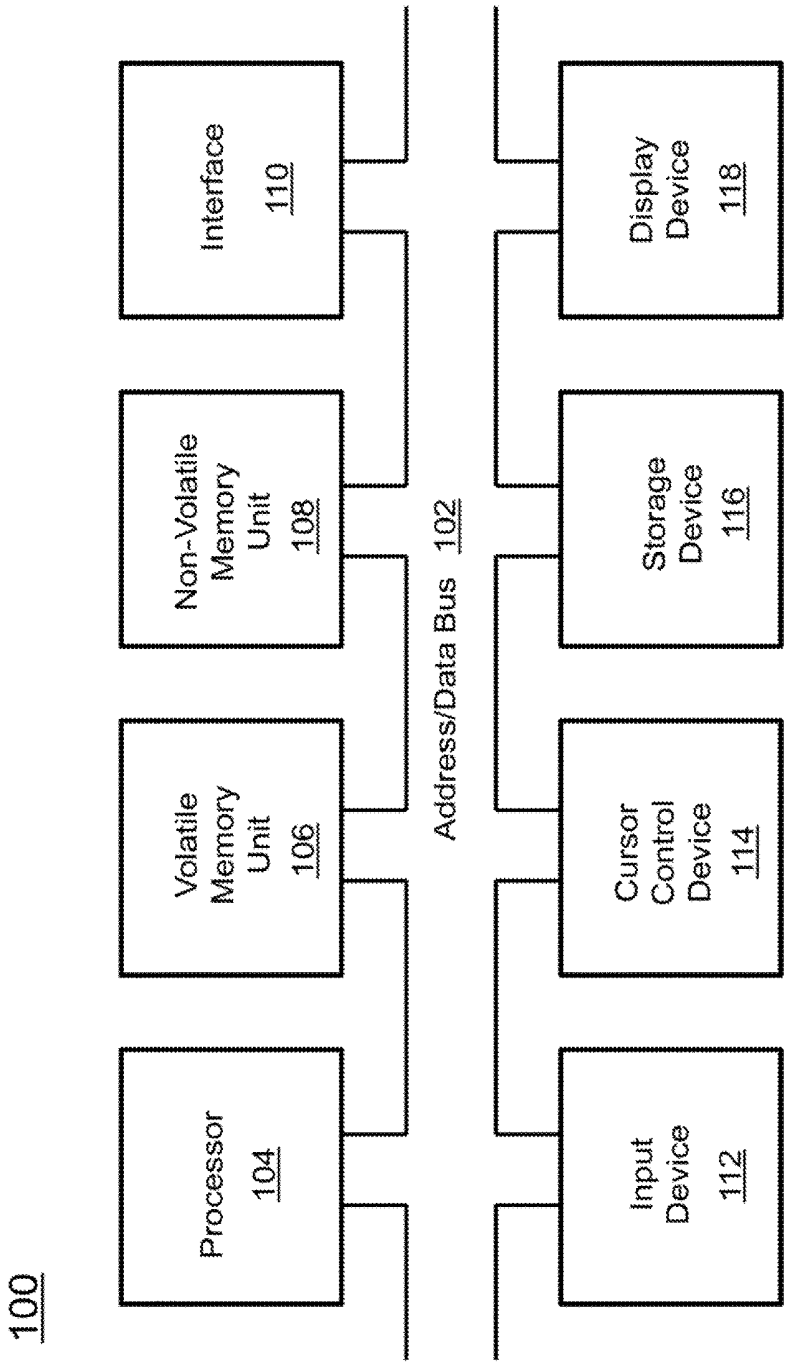

100
Processor 104
Volatile Memory Unit 106
Non-Volatile Memory Unit 108
Interface 110
Address/Data Bus 102
Input Device 112
Cursor Control Device 114
Storage Device 116
Display Device 118

FIG. 1

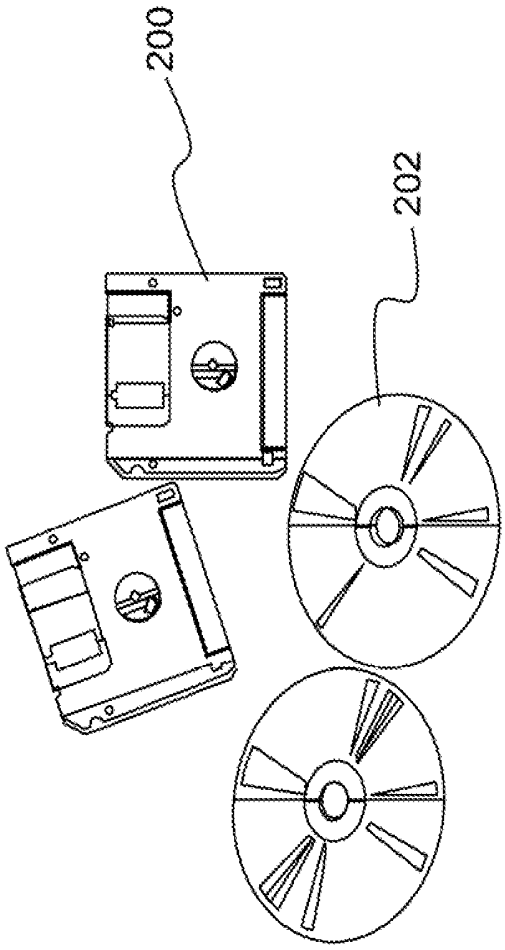
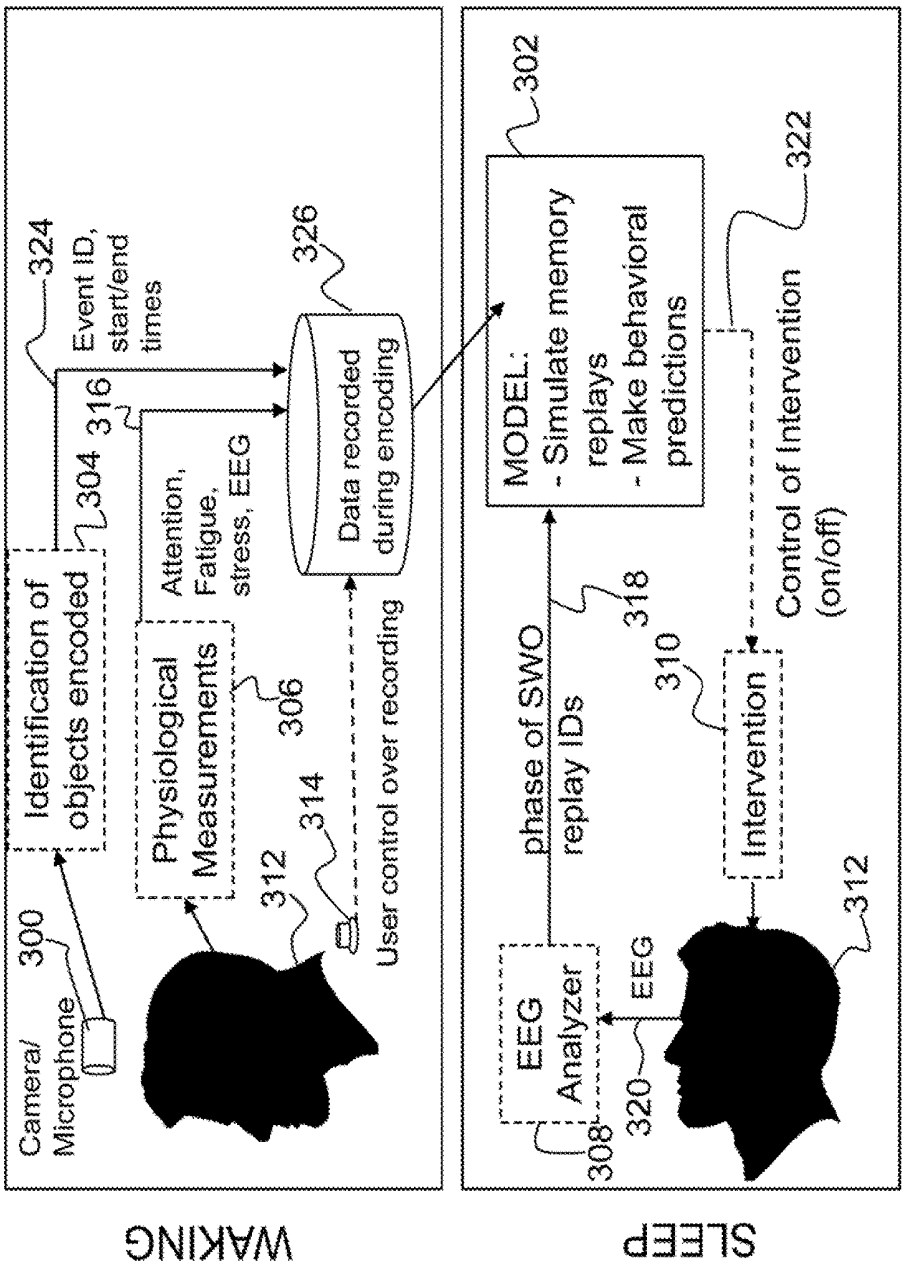


FIG. 2

FIG. 3A

FIG. 3B


WAKING
SLEEP
Camera/ Microphone
300
Identification of objects encoded
304
Physiological Measurements
306
Attention, Fatigue, stress, EEG
316
Event ID, start/end times
324
User control over recording
312
314
Data recorded during encoding
326
EEG Analyzer
308
EEG
320
phase of SWO
replay IDs
318
MODEL:
- Simulate memory replays
- Make behavioral predictions
302
Intervention
310
Control of Intervention (on/off)
322
312

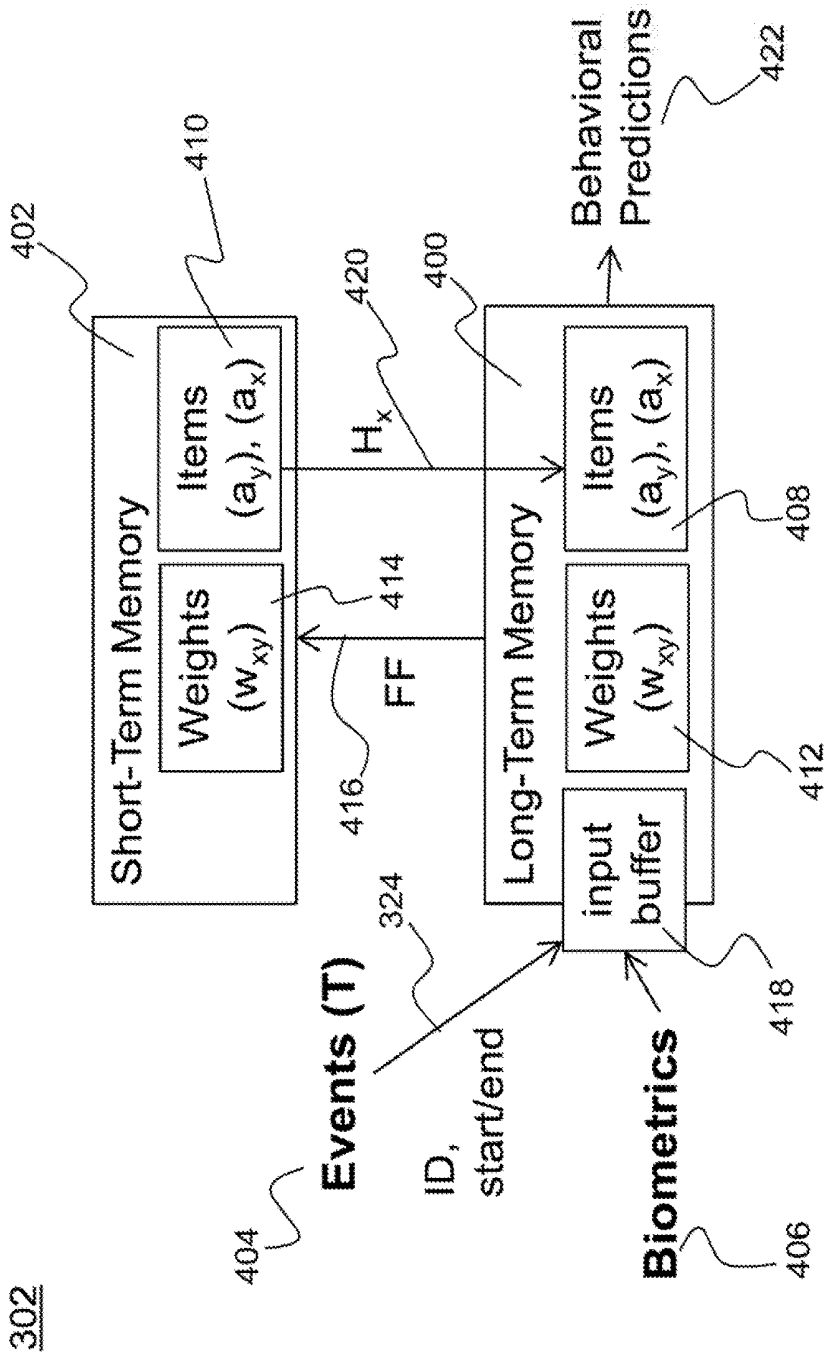

302
402
Short-Term Memory
Items
(a_y), (a_x)
Weights
(w_{xy})
410
414
416
FF
420
H_x
400
Long-Term Memory
Items
(a_y), (a_x)
Weights
(w_{xy})
input buffer
408
412
418
Behavioral Predictions
422
Events (T)
404
324
ID, start/end
Biometrics
406

FIG. 4

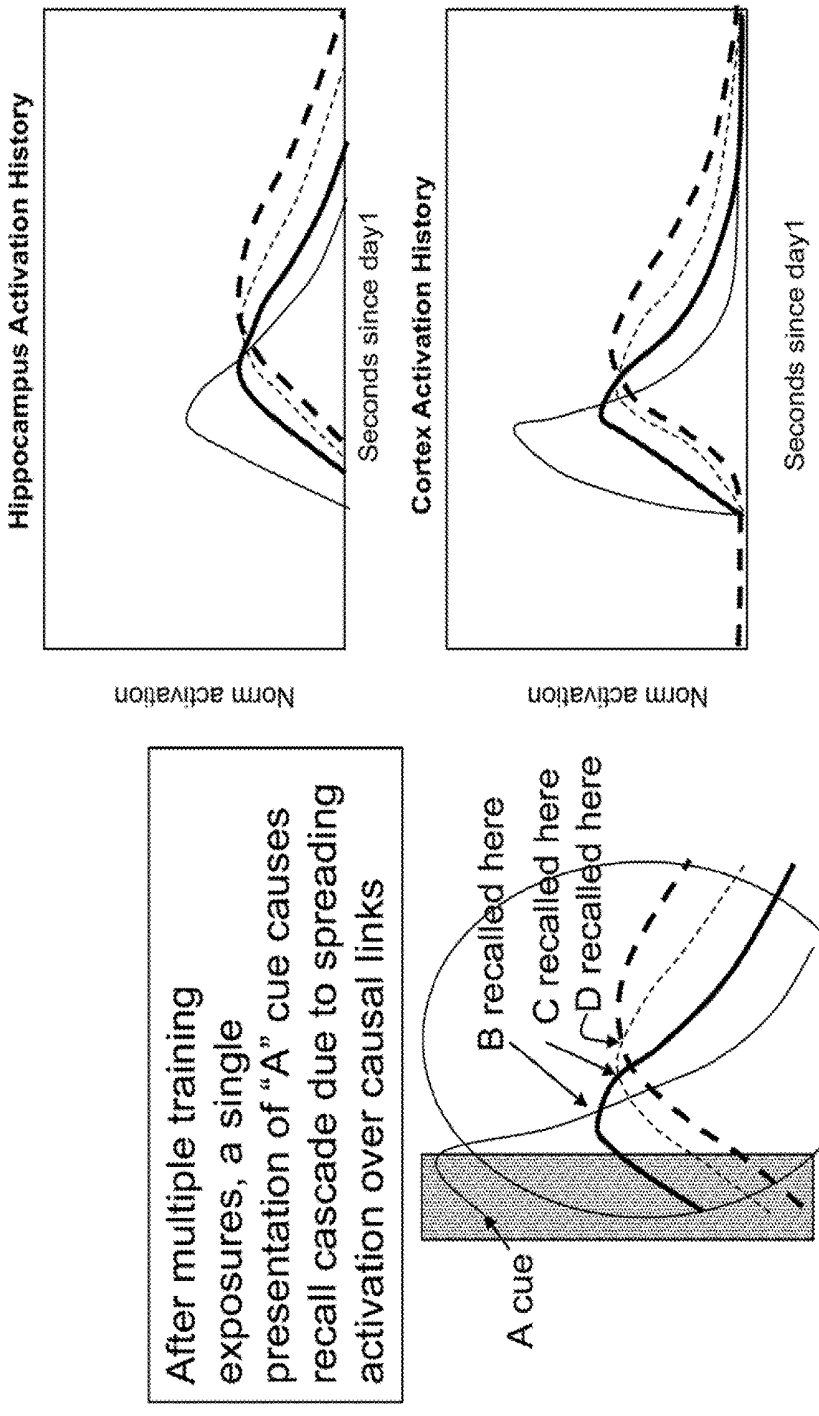

Hippocampus Activation History
Norm activation
Seconds since day1
Cortex Activation History
Norm activation
Seconds since day1
After multiple training exposures, a single presentation of "A" cue causes recall cascade due to spreading activation over causal links
B recalled here
C recalled here
D recalled here
A cue

FIG. 5

Param	Values
• η = *learning rate*	• η HC=2, COR=2/40
• α = strength of inactivation current	• α = 0.5
• β = strength of inhibition from other items	• β = 15
• γ = strength of excitation from weighted inputs to item	• γ = 20
• c_a = activation dynamics of item	• c_a = 20
• τ_a = activation decay rate^{-1}	• τ_a = 0.8
• ζ = feedback from HC to cortex	• ζ = 0.1
• λ = threshold on HC feedback	• λ = 0
• t_a= a_x threshold for self-activation to kick in	• t_a=.09
• $\delta_{ai,r}$ = strength of attention on goal relevant/irrelevant items	• δ_{ai} = 0
• μ = strength of feedforward inputs	• δ_{ar} = 0
	• μ HC=2, COR=1
Inactivation Current	***Inactivation***
• κ = dependence of inactivation current on f(x)	• κ = 1
• $f(x)$ = *function of activation level of item x*	• $f(x) = a_x$
• c_{xs} = dynamics of inactivation current	• c_{xs} = 5*c_a
• θ = strength of inactivation current	• θ = 20
• ex = degree of inactivation current sigmoid	• ex = 20
• τ_{xs}=inactivation decay rate^{-1}	• τ_{xs}=1.2

FIG. 6

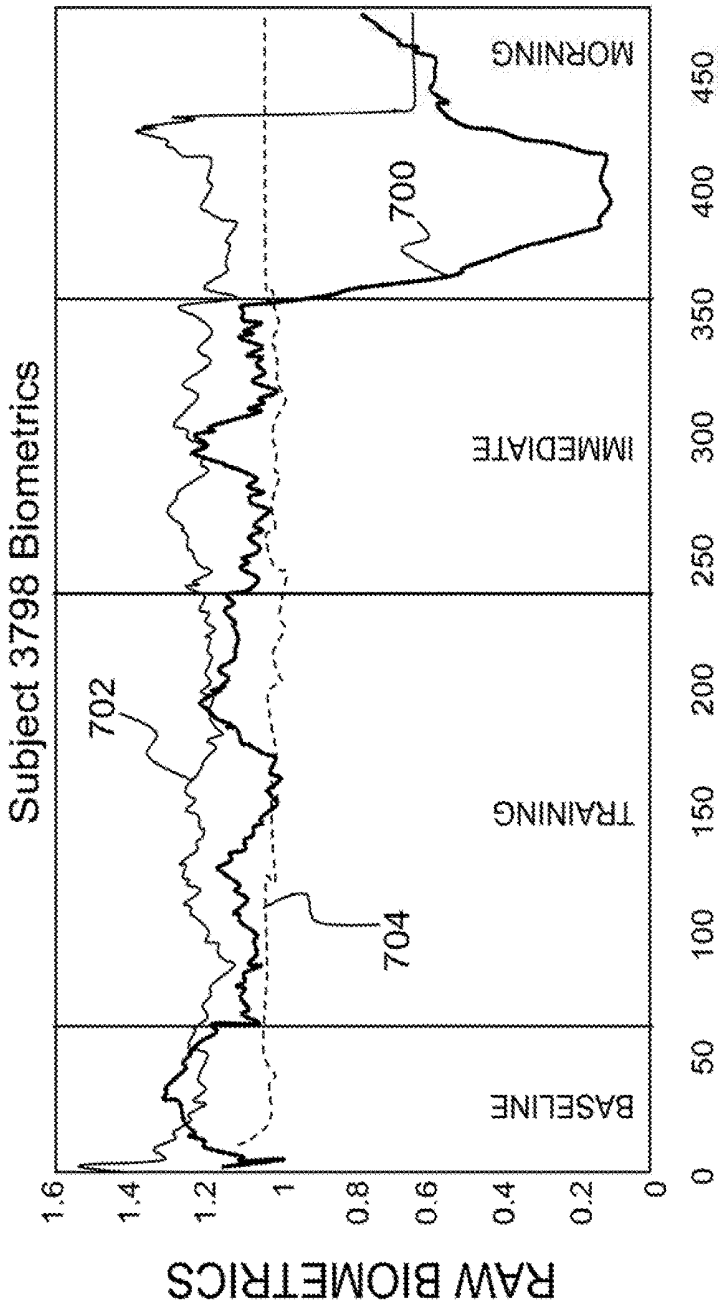

Subject 3798 Biometrics
RAW BIOMETRICS
Trial number
BASELINE
TRAINING
IMMEDIATE
MORNING
700
702
704
0
50
100
150
200
250
300
350
400
450
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6

FIG. 7

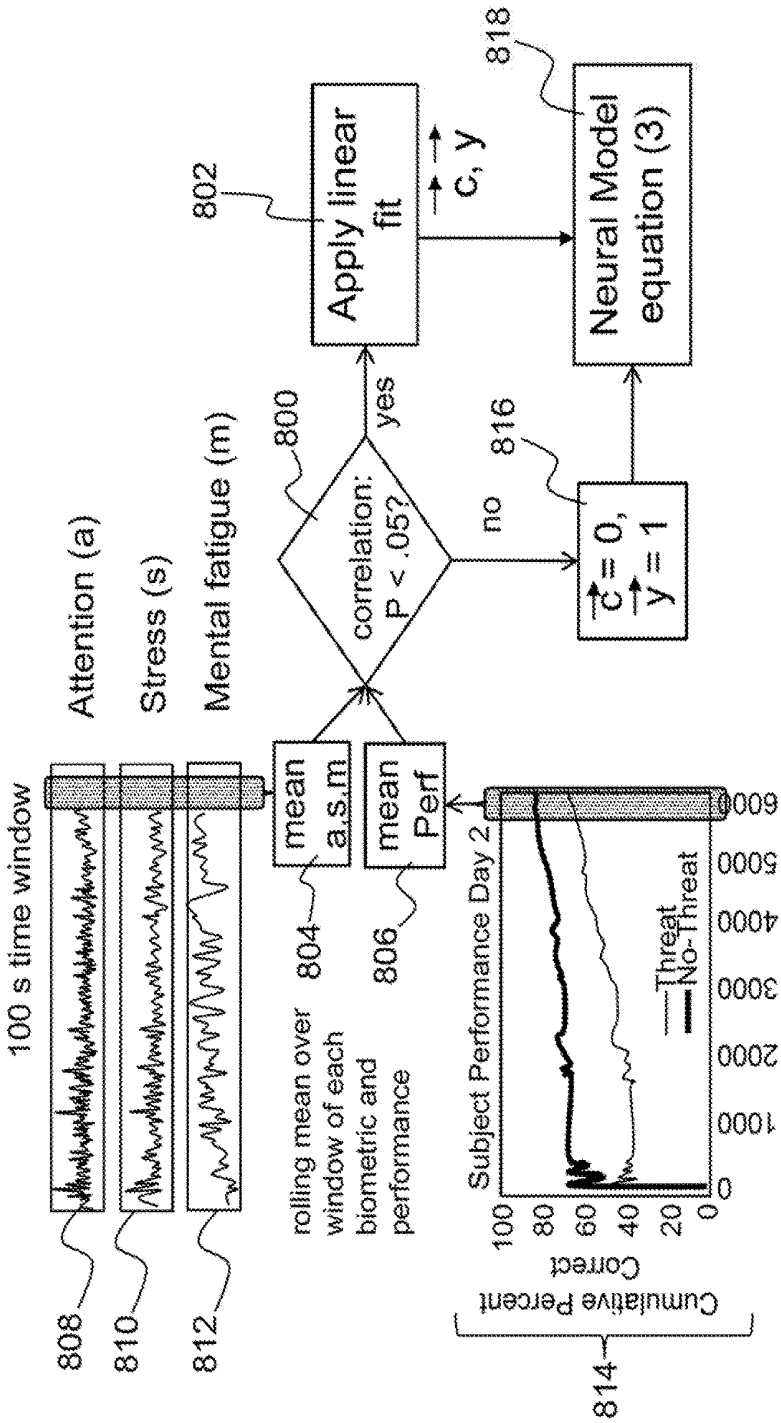

Attention (a)
Stress (s)
Mental fatigue (m)
100 s time window
808
810
812
mean a.s.m
mean Perf
804
806
rolling mean over window of each biometric and performance
800
correlation: P < .05?
yes
no
802
Apply linear fit
c, y
816
c = 0, y = 1
818
Neural Model equation (3)
Subject Performance Day 2
Threat
No-Threat
Cumulative Percent Correct
814

FIG. 8

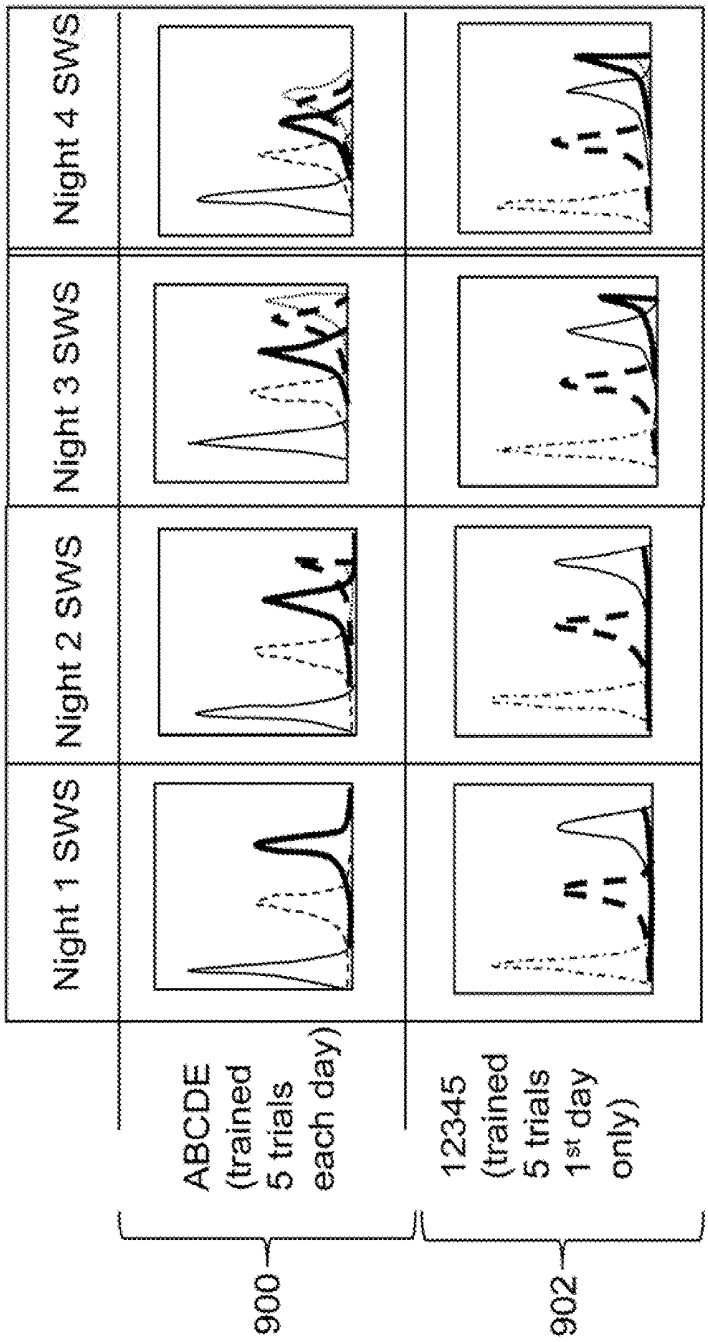

Night 1 SWS
Night 2 SWS
Night 3 SWS
Night 4 SWS
ABCDE (trained 5 trials each day)
12345 (trained 5 trials 1st day only)
900
902

FIG. 9

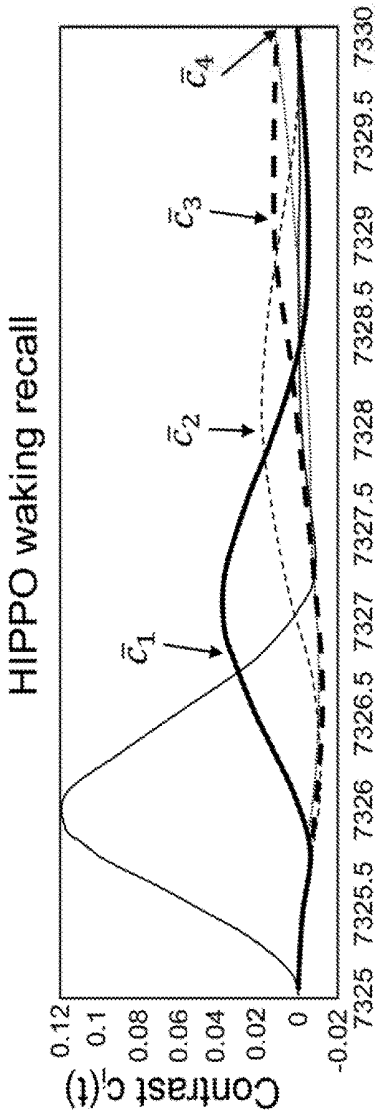


FIG. 10A

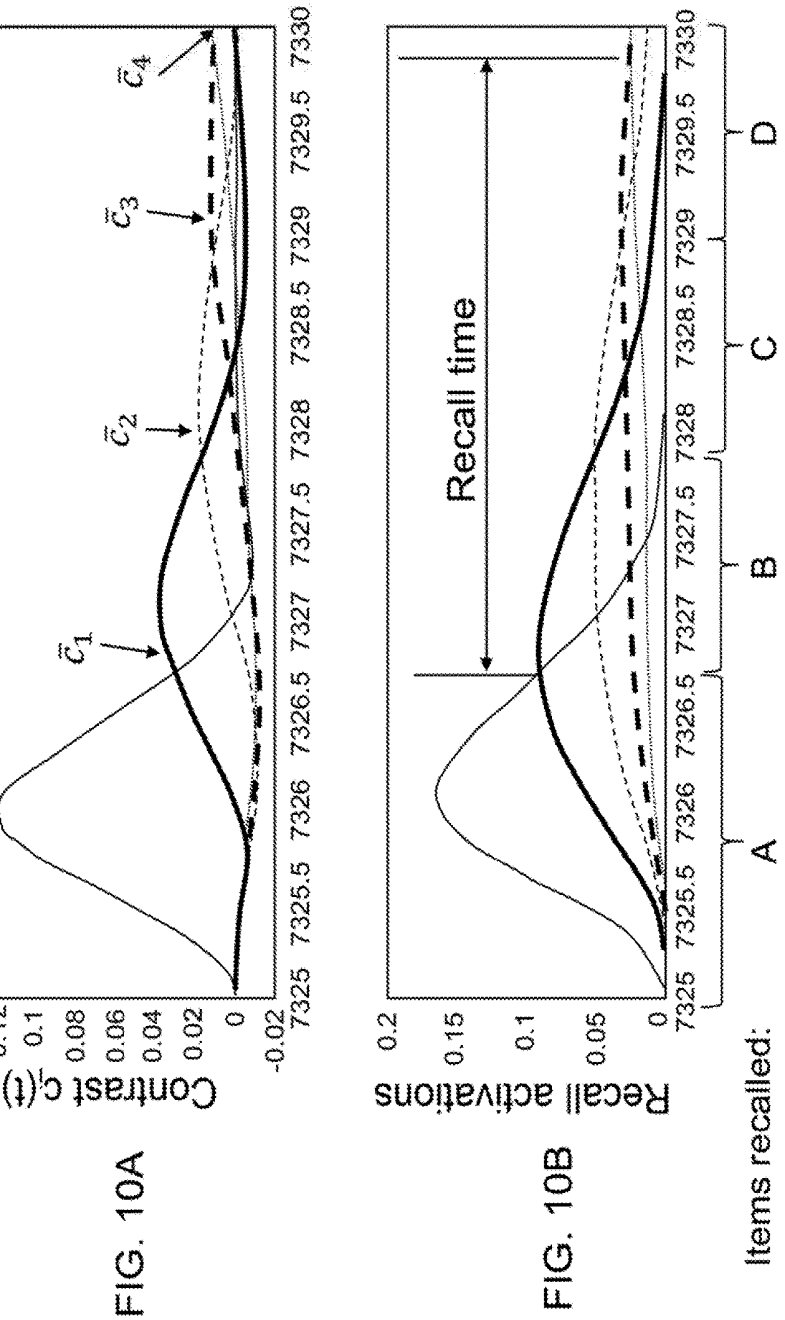
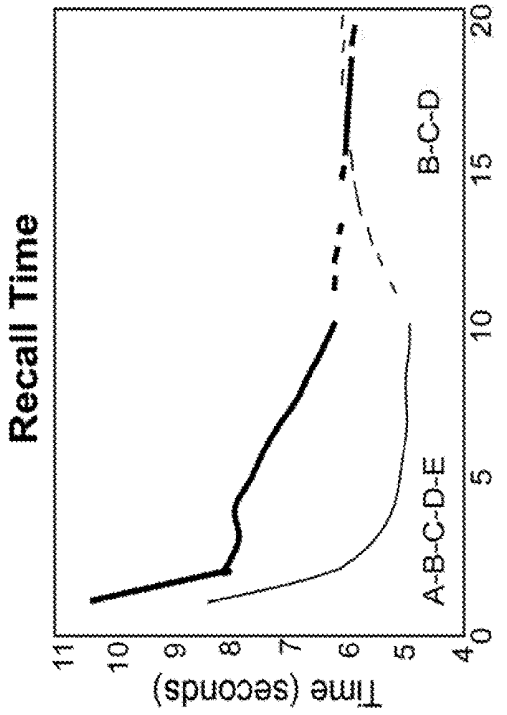
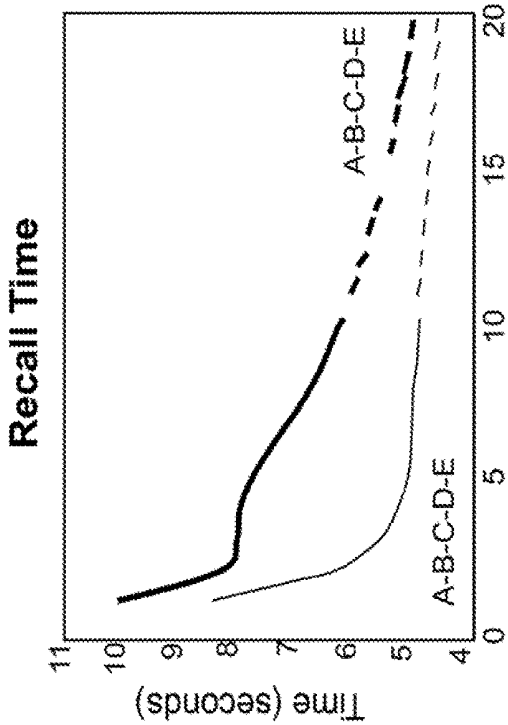


FIG. 10B



Complementary:
B-C-D

FIG. 11B



More practice with
A-B-C-D-E

FIG. 11A

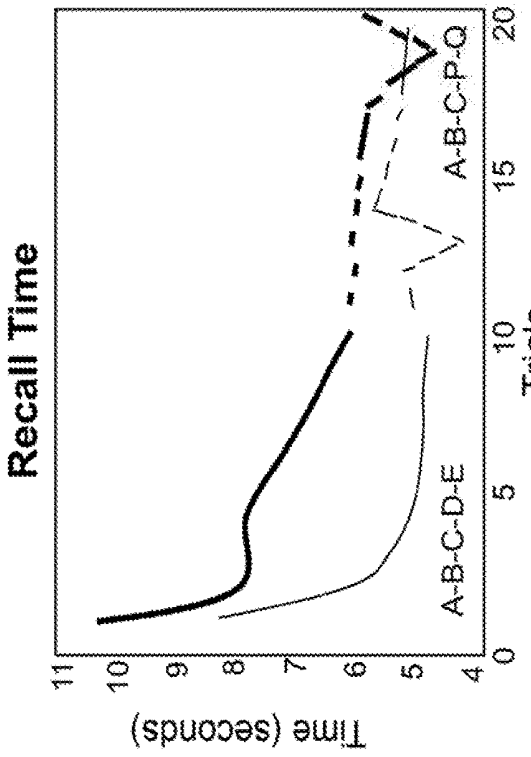


FIG. 11D

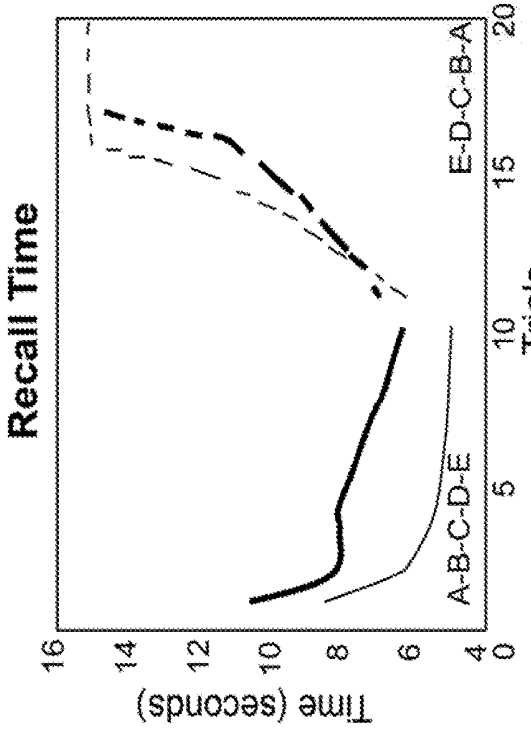
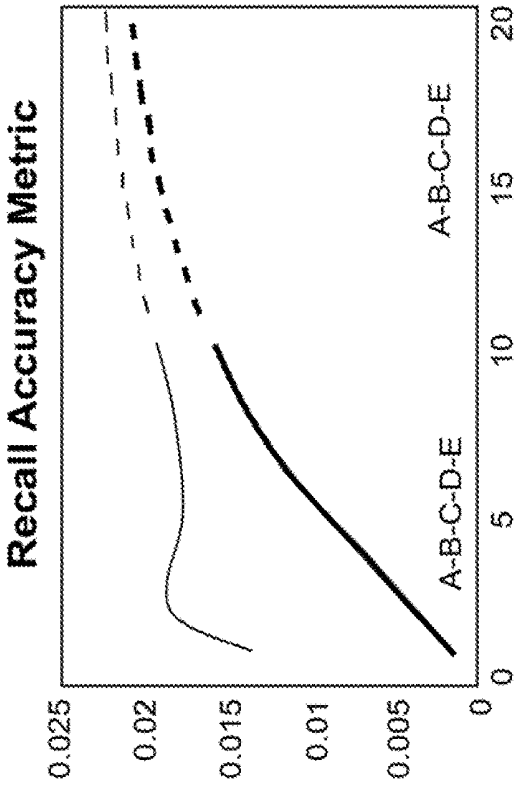
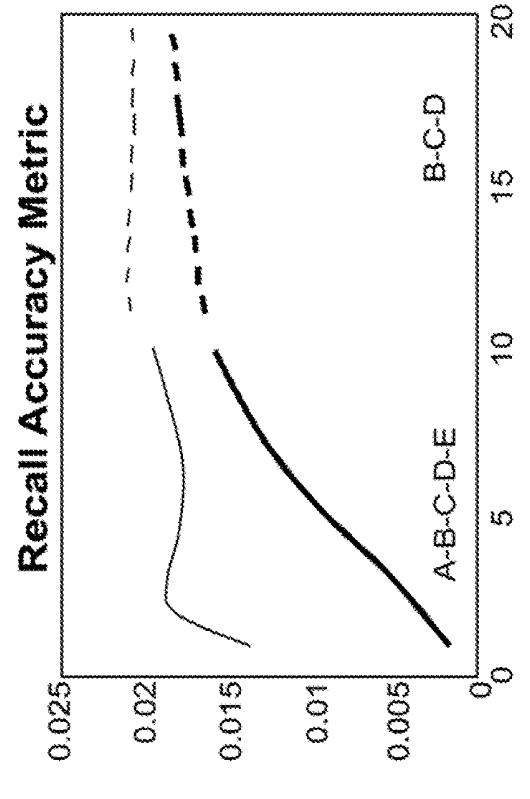


FIG. 11C



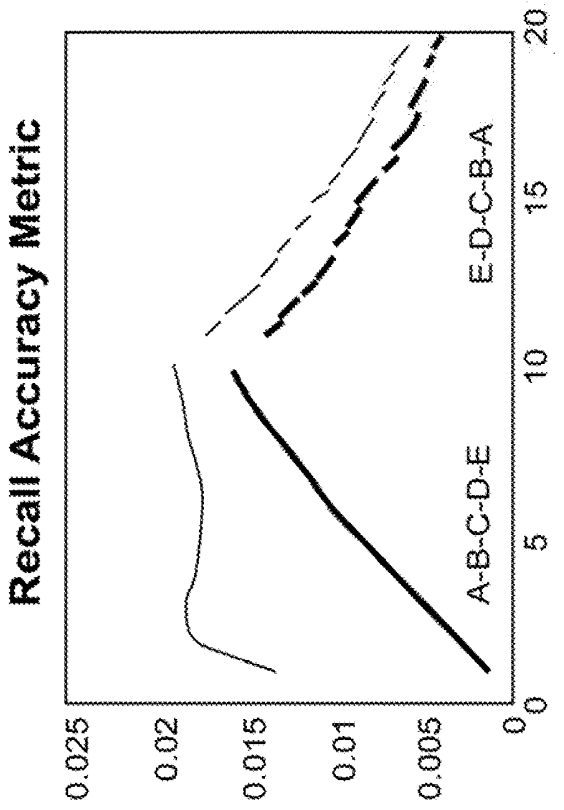
More practice with A-B-C-D-E

FIG. 12A



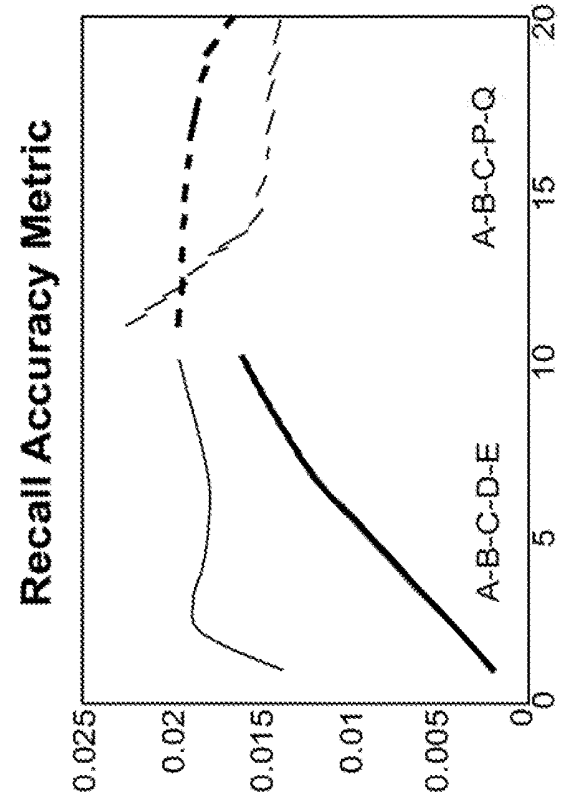
Complementary: B-C-D

FIG. 12B



Contradictory:
E-D-C-B-A

FIG. 12C



Part Complementary,
Part Contradictory

FIG. 12D

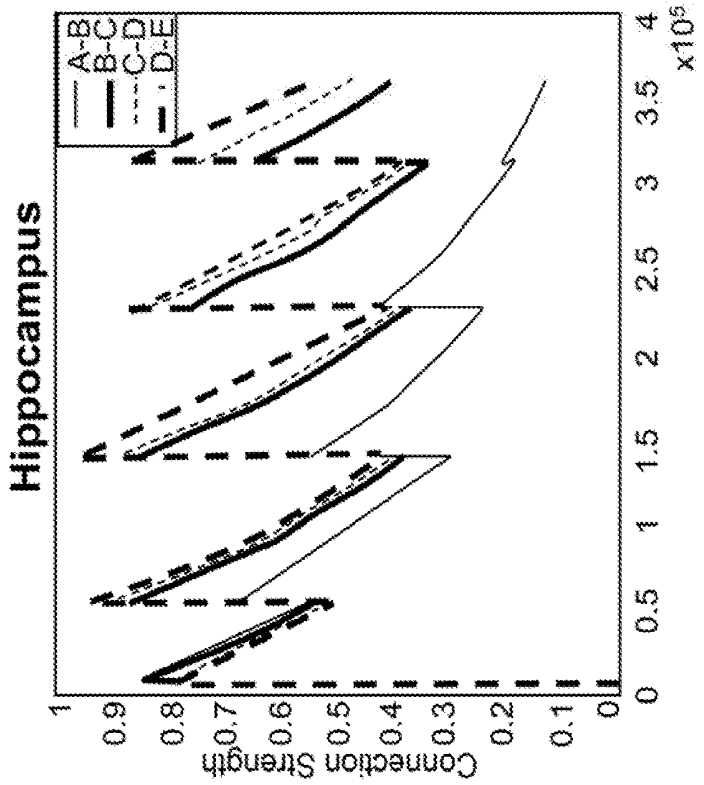


FIG. 13B

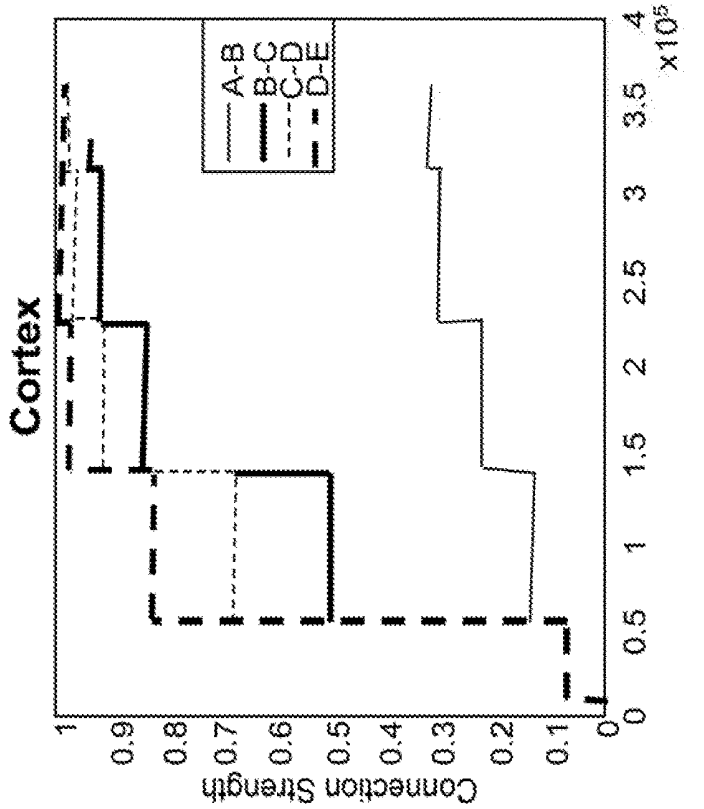


FIG. 13A

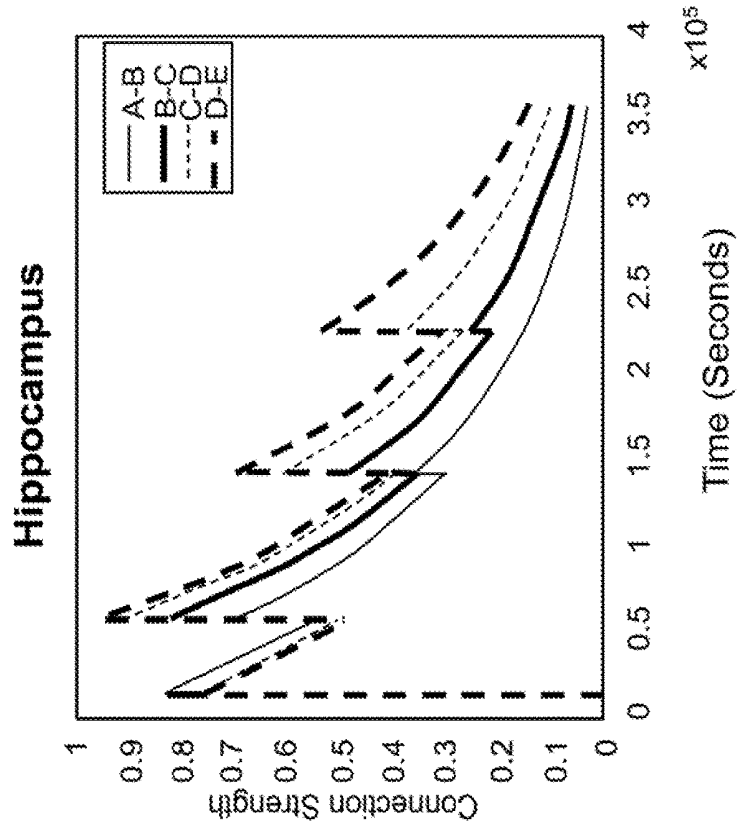


FIG. 13D

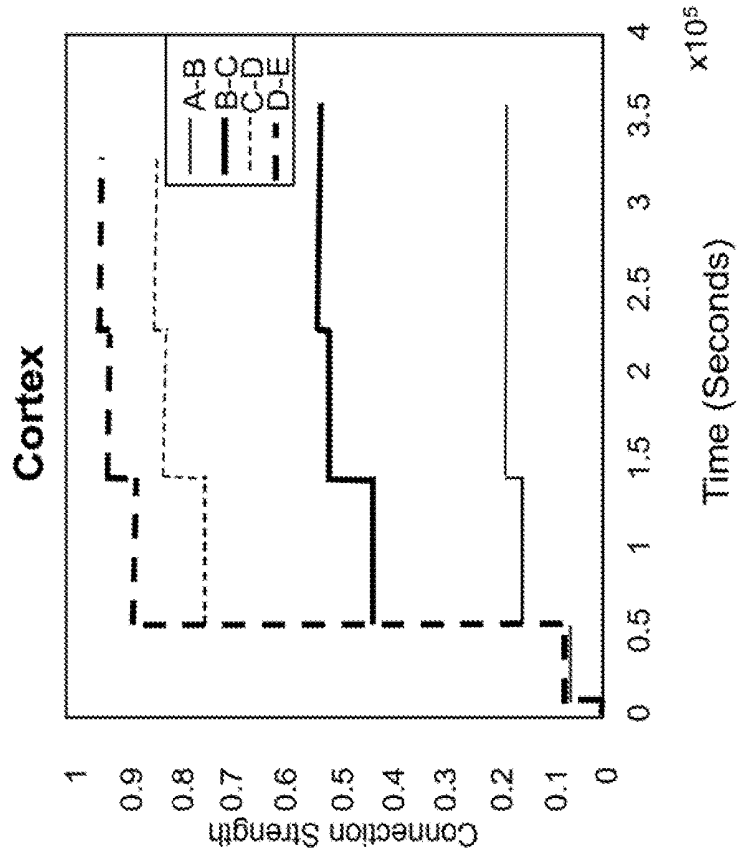


FIG. 13C

NEURAL MODEL-BASED CONTROLLER

CROSS-REFERENCE TO RELATED APPLICATIONS

[0001] This is a Continuation-in-Part patent application of U.S. application Ser. No. 15/332,787, filed in the United States on Oct. 24, 2016, entitled, "Method and System to Accelerate Consolidation of Specific Memories Using Transcranial Stimulation," which is a Non-Provisional patent application of 62/245,730, filed in the United States on Oct. 23, 2015, entitled, "Method and System to Accelerate Consolidation of Specific Memories Using Transcranial Stimulation," the entirety of which are hereby incorporated by reference.

[0002] This is ALSO a Continuation-in-Part patent application of U.S. application Ser. No. 15/682,065, filed in the United States on Aug. 21, 2017, entitled, "A Closed-Loop Model-Based Controller For Accelerating Memory And Skill Acquisition, which is a Non-Provisional patent application of U.S. Provisional Application No. 62/410,533, filed in the United States on Oct. 20, 2016, entitled, "A Closed-Loop Model-Based Controller for Accelerating Memory and Skill Acquisition," the entirety of which are hereby incorporated by reference.

[0003] This is ALSO a Non-Provisional patent application of U.S. Provisional Application No. 62/570,663, filed in the United States on Oct. 11, 2017, entitled, "System and Method for Predicting Performance," the entirety of which is hereby incorporated by reference.

[0004] This is ALSO a Non-Provisional patent application of U.S. Provisional Application No. 62/478,020, filed in the United States on Mar. 28, 2017, entitled, "A Neural Model-Based Controller," the entirety of which is hereby incorporated by reference.

GOVERNMENT LICENSE RIGHTS

[0005] This invention was made with government support under U.S. Government Contract Number W911NF-16-0018. The government may have certain rights in the invention.

BACKGROUND OF INVENTION

(1) Field of Invention

[0006] The present invention relates to a system for memory improvement intervention and, more particularly, to a system for memory improvement intervention using a realistic brain model.

(2) Description of Related Art

[0007] In state-of-the-art laboratory experiments, auditory or olfactory cues are associated with memory tasks during task performance, and these cues are then used during sleep to trigger replays of that task performance memory. For instance, Rudoy (see Literature Reference No. 1 of the List of Incorporated Literature References) reported memory retention rates on object location experiments with audio cues of 97% after 1.5 hours (hrs), which can be extrapolated to 4% after 48 hrs. Additionally, Diekelman (see Literature Reference No. 2) reported 84% retention on object location experiments with odor cues after 1.67 hrs, which can be extrapolated to 5% after 10 hrs. Further, Marshall (see Literature Reference No. 3) reported 90% retention after 8.5 hrs on paired associates tasks after 10 hrs using transcranial direct current stimulation (tDCS) cues, but Marshall's technique improved every memory; it did not target specific memories.

[0008] The prior art memory intervention techniques described above were only tested in a laboratory, under supervised sleep conditions. They were never intended for real-world use; only for research on memory consolidation. ACT-R (described in Literature Reference No. 5) is a notional model of long-term memory that makes predictions about probability and speed of recall and even localization of activated neural regions in functional magnetic resonance imaging (fMRI).

[0009] Thus, a continuing need exists for a model-based intervention system for modeling long-term memory as well as short-term, with explicit modeling of the effect of sleep replays on the consolidation of short-term memories into long-term for simulating the behavior improvement possible based on the treatment given so far, online, allowing a decision of whether the intervention should be continued or should be stopped.

SUMMARY OF INVENTION

[0010] The present invention relates to a system for memory improvement intervention and, more particularly, to a system for memory improvement intervention using a realistic brain model. The system comprises one or more processors and a non-transitory computer-readable medium having executable instructions encoded thereon such that when executed, the one or more processors perform multiple operations. Based on both real-time EEG data and a neural model, the system simulates replay of a person's specific memory during a sleep state. Using the neural model, a prediction of behavioral performance of the replay of the specific memory is generated. If the prediction is below a first threshold, then using a memory enhancement intervention system, an intervention is applied during the sleep state to improve consolidation of the specific memory. If the prediction is below a second threshold, the intervention performed is reduced using the memory enhancement intervention system.

[0011] In another aspect, the system further comprises a plurality of brain sensors to provide EEG signals and the memory enhancement intervention system, wherein the neural model is part of a closed-loop control system.

[0012] In another aspect, a recall metric is used to predict behavioral performance based on strengths of memories in the neural model.

[0013] In another aspect, the prediction is applied to the recall metric, and the first threshold and second threshold are values of the recall metric.

[0014] In another aspect, the system controls intervention that applies to the specific memory such that consolidation of other memories is also allowed to occur.

[0015] In another aspect, the neural model comprises a short-term memory store and a long-term memory store, wherein each memory store comprises a plurality of items, each item having an activation level that evolves dynamically over time, wherein while an item is active, it forms links with other items that are active at the same time, wherein the links are directional to represent an order in which the linked items are experienced.

[0016] In another aspect, the links are represented as weight values, and wherein weight values are updated based on the activation levels of the linked items.

[0017] In another aspect, recall is a function of the activation level of each item, wherein an item is considered recalled if its activation level rises above the other activations going on at the same time.

[0018] Finally, the present invention also includes a computer program product and a computer implemented method. The computer program product includes computer-readable instructions stored on a non-transitory computer-readable medium that are executable by a computer having one or more processors, such that upon execution of the instructions, the one or more processors perform the operations listed herein. Alternatively, the computer implemented method includes an act of causing a computer to execute such instructions and perform the resulting operations.

BRIEF DESCRIPTION OF THE DRAWINGS

[0019] The objects, features and advantages of the present invention will be apparent from the following detailed descriptions of the various aspects of the invention in conjunction with reference to the following drawings, where:

[0020] FIG. **1** is a block diagram depicting the components of a system for memory improvement intervention according to some embodiments of the present disclosure;

[0021] FIG. **2** is an illustration of a computer program product according to some embodiments of the present disclosure;

[0022] FIG. **3**A is an illustration of data being captured for model updating during waking according to some embodiments of the present disclosure;

[0023] FIG. **3**B is an illustration of the model simulating memory consolidation during sleep or quiet waking according to some embodiments of the present disclosure;

[0024] FIG. **4** is an illustration of the neural memory model simulating encoding, decay, consolidation, and recall of novel multi-modal experiences and knowledge in real-world environments according to some embodiments of the present disclosure;

[0025] FIG. **5** is an illustration of a cued recall cascade according to some embodiments of the present disclosure;

[0026] FIG. **6** is a table illustrating parameters for a neural model according to some embodiments of the present disclosure;

[0027] FIG. **7** is a plot illustrating raw biometric values for fatigue, stress, and attention extracted from an electroencephalogram subject according to some embodiments of the present disclosure;

[0028] FIG. **8** is an illustration of determining modulation parameters for biometric influence on model predictions according to some embodiments of the present disclosure;

[0029] FIG. **9** is an illustration of representative replays of two separate sequences trained over 4 days and 4 nights according to some embodiments of the present disclosure;

[0030] FIG. **10**A is a plot illustrating contrast on recalled items according to some embodiments of the present disclosure;

[0031] FIG. **10**B is a plot illustrating recall time on recalled items according to some embodiments of the present disclosure;

[0032] FIG. **11**A is a plot of a recall time metric for a more practice condition according to some embodiments of the present disclosure;

[0033] FIG. **11**B is a plot of a recall time metric for a complementary condition according to some embodiments of the present disclosure;

[0034] FIG. **11**C is a plot of a recall time metric for a contradictory condition according to some embodiments of the present disclosure;

[0035] FIG. **11**D is a plot of a recall time metric for a part complementary, part contradictory condition according to some embodiments of the present disclosure;

[0036] FIG. **12**A is a plot of a recall accuracy metric for a more practice condition according to some embodiments of the present disclosure;

[0037] FIG. **12**B is a plot of a recall accuracy metric for a complementary condition according to some embodiments of the present disclosure;

[0038] FIG. **12**C is a plot of a recall accuracy metric for a contradictory condition according to some embodiments of the present disclosure;

[0039] FIG. **12**D is a plot of a recall accuracy metric for a part complementary, part contradictory condition according to some embodiments of the present disclosure;

[0040] FIG. **13**A is a plot of connection strength in the cortex without interference according to some embodiments of the present disclosure;

[0041] FIG. **13**B is a plot of connection strength in the hippocampus without interference according to some embodiments of the present disclosure;

[0042] FIG. **13**C is a plot of connection strength in the cortex with interference according to some embodiments of the present disclosure; and

[0043] FIG. **13**D is a plot of connection strength in the hippocampus with interference according to some embodiments of the present disclosure.

DETAILED DESCRIPTION

[0044] The present invention relates to a system for memory improvement intervention and, more particularly, to a system for memory improvement intervention using a realistic brain model. The following description is presented to enable one of ordinary skill in the art to make and use the invention and to incorporate it in the context of particular applications. Various modifications, as well as a variety of uses in different applications will be readily apparent to those skilled in the art, and the general principles defined herein may be applied to a wide range of aspects. Thus, the present invention is not intended to be limited to the aspects presented, but is to be accorded the widest scope consistent with the principles and novel features disclosed herein.

[0045] In the following detailed description, numerous specific details are set forth in order to provide a more thorough understanding of the present invention. However, it will be apparent to one skilled in the art that the present invention may be practiced without necessarily being limited to these specific details. In other instances, well-known structures and devices are shown in block diagram form, rather than in detail, in order to avoid obscuring the present invention.

[0046] The reader's attention is directed to all papers and documents which are filed concurrently with this specification and which are open to public inspection with this specification, and the contents of all such papers and docu-

ments are incorporated herein by reference. All the features disclosed in this specification, (including any accompanying claims, abstract, and drawings) may be replaced by alternative features serving the same, equivalent or similar purpose, unless expressly stated otherwise. Thus, unless expressly stated otherwise, each feature disclosed is one example only of a generic series of equivalent or similar features.

[0047] Furthermore, any element in a claim that does not explicitly state "means for" performing a specified function, or "step for" performing a specific function, is not to be interpreted as a "means" or "step" clause as specified in 35 U.S.C. Section 112, Paragraph 6. In particular, the use of "step of" or "act of" in the claims herein is not intended to invoke the provisions of 35 U.S.C. 112, Paragraph 6.

[0048] Before describing the invention in detail, first a list of cited references is provided. Next, a description of the various principal aspects of the present invention is provided. Finally, specific details of various embodiment of the present invention are provided to give an understanding of the specific aspects.

[0049] (1) List of Incorporated Literature References

[0050] The following references are cited and incorporated throughout this application. For clarity and convenience, the references are listed herein as a central resource for the reader. The following references are hereby incorporated by reference as though fully set forth herein. The references are cited in the application by referring to the corresponding literature reference number as follows:

[0051] 1. Rudoy J D, Voss J L, Westerberg C E, Paller K A. Strengthening Individual Memories by Reactivating Them During Sleep. Science. 2009; 326:1079-1079.

[0052] 2. Diekelmann S, Biggel S, Rasch B, Born J. Offline consolidation of memory varies with time in slow wave sleep and can be accelerated by curing memory reactivations. Neurobiol. Learn. Mem. 2012; 98:103-111.

[0053] 3. Marshall L, Helgadóttir H, Mölle M, Born J. Boosting slow oscillations during sleep potentiates memory. Nature. 2006; 444: 610-613.

[0054] 4. Jaar O, Pilon M, Carrier J, Montplaisir J, Zadra A. Analysis of Slow-Wave Activity and Slow-Wave Oscillations Prior to Somnambulism. Sleep. 2010; 33:1511-1516.

[0055] 5. Anderson, J. R., Bothell, D., Byrne, M. D., Douglass, S., Lebiere, C., & Qin, Y. An integrated theory of the mind. Psychological Review. 2004; 111, 4: 1036-1060.

[0056] 6. Hassabis D., Chu C., Rees G., Weiskopf N., Molyneux P. D., Maguire E. A. Decoding Neuronal Ensembles in the Human Hippocampus. Current Biology. 2009; 19(7-3):546-554.

[0057] (2) Principal Aspects

[0058] Various embodiments of the invention include three "principal" aspects. The first is a system for memory improvement intervention. The system is typically in the form of a computer system operating software or in the form of a "hard-coded" instruction set. This system may be incorporated into a wide variety of devices that provide different functionalities. The second principal aspect is a method, typically in the form of software, operated using a data processing system (computer). The third principal aspect is a computer program product. The computer program product generally represents computer-readable instructions stored on a non-transitory computer-readable medium such as an optical storage device, e.g., a compact disc (CD) or digital versatile disc (DVD), or a magnetic storage device such as a floppy disk or magnetic tape. Other, non-limiting examples of computer-readable media include hard disks, read-only memory (ROM), and flash-type memories. These aspects will be described in more detail below.

[0059] A block diagram depicting an example of a system (i.e., computer system **100**) of the present invention is provided in FIG. **1**. The computer system **100** is configured to perform calculations, processes, operations, and/or functions associated with a program or algorithm. In one aspect, certain processes and steps discussed herein are realized as a series of instructions (e.g., software program) that reside within computer readable memory units and are executed by one or more processors of the computer system **100**. When executed, the instructions cause the computer system **100** to perform specific actions and exhibit specific behavior, such as described herein.

[0060] The computer system **100** may include an address/data bus **102** that is configured to communicate information. Additionally, one or more data processing units, such as a processor **104** (or processors), are coupled with the address/data bus **102**. The processor **104** is configured to process information and instructions. In an aspect, the processor **104** is a microprocessor. Alternatively, the processor **104** may be a different type of processor such as a parallel processor, application-specific integrated circuit (ASIC), programmable logic array (PLA), complex programmable logic device (CPLD), or a field programmable gate array (FPGA).

[0061] The computer system **100** is configured to utilize one or more data storage units. The computer system **100** may include a volatile memory unit **106** (e.g., random access memory ("RAM"), static RAM, dynamic RAM, etc.) coupled with the address/data bus **102**, wherein a volatile memory unit **106** is configured to store information and instructions for the processor **104**. The computer system **100** further may include a non-volatile memory unit **108** (e.g., read-only memory ("ROM"), programmable ROM ("PROM"), erasable programmable ROM ("EPROM"), electrically erasable programmable ROM "EEPROM"), flash memory, etc.) coupled with the address/data bus **102**, wherein the non-volatile memory unit **108** is configured to store static information and instructions for the processor **104**. Alternatively, the computer system **100** may execute instructions retrieved from an online data storage unit such as in "Cloud" computing. In an aspect, the computer system **100** also may include one or more interfaces, such as an interface **110**, coupled with the address/data bus **102**. The one or more interfaces are configured to enable the computer system **100** to interface with other electronic devices and computer systems. The communication interfaces implemented by the one or more interfaces may include wireline (e.g., serial cables, modems, network adaptors, etc.) and/or wireless (e.g., wireless modems, wireless network adaptors, etc.) communication technology.

[0062] In one aspect, the computer system **100** may include an input device **112** coupled with the address/data bus **102**, wherein the input device **112** is configured to communicate information and command selections to the processor **100**. In accordance with one aspect, the input device **112** is an alphanumeric input device, such as a keyboard, that may include alphanumeric and/or function keys. Alternatively, the input device **112** may be an input device other than an alphanumeric input device. In an

aspect, the computer system **100** may include a cursor control device **114** coupled with the address/data bus **102**, wherein the cursor control device **114** is configured to communicate user input information and/or command selections to the processor **100**. In an aspect, the cursor control device **114** is implemented using a device such as a mouse, a track-ball, a track-pad, an optical tracking device, or a touch screen. The foregoing notwithstanding, in an aspect, the cursor control device **114** is directed and/or activated via input from the input device **112**, such as in response to the use of special keys and key sequence commands associated with the input device **112**. In an alternative aspect, the cursor control device **114** is configured to be directed or guided by voice commands.

[0063] In an aspect, the computer system **100** further may include one or more optional computer usable data storage devices, such as a storage device **116**, coupled with the address/data bus **102**. The storage device **116** is configured to store information and/or computer executable instructions. In one aspect, the storage device **116** is a storage device such as a magnetic or optical disk drive (e.g., hard disk drive ("HDD"), floppy diskette, compact disk read only memory ("CD-ROM"), digital versatile disk ("DVD")). Pursuant to one aspect, a display device **118** is coupled with the address/data bus **102**, wherein the display device **118** is configured to display video and/or graphics. In an aspect, the display device **118** may include a cathode ray tube ("CRT"), liquid crystal display ("LCD"), field emission display ("FED"), plasma display, or any other display device suitable for displaying video and/or graphic images and alphanumeric characters recognizable to a user.

[0064] The computer system **100** presented herein is an example computing environment in accordance with an aspect. However, the non-limiting example of the computer system **100** is not strictly limited to being a computer system. For example, an aspect provides that the computer system **100** represents a type of data processing analysis that may be used in accordance with various aspects described herein. Moreover, other computing systems may also be implemented. Indeed, the spirit and scope of the present technology is not limited to any single data processing environment. Thus, in an aspect, one or more operations of various aspects of the present technology are controlled or implemented using computer-executable instructions, such as program modules, being executed by a computer. In one implementation, such program modules include routines, programs, objects, components and/or data structures that are configured to perform particular tasks or implement particular abstract data types. In addition, an aspect provides that one or more aspects of the present technology are implemented by utilizing one or more distributed computing environments, such as where tasks are performed by remote processing devices that are linked through a communications network, or such as where various program modules are located in both local and remote computer-storage media including memory-storage devices.

[0065] An illustrative diagram of a computer program product (i.e., storage device) embodying the present invention is depicted in FIG. **2**. The computer program product is depicted as floppy disk **200** or an optical disk **202** such as a CD or DVD. However, as mentioned previously, the computer program product generally represents computer-readable instructions stored on any compatible non-transitory computer-readable medium. The term "instructions" as used with respect to this invention generally indicates a set of operations to be performed on a computer, and may represent pieces of a whole program or individual, separable, software modules. Non-limiting examples of "instruction" include computer program code (source or object code) and "hard-coded" electronics (i.e. computer operations coded into a computer chip). The "instruction" is stored on any non-transitory computer-readable medium, such as in the memory of a computer or on a floppy disk, a CD-ROM, and a flash drive. In either event, the instructions are encoded on a non-transitory computer-readable medium.

[0066] (3) Specific Details of Various Embodiments

[0067] Described is a detailed model of the way that humans learn new sequences of actions and skills. Specifically, the model is in terms of how the representations in the brain are initially encoded into connections between ensembles in volatile short-term memory in the hippocampus, and then gradually get consolidated into more stable and persistent connections in the cortex. This model expands upon one disclosed as part of a closed-loop model-based control system in U.S. Non-Provisional application Ser. No. 15/682,065 (hereinafter referred to as the '065 application), which is hereby incorporated by reference as though fully set forth herein. The model described herein is critical for coordinating with natural consolidation processes to avoid unnecessary interventions by prioritizing skills predicted to perform below desired levels (e.g., memories of specific things that must be learned quickly and remembered clearly and easily).

[0068] The model described herein simulates, at a detailed neural ensemble level, the encoding and consolidation of memories, and makes predictions of the resulting behavioral performance (i.e., the subsequent ability to recall and use memories of interest). Used in a control loop with brain sensors and the intervention system, this model turns on the intervention when the behavioral predictions are below a desired level (e.g., a first threshold), and turns it off when behavioral predictions surpass a threshold of performance (e.g., a second threshold). The first threshold and second threshold may be the same or different. Since there are many memories that need to be consolidated during the night, an intervention to improve one specific memory must not prevent consolidation of other memories; this is one benefit of the model-based controller according to embodiments of the present disclosure. Importantly, the model updates its representations and makes new predictions very quickly and efficiently. Such a control system for a memory improvement intervention, using a realistic brain model to decide when interventions are needed during sleep, has never been conceived.

[0069] The model-based controller (elements **302** and **322**) is the software memory simulation that runs on a processor and predicts the behavioral performance level related to a specific memory. Note that the intervention module (element **310**) associates a cue with a memory during waking. However, then during sleep, it must apply that cue to promote replays of the memory during slow-wave-sleep. Without the invention described herein, the intervention is applied blindly; there is no way to know whether the memory is sufficiently consolidated to get the desired level of performance. When the intervention is operating, other memories (e.g., people the user has met, things the user has learned) can't be consolidated. Therefore, the system according to embodiments of the present disclo-

sure predicts when the user has sufficiently consolidated the memory of interest, and then stops the intervention so the user can consolidate other memories.

[0070] In operational tasks (as in many business and educational scenarios), it can be critically important to quickly integrate new information (based on limited exposure) and accurately recall it. The purpose of the invention described herein is to control interventions that enhance memory consolidation to make this possible. It is widely accepted that memories are consolidated during sleep, and a few prior art laboratory experiments have implemented some targeted interventions. However, the system according to embodiments of the present disclosure is the first to implement a control loop around an intervention in order to control exactly when an intervention should be applied in order to achieve the desired level of performance.

[0071] The invention will automatically determine if and when certain interventions should be applied during sleep and quiet waking periods. The system does this by predicting behavioral performance outcomes resulting from memory replay activity during quiet waking or slow wave sleep (within the 0.5-1.2 Hertz (Hz) frequency band of slow wave oscillations), thereby allowing selection of the best replay intervention options to achieve a desired performance. When the predicted performance reaches a desired level, the model turns off the interventions, allowing other memories to be consolidated. The model is shaped by the sequence and content of all experienced stimuli in a situation paradigm, as well as the characteristics of prior replay events. Thus, it can predict the impact that further intervention will have on behavior. Without the control system described herein, the interventions during sleep to improve consolidation of a specific memory or memories are uninformed, because there is no way to get feedback on behavioral performance until the subject wakes up and is tested. If the interventions are applied more than necessary, it prevents other memories from being consolidated and can even cause deterioration of the memory the intervention is attempting to reinforce. If the interventions are applied less than necessary, the desired behavioral performance will not be achieved.

[0072] There are many uses for such a detailed personalized model of human learning and retention of learning. The model can be used to inform any training system as to how well an individual subject is learning. Additionally, the model can be utilized to predict behavioral performance gains resulting from further exposure to training and determine how well a particular skill or memory is consolidated during sleep. Further, the model could be used to estimate how current skills and memories decay as a result of encountering interfering skills or memories, which can be used as a proactive tool to interfere with undesirable memories or bad habits. In addition, it can be utilized to simulate the effects of lack of sleep in an individual.

[0073] The concept behind the invention described herein is based on the widely accepted and well-supported idea that new memories are first encoded as connections in short-term memory in the human brain's hippocampal region. Then, gradually over a period of days, weeks, or months, they are consolidated into a slower-learning, more stable, brain region known as cortex in which long term memories are stored. Once information is consolidated into long-term memory, it becomes more resistant to decay. This consolidation process involves events called "replays" that occur during a deep stage of sleep called slow-wave sleep during non-rapid-eye-movement sleep (NREM). The theory holds that the more often a memory is replayed, the better a person performs when tested on a behavior dependent on recall of that memory. Although any memory in the short-term store has a chance of being replayed during sleep, there is a higher probability that a specific memory will be replayed if it was related to some emotional content or high immediate reward. Unfortunately, many things humans need to learn are boring or tedious, and the reward for learning them may be a long way off. This is the motivation behind memory interventions. Accordingly, the system according to embodiments of the present disclosure is an automation technique—an intervention control system that will improve the effectiveness and efficiency of any of these interventions that produce replay of specific memories.

[0074] The model described herein models the way the human brain encodes and consolidates memories of events and skills during waking experience and sleep. The model is personalized to simulate a particular individual subject based on biometric data from the subject. There are surely many uses for such a model, but one implementation is to use it to predict how well a particular person can recall a specific sequence of inputs. When the prediction is above the threshold for the desired level of performance, the model sends a signal to control an intervention to improve the memory or skill. That is, the intervention is actively applied until the performance predictions exceed the desired level, and then the intervention is turned off.

[0075] The current invention describes a design for a neural model that can make accurate behavioral predictions. The model according to embodiments of the present disclosure quantitatively simulates the impact of sleep on long-term memory function and teases apart equally important contributions from waking encoding in short-term memory and sleep consolidation in long-term memory. Speed and efficiency can be critically important for interventions, such as the implementation described above, that decide how to intervene on every positive phase of the slow-wave sleep oscillation (SWO) during the deepest stage of sleep (NREM sleep stages 3 and 4). There are a limited number of these oscillations during a night of sleeping (SWOs are at a frequency of 0.5-1.2 Hz for often much less than 90 minutes of a night's sleep), and the EEG analysis of the dynamically changing SWO frequency and recognition of the identity of a replay takes time before the model can simulate the results. Therefore, it is desirable for the model to make behavioral predictions well within 100 milliseconds (ms) after a reported memory replay during the average 500 ms time between the positive phases of SWO to control memory interventions during the next positive phase of SWO. The model's subject-specific predictive power in the context of task performance comes from simulating non-invasively assessed markers of attention during encoding as well as the duration and quality of consolidation periods.

[0076] (3.1) Basic Architectural Diagram

[0077] FIGS. **3**A and **3**B illustrate the basic architecture of the entire system described herein. During waking (e.g., a higher activity state) (FIG. **3**A), data is captured (via a camera and/or microphone **300**) for model **302** updating, and during sleep or quiet waking (e.g., a lower activity state) (FIG. **3**B), the model **302** simulates memory consolidation. The model **302** simulates behavioral performance and controls when to apply the intervention. Operations/modules in

dashed lines (identification of objects encoded **304**; physiological measurements **306**; EEG analyzer **308**; intervention **310**) are prior art.

[0078] During a waking experience (FIG. **3**A), when a user **312** is about to experience an event that must be remembered accurately, data recording is initiated either by some automated decision system or by the user **312**, such as via a button **314** that initiates recording. Prior art systems identify the percepts that are most salient to the subject at that time (i.e., identification of objects encoded **304**).

[0079] For visual items, an eye tracker can be used to decide what the user **312** is looking at (e.g., an image chip is formed around visual fixations averaged over a short (1 second) time window). Alternatively, the user **312** can actually take a static picture of the item of interest. These images can be identified using an open-source system, such as ImageNet/GoogleNet, to provide a semantic symbol that identifies the object. For speech recognition, there are many known systems that are can recognize speech. Physiological measurements **306** are made by analyzing electroencephalograms (EEG), electromyograms (EMG), and electrocardiograms (ECG) based on biometric sensor data from the user **312**. Mental fatigue significantly modulates the amplitude of certain event-related potentials (ERPs), and stress can be inferred from ECG read-outs of heart rate variability. A small amount of stress can improve encoding strength, but higher levels of stress interfere with encoding. Attention, or vigilance, can be estimated from EEG and EMG (element **316**).

[0080] In FIG. **3**B, the intervention module (element **310**) is a prior art system (described in U.S. application Ser. No. 15/332,787, hereinafter referred to as the '787 application, which is hereby incorporated by reference as though fully set forth herein). The system described in the '787 application associates a cue like an odor (see, for example, Literature Reference No. 2), a sound (see, for example, Literature Reference No. 1), or electrical stimulation with the memory of interest during waking, and reapplies it during sleep or quiet waking as a cue to trigger a recall of the specific cued memory. The intervention module (element **310**) is also referred to as a memory enhancement system. Later, the cue can be replayed to cue the memory during sleep, consolidating the memory from short term to long term memory.

[0081] The EEG analyzer module (element **308**) is a prior art module that can detect the sleep stage **318**, including detection of slow wave oscillations (SWOs). SWOs occur mostly during the deepest stages of sleep (NREM stage 3 and 4), although they can occur during times of deep restfulness in a quiet waking state as well. Sleep stages are detectable by commercial sleep monitors. The phase of SWO can be ascertained currently by analysis of the EEG signal **320**. An automated analysis system is not commercially available, but the methods for EEG signal analysis are known to those skilled to the art (see Literature Reference No. 4). The model **302** simulates the replay of memories during sleep and predicts the behavioral results of such replay. Based on the model **302**'s prediction, the intervention may be controlled **322** on or off. The model **302**, which is the subject of this disclosure, is described in detail below. The model-based controller can turn the intervention on and off (element **322**) all night long as the subject sleeps. If a memory is fully consolidated and the intervention is turned off, the memory may decay as other, possibly conflicting memories, are replayed during sleep. In this situation, the system would turn the intervention on again.

[0082] (3.2) Neural Memory Computational Model

[0083] The neural model **302** according to embodiments of this disclosure is depicted in FIG. **4**. The neural memory model **302** described in this disclosure simulates encoding, decay, consolidation, and recall of novel multi-modal experiences and knowledge in real-world environments. The main modules of the model are a short-term memory store **400** and a long-term memory store **402**. During waking (FIG. **3**A), a sensory event is identified with a unique ID, as well as a start and end time **324**, and is given as a training input (T) **404** to identify each relevant experience (both task related and distractions or interfering experiences). Both the event ID, start/end times **324**, and attention, fatigue, and stress measurements **316** are recorded and stored during encoding **326**, as shown in FIG. **3**A. As depicted in FIG. **4**, biometrics **406** are reported by the physiological measurements module **306** of FIG. **3**A, in terms of levels of attention (a), mental fatigue (m), and stress (s) during the training period.

[0084] During sleep, EEG signals **320** are analyzed. During the slow-wave sleep stage, the start and end time of each positive phase is reported to the model **302**, along with a probability distribution across specific memory events that may have been replayed during that time period. The model **302** is not specific to the type of skill being learned and can be easily adapted to a number of tasks.

[0085] In the following, the term "skill" is used to describe a memory, possibly associated with actions, such as how to assemble a complex piece of equipment, or what happened during a mission for later debrief. The model **302** represents the user's ability to recall that skill quickly and easily in terms of the strength of integration with other memories in both short term (STM) memory **400** and long term (LTM) memory **402**. The idea that memories are represented by the level of spiking activity of an ensemble of neurons in the brain is widely accepted (see Literature Reference No. 6). The activation level of an item in short term memory is ephemeral and dies down soon after the item is experienced or recalled. However, while an item is active, it forms links with other items that are active at the same time. These links are directional to represent the order in which the linked events are experienced. In STM **400**, both the item activations and their links to other items change on the order of minutes to hours, whereas in LTM **402**, they change slowly, on the order of days to years. This is the reason why memories encoded quickly in STM **400** must be transferred to LTM **402**. This transfer is called consolidation, and the invention described herein models this process more thoroughly than any model to date.

[0086] There are several ways of modeling of the interaction between memories in the dual-store system (elements **400** and **402**) described. The invention includes an adaptive cortico-hippocampal architecture that accounts for emergent sleep replays underlying the transfer of long-term memory/skill representation from hippocampus to neocortex. The following set of equations is one implementation, but there are many roughly equivalent ways to express the sort of dynamical relationships between memories. The user's interactions with each skill are called either training or testing. The difference is that training, which could be a formal pedagogical training session with an instructor, provides feedback. Testing, or simply experiences in the envi-

ronment, provides no feedback. The neural model **302** according to embodiments of the present disclosure is defined by three equations: a pair of differential equations (1) and (2) that govern the item activation updates (elements **408** and **410** in FIG. **4**), and a weight update (elements **412** and **414** in FIG. **4**) equation (3). Item activations (a_X represents the activation of item X) evolve dynamically over time as follows:

$$\sigma c_a \frac{da_X}{dt} = -\frac{a_X}{\tau_a} - a_X\left[\beta \sum_{Y \neq X} a_Y + \frac{\Theta x_s^{ex}}{x_s^{ex} + t_{xs}^{ex}}\right] + (1 - a_X)\left[\mu \cdot FF + \gamma \sum_{Y \neq X} w_{YX} a_Y + \frac{\alpha a_X^{ex}}{a_X^{ex} + t_a^{ex}} + \zeta[H_X - \lambda]^+\right] \quad (1)$$

The table in FIG. **6** lists the meaning of each variable and some default values. The x_s variable is an "inactivation current" modeled after ion channel dynamics. X_s evolves at a slower rate than a_X, and increases inhibition on the item activation when it gets large.

$$\sigma_s c_{xs} \frac{dx_s}{dt} = -\frac{x_s}{\tau_{xs}} + (1 - x_s)[\kappa f(x)],\ c_{xs} > c \quad (2)$$

In the model **302** described herein, these relational links are represented as weight values. Weight updates (elements **412** and **414**) are based on the activation (elements **408** and **410**) of the pre-synaptic item and the derivative of the activation of the post-synaptic item, which learn casual connections for the spreading activation by means of equation (3).

$$\frac{dw_{XY}}{dt} = \eta a_X (1 - w_{XY})\left[\left[\frac{da_Y}{dt}\right]^+ - \frac{1}{2}\left[-\frac{da_Y}{dt}\right]^+\right] f(biometricFactors) f(distractionFactor) \quad (3)$$

Cell and inactivation current dynamics are scaled by a factor ƒ. Other variables are shown in the table in FIG. **6**.

[0087] Equation (1) updates the activation value of each item x by subtracting a decay term and an inhibitory term, and adding an excitatory term. The inhibitory current is a function $a_X[\beta E_{Y \neq X} a_Y + \Theta f(x_s)]$. β is an inhibition parameter, and the sum of a_Y provides competition from other items. x_s is a slow variable undated in equation (2) with a dynamics speed variable $\sigma_s << \sigma$, where Θ is a parameter and $f(x_s)$ is sigmoid

$$\frac{x_s^{ex}}{x_s^{ex} + t_{xs}^{ex}}$$

to smoothly bound the values. T_{xs} is a threshold for the x_s value at the point, where the sigmoid value is half of its maximum value, and ex is an exponent controlling the steepness of the sigmoid rise.

[0088] The excitatory current is a function of feed-forward excitation FF (element **416**) and a weighted sum of inputs from activated items linked to item x. For STM **402**, FF (element **416**) is the activation of items in the input buffer **418** exciting their representations in the STM **402**. For LTM **400**, FF (element **416**) is the activation of the corresponding item in STM **402**, and the factor $\zeta([H_X - \lambda]^+$ (element **420**) is a feedback excitation from STM to LTM, subject to a threshold parameter A. For the hippocampus, ζ=0.1. $(1-a_X)$ is reversal potential, which is a homeostasis term that means that if a_x overshoots the maximum value of 1, the spreading activation from other items becomes a negative term, thereby reducing the value of a_x.

[0089] $\gamma \Sigma_{Y \neq X} W_{YX} a_Y$ spreads activation to a_x (elements **408** and **410**) as a function of the weighted sum of activations of items Y that are directionally linked to item X by weight W_{yx} (elements **412** and **414**). Activation is spread within items in each memory region. γ is a tuning parameter that defaults to 0.4.

$$\frac{\alpha a_X^{ex}}{a_X^{ex} + t_{xs}^{ex}}$$

is a self-excitation term to accelerate the increase in activation, but it is a sigmoid form that does not increase the activation of a_x beyond the value of the multiplier α, which defaults to 0.5.

[0090] Learning occurs through the change of weights between active items as described in equation (3). All weights are initialized at 0 and can never be negative. The learning rate, η is a constant that scales how quickly the model learns in all situations. Higher learning rates allow more rapid integration of information but also increase the likelihood that random events will be learned along with the more meaningful stable patterns. The change in weight of the connection from item x to item y includes a factor of $(1-w_{XY})$ which will cause the rate of weight change to reduce as the weight approaches 1 and sets 1 as the maximum obtainable weight. The weight of the connection between x and y changes whenever the activity of x (a_X) is not 0, and the activity of item y (a_y) is not constant. Weight change is directly proportional to the activity of x (a_x) and proportional to the rate of change in the activity of y (da_Y). If (da_Y) is negative, the weight change is reduced by half. This is necessary for the learning of connections between simultaneous events.

[0091] The dependency of the weight upon the activity of the presynaptic ensemble (item x) and the rate of change in the activity of the post synaptic ensemble (item y) creates a type of Hebbian plasticity. In Hebbian theory, as in the model described herein, if activation of item x reliably increases the activity in item y, the connection from x to y increases in strength. If the activity in item y declines despite strong input from item x, indicating that the ensemble associated with x is ineffective at activating the ensemble associated with y, the connection is reduced in strength. When items are activated in succession, the first item will still be active when the second item's activity begins to rise; this results in an increase in the strength of their connection. If the first item has already reached the peak of its activation by the time the next item begins activating, the resulting changes in weight in the reverse direction (from y to x) will be negative. The model **302** described herein incorporates the effects (physical or psychological factors) that can be observed in the subject's biometric data (element **406**). Lack of attention, stress level, or fatigue can all have an impact on learning. Introduction of task irrelevant distractors can also

play a part. This is represented by the factor f(biometrics) in equation (3), as described below in equations (4) and (5).

[0092] (3.3) Personalization: Biometric and Distraction Factors

[0093] The neural memory model **302** described above is personalized by incorporating biometrics **406** measured by prior art techniques, including measurements of the subject's fatigue, stress, and attention during waking. These inputs are used to modulate the initial activation level of the memories when they are learned or trained (i.e., the time of memory encoding). At times other than task-relevant training and testing, biometric parameters identify memory-relevant physiological states and replay parameters that change the model's mode of operation during periods of waking, quiet waking, and the stages of sleep.

[0094] In one embodiment, three biometrics **406** are extracted from EEG using prior art techniques, including mental fatigue, stress, and attention. Raw biometric values for fatigue, stress, and attention are shown in FIG. **7** as extracted from EEG from subject **3798** in a pilot task. The values range from 0 to 2. Baseline is an acclimation period trials 0-60. Task training was trials 61-240, and the immediate test was right after training. Biometrics were fairly flat through the first day training and testing (to trial 355), but in the morning tests (trials 356-475 after sleeping) the fatigue metric (bold line **700**) is significantly lower. The plot in FIG. **7** shows that mental fatigue (bold line **700**) is significantly reduced after sleep. The solid, unbolded line **702** represents attention, and the dashed line **704** represents stress.

[0095] FIG. **8** depicts a method of determining modulation parameters for biometric influence on model predictions (i.e., behavioral predictions **422** in FIG. **4**) according to embodiments of the present disclosure. Only biometrics significantly correlated with performance are used in the model **302**. The effect of biometrics on the model simulation is modulated by the amount of correlation **800** between each biometric value and the subject's performance. An online update method according to embodiments of the present disclosure is based on degree of correlation **800** with performance (using linear fit parameters for significant correlations (i.e., apply linear fit **802**)). The biometric influence is updated every m trials (currently m=1). A rolling mean of each biometric (mean a (attention), s (stress), f (fatigue) **804**) and subject behavioral performance metric (mean perf **806**) is computed in a temporal window (e.g., 100 seconds). Each biometric (e.g., attention **808**, stress **810**, mental fatigue **812**) is correlated (element **800**) with each performance metric (element **814**) and only incorporated into the cognitive model for periods when the correlation **800** is significant (e.g., where the p-value is <0.05). Equation (4) below shows the biometric factors shown in equation (3) for the cognitive model's update to the short-term memory level E_x.

$$\text{biometric_factors}=(c_a A+y_a)(c_m M+y_m)(c_s S+y_s) \tag{4}$$

Here A, M, and S represent attention factor, mental fatigue factor, and stress factor (each adjusted to −1 to 1 range by subtracting 1), respectively. $\vec{C}_*$ is a vector of parameters that modulate the impact of the respective biometric. If the correlation **800** for a biometric is not significant, the $\vec{C}_*$ parameter is set to 0 for that biometric, and the corresponding $\vec{Y}_*$ is set to 1 (element **816**). However, if the correlation **800** is significant for a certain time period, a first-order linear fit **802** is used to find a slope and intercept of a regression line that relates the biometric to the performance. For example, a MATLAB implementation of such a linear fit **802** uses the function polyfit as follows:

```
[c,y]=polyfit(biometric_vector, matching_performance vector, 1).
```

Equation (4) incorporates the correlation between attention (a metric extracted from EEG by a prior an method) and performance. However, there are also externally observable indications of distraction, such as the gaze moving to task irrelevant areas of the field-of-view, or physical body orientation (e.g., orientation of head and/or arms) in a task irrelevant manner. These indications can be incorporated into equation (3) if it makes sense for the task being modeled (element **818**). A non-limiting example is a surveillance task in which the subject has to take pictures of people that appear in the windows of a building. If a distraction occurs in one of the windows, such as a dog running across the room, and the subject takes a picture of it by mistake, then the subject's action (taking the picture) is an external indication that the subject was distracted by the dog. In Equation (5) below, D is a binary signal that is 1 when any distractor is present, and 0 when no distractor is present. Y_d is a modulation parameter for the strength of the distraction factor (e.g., y_d=0.00005), and d is a modulation parameter for the interaction (e.g., d=1). The interaction variable is a binary value that goes to 1 if there is interaction with the distractor and is otherwise 0. The prefixed (T_x (x)>0) factor provides that the distraction factor is only used for a skill x that is currently active, which is when training happens and Tx>0.

$$\text{distraction_factor}=(T_x(x)>0)*(y_d*(D>0)+ d*\text{interaction}) \tag{5}$$

[0096] (3.4) Simulation of Memory/Skill Consolidation During Sleep

[0097] In the brain, the fast-learning, fast-decaying hippocampus (simulated by the short-term memory **400** described herein) must train the slow-learning cortex (simulated by the long-term memory **402** described herein) (shown in FIG. **4**). During slow-wave sleep, salient memories can become randomly reactivated in short-term memory **400**, driving replays in the long-term memory **402** and strengthening the long-term connections. These reactivated memories are called emergent replays. After a sufficient number of replays, hippocampal connections are no longer needed to drive the spread of activation along learned links when an item is activated.

[0098] Replays are modeled as a brief increase in activation, called a 'cue', of a single item randomly selected from a weighted distribution of recently active items taking place during the positive phase of the slow wave oscillation (the "UP state"). Due to the excitation caused by the connections between items, this results in sequential activations of other items that have been learned to be associated with the first. As a result, sequences that were presented multiple times during waking will be replayed whenever the first item of the sequence is cued. If a later item is cued, a partial sequence often replays starting from the cued item. As all replay activity must occur within the approximately 500 ms of the UP state, the temporal coefficient is increased during sleep, causing all rates of change to be increased. FIG. **9** depicts representative replays of two separate sequences **900** and **902** trained over 4 days and 4 nights. Each curve in each plot is the temporal activation level of one item in the sequence.

For example, on night **1** in **900**, the 3 curves are the level of item A as it becomes active and then dies out, and its activation is spread to item B neurons which become active (dotted curve) and then die down, and then to item C neurons that become active (bold line) and die down. In **902** night **1**, the sequence **12345** is trained and the curves show item 1 then 2 then 3 in turn. The activations do cross over (it is hard to see in the drawing). One sequence (ABCDE) **900** is trained far more extensively than the other sequence **902** (4 nights training vs. 1) and as a result has significantly faster replays. This can be seen as the curves peak more closely together in time from night to night because the links between items are becoming stronger, thus activation spreads faster. Also, with stronger links the activation level spreads farther so during night **1** both sequences have their first 3 items activated, but on night **2 900** gets 4 items activated, and by night **3** all 5 items are activated. Sequence **900**, which does not get as much training, never gets more than 4 items activated, and there is not as much speedup.

[0099] The item to be cued is selected from a weighted distribution, where the weight for each item is a factor called 'salience'. The salience factor of an item increases whenever a given item is active and decays over time. In each UP state, an item is selected to be cued, with selection probability proportional to the salience weight (i.e., how often it has been active in the recent past in comparison with other items). A "none" cue is represented in the distribution as well, meaning the probability that no replay will be cued. A fixed weight is assigned to the "none" cue. This results in a no cue probability that increases when no items have been active recently.

[0100] Because learning is still enabled during sleep, reactivated connections tend to increase their connection strengths. Additionally, because of the faster time scale of activation and the dependence of learning upon the rate of change of activation of the post synaptic cell, the rate of weight changes is considerably higher during replays. This is most important in the slower learning cortex. Sleep replays allow the connections in the cortex to become much stronger in a short period of time with no additional training.

[0101] (3.5) Waking Recall Metric

[0102] In sequence learning experiments, the model is trained on repeated exposures to sequences of events that are represented by letters or numbers. Performance improvement with each presentation of a training stimulus may be tracked by measuring the ability to recall. Below is a description of how the metric data collection and computation works (see equations (6) and (7)). The recall metric described below is a function of the activation levels of each item constituting the memory, and its ability to rise above the other activations going on at the same time (refer to the contrast and P in equations (6) and (7) below). In this way, the recall metric is used to predict behavioral performance based on strengths of memories in the neural model.

[0103] (3.5.1) Algorithm for the Recall Metric

[0104] a. Get activation history for the current recall, which is an array of current activations for each item (i.e., the activation of the item at each time point (dt) from the time when the recall is cued until all item activations return to zero, assuming no other events are perceived during this time period).

[0105] b. For each item, identify the time period that begins when the item's activation level becomes higher than the rest of the items, and ends when its level is surpassed by that of another item.

[0106] c. Compute the contrast of each item at each timestep with respect to the mean activations of every other item using equation (6).

[0107] d. Compute the mean value of contrast for each item i ($\overline{c_i}$) during the times when its contrast is at a maximum.

[0108] e. Compute P using equation (7), which sums up the respective contrasts, with a factor added for permutation of the sequence ($|p_i|$, which is an edit distance of the recalled list from the trained list).

$$C_i(t) = \frac{a_i - \text{mean}(a_{j \neq i})}{a_i + \text{mean}(a_{j \neq i})} \tag{6}$$

$$P = \sum_i \frac{1}{N}\left(\frac{1}{|p_i|+1}\right)\overline{c_i} \tag{7}$$

N = length (# items) of sequence

i = index of an item in sequence

ct_i = activation level of item i

$\overline{c_i}$ = mean contrast of item i during 1^{st} 200 ms of period when $c_i > c_k$, $k \neq i$

p = transposition error: difference between position of item in practiced sequence vs. position during $recallc_i(t)$ = contrast of item i at time t (amount $act_i(t)$ compared to mean $(act_{-i}(t))$

[0109] The recall metric described herein considers an item as being recalled if its contrast rises above that of all the other items. FIGS. **10**A and **10**B show an example in short-term memory (hippocampus) of simulation of recall of a sequence of items A, B, C, D, after the sequence was trained and subsequently A is presented as a cue. Recall time is computed only on the subsequently recalled items in the sequence A, B, C, D. FIG. **10**A plots the contrast $c_i(t)$ compared to the actual activation levels (shown in FIG. **10**B) of each item as they are recalled. Contrast is computed over multiple 200 ms time windows. This technique is used to make behavioral predictions based on the training and sleep consolidation. The recall metric is based on item activations, but a simple averaging of weights between items could offer a reasonable prediction of recall ability as well.

[0110] (3.6) Experimental Studies

[0111] The neural model (FIG. **4**, **302**) exhibits key properties of memory, based on the literature. The properties include: practice increases speed of memory access and strength of recall; hippocampus (short-term memory **400**) learns faster than cortex (long-term memory **402**); contradictory inputs degrade the ability to recall the conflicting practiced items; complementary inputs don't degrade performance; and memory traces decay over time, faster in short-term memory than in long-term memory.

[0112] Using simulated inputs, the neural model simulates sequence learning (see FIGS. **9**, **10**A, and **10**B). A paired associates task is another common experiment used in psychology and neuroscience in which two items are presented together, and when subsequently presented with one, the subject must recall the other. It can also be simulated in the neural model described herein, since it has the same properties as a two item sequence. In effect, a pair is a simultaneous sequence. In the experiment described below,

the neural model's simulation of recall accuracy assessed by the metric described above is compared. The first ten exposures of the main sequence A-B-C-D-E is followed by another training session often exposures on one of four second sequences, including the same (A-B-C-D-E), contradictory (E-D-C-B-A), complementary (B-C-D), and part contradictory and part complementary (A-B-C-P-Q).

[0113] After each training session, the performance was tested by presenting "A" as a cue. The metric compared the recall cascade of item activations with the first practice sequence (A-B-C-D-E). This was only waking practice and testing; there was no sleep consolidation. FIGS. **11**A-**11**D and **12**A-**12**D illustrate the recall metric plotted for each of the four conditions described above: the same sequence, a complementary sequence, a contradictory sequence, and a mixed sequence. FIGS. **11**A-**11**D depict the recall time metric plotted for each of four conditions. FIG. **11**A is a plot of continued practice of the same sequence, FIG. **11**B is a plot of a complementary sequence, FIG. **11**C is a plot of a contradictory sequence, and FIG. **11**D is a plot of a mixed sequence. In each of the plots, the unbolded line represents the hippocampus, and the bold line represents the cortex. Continued practice (FIG. **11**A) lead to more improvement than other sequences. Contradictory sequences (FIG. **11**C) actively reduced the model's performance. Partially complementary presentations (FIG. **11**D) resulted in some performance improvement. In summary, practice increases speed of memory access, and contradictory items slow access.

[0114] FIGS. **12**A-**12**D are plots of the recall accuracy metric plotted for the same sequence (FIG. **12**A), a complementary sequence (FIG. **12**B), a contradictory sequence (FIG. **12**C), and a mixed sequence (FIG. **12**D). In each of the plots, the unbolded line represents the hippocampus, and the bold line represents the cortex. Accuracy improves for continued training and complementary sequences, but degrades for contradictory sequences. In summary, practice increases the strength of recall. Contradictory information degrades the ability to recall practiced information. This could explain the decay of memory over longer time periods.

[0115] FIGS. **13**A and **13**B show how the weights between items in the short-term memory (cortex, FIG. **13**A) and long-term memory (hippocampus, FIG. **13**B) vary over 4 days after being initially trained without interference. Each night, the memories are reactivated in slow-wave-sleep, strengthening the weights in cortex (which decay over very long time scales). During the day, the short-term memory weights decay. Hippocampal feedback is maintained. Replays continue for all 4 days, and significant strength is developed in cortical connections.

[0116] FIGS. **14**A and **14**B show the same plots for the case where contradictory interfering items are learned. FIG. **14**A depicts short-term memory, and FIG. **14**B depicts long-term memory. As shown, the decay is steeper, and the short term weights are learned more slowly. Hippocampal feedback is maintained. Interference reduces, then eliminates, replays. The plots show strong growth of cortical connections early on but very little in the second night and beyond.

[0117] The invention described herein makes possible, for the first time, a targeted personalized closed-loop system for enhancing memory in both normal subjects and those with learning difficulties related to memory consolidation. There are multiple applications for the invention of this disclosure. For instance, vehicle manufacturers could use the system for training, or as a commercial product. Since there is recent widespread interest into brain enhancement technologies, and there are several commercial systems on the market today, the control technique system according to embodiments of the present disclosure can be incorporated into a product and reach the market in the near future. For example, the closed-loop model-based control of interventions can be incorporated into the products of companies that stimulate and treat the brain.

[0118] This invention makes behavioral predictions by computing a recall metric based on the weights of the memories. This recall metric can be mapped to actual performance metrics of particular subjects by adding a readout model, as described in U.S. Provisional Application No. 62/570,663, which is hereby incorporated by reference as though fully set forth herein.

[0119] The prior art memory intervention techniques described in Literature Reference Nos. 1, 2, and 3 were only tested in a laboratory, under supervised sleep conditions. They were never intended for real-world use; only for research on memory consolidation. Whether in the laboratory or in real-world settings, there exists no method to control which particular memories need to be enhanced, or to stop the intervention for a particular memory when it has been enhanced sufficiently, to allow other memories to consolidate. To provide such control over specific memory enhancement interventions in the laboratory, and to make this into a commercial product that could be used by individuals apart from a supervised laboratory setting, the intervention delivery system must be automated. That is because, while the subject is in slow-wave sleep or any other cognitive state when memory replays occur, EEG must be analyzed in real time (within the slow-wave oscillation half cycle) to decide which memory intervention should be applied in the next cycle, if at all. No human supervisor can make these determinations as fast as an automated system, and without waking up the subject for performance testing. The purpose of the present invention is to add such automation, making these approaches efficient and effective by assessing the subject's brain state and predicting in real time when to apply the intervention.

[0120] Products resulting from this disclosure will enable people to reinforce episodic memories and acquire skills faster, while they sleep. The system, when appropriately paired with a memory consolidation technique, could be an enormous commercial success, since it automates some of the supervision required to use the technique. Thus, the invention is part of the transition to move these techniques out of clinical settings and into home use.

[0121] Additionally, the model described herein will also prove exceedingly useful in a pedagogical automated system, such as teaching and training software. Having a more accurate assessment of information retained by the user will allow such software to focus on the areas of learning where additional training will be the most useful. Furthermore, missions such as surveillance and after-mission debriefs require detailed memories that can be enhanced and clarified by the system according to embodiments of this disclosure, which can accelerate mission rehearsal time.

[0122] Finally, while this invention has been described in terms of several embodiments, one of ordinary skill in the art will readily recognize that the invention may have other applications in other environments. It should be noted that many embodiments and implementations are possible. Fur-

ther, the following claims are in no way intended to limit the scope of the present invention to the specific embodiments described above. In addition, any recitation of "means for" is intended to evoke a means-plus-function reading of an element and a claim, whereas, any elements that do not specifically use the recitation "means for", are not intended to be read as means-plus-function elements, even if the claim otherwise includes the word "means". Further, while particular method steps have been recited in a particular order, the method steps may occur in any desired order and fall within the scope of the present invention.

What is claimed is:

1. A system for memory improvement intervention, the system comprising:

one or more processors and a non-transitory computer-readable medium having executable instructions encoded thereon such that when executed, the one or more processors perform operations of:

based on both real-time EEG data and a neural model, simulating replay of a person's specific memory during a sleep state;

using the neural model, generating a prediction of behavioral performance of the replay of the specific memory;

if the prediction is below a first threshold, then using a memory enhancement intervention system, applying an intervention during the sleep state to improve consolidation of the specific memory; and

if the prediction is below a second threshold, reducing the intervention performed using the memory enhancement intervention system.

2. The system as set forth in claim **1**, the system further comprising:

a plurality of brain sensors to provide EEG signals; and

the memory enhancement intervention system, wherein the neural model is part of a closed-loop control system.

3. The system as set forth in claim **1**, wherein a recall metric is used to predict behavioral performance based on strengths of memories in the neural model.

4. The system as set forth in claim **3**, wherein the prediction is applied to the recall metric, and the first threshold and second threshold are values of the recall metric.

5. The system as set forth in claim **1**, wherein the system controls intervention that applies to the specific memory such that consolidation of other memories is also allowed to occur.

6. The system as set forth in claim **1**, wherein the neural model comprises a short-term memory store and a long-term memory store, wherein each memory store comprises a plurality of items, each item having an activation level that evolves dynamically over time, wherein while an item is active, it forms links with other items that are active at the same time, wherein the links are directional to represent an order in which the linked items are experienced.

7. The system as set forth in claim **6**, wherein the links are represented as weight values, and wherein weight values are updated based on the activation levels of the linked items.

8. The system as set forth in claim **6**, wherein recall is a function of the activation level of each item, wherein an item is considered recalled if its activation level rises above the other activations going on at the same time.

9. A computer implemented method for memory improvement intervention, the method comprising an act of:

causing one or more processors to execute instructions encoded on a non-transitory computer-readable medium, such that upon execution, the one or more processors perform operations of:

based on both real-time EEG data and a neural model, simulating replay of a person's specific memory during a sleep state;

using the neural model, generating a prediction of behavioral performance of the replay of the specific memory;

if the prediction is below a first threshold, then using a memory enhancement intervention system, applying an intervention during the sleep state to improve consolidation of the specific memory; and

if the prediction is below a second threshold, reducing the intervention performed using the memory enhancement intervention system.

10. The method as set forth in claim **9**, wherein a recall metric is used to predict behavioral performance based on strengths of memories in the neural model.

11. The method as set forth in claim **10**, wherein the prediction is applied to the recall metric, and the first threshold and second threshold are values of the recall metric.

12. The method as set forth in claim **9**, wherein the system controls intervention that applies to the specific memory such that consolidation of other memories is also allowed to occur.

13. The method as set forth in claim **9**, wherein the neural model comprises a short-term memory store and a long-term memory store, wherein each memory store comprises a plurality of items, each item having an activation level that evolves dynamically over time, wherein while an item is active, it forms links with other items that are active at the same time, wherein the links are directional to represent an order in which the linked items are experienced.

14. The method as set forth in claim **13**, wherein the links are represented as weight values, and wherein weight values are updated based on the activation levels of the linked items.

15. The method as set forth in claim **13**, wherein recall is a function of the activation level of each item, wherein an item is considered recalled if its activation level rises above the other activations going on at the same time.

16. A computer program product for memory improvement intervention, the computer program product comprising:

computer-readable instructions stored on a non-transitory computer-readable medium that are executable by a computer having one or more processors for causing the processor to perform operations of:

based on both real-time EEG data and a neural model, simulating replay of a person's specific memory during a sleep state;

using the neural model, generating a prediction of behavioral performance of the replay of the specific memory;

if the prediction is below a first threshold, then using a memory enhancement intervention system, applying an intervention during the sleep state to improve consolidation of the specific memory; and

if the prediction is below a second threshold, reducing the intervention performed using the memory enhancement intervention system.

17. The computer program product as set forth in claim **16**, wherein a recall metric is used to predict behavioral performance based on strengths of memories in the neural model.

18. The computer program product as set forth in claim **17**, wherein the prediction is applied to the recall metric, and the first threshold and second threshold are values of the recall metric.

19. The computer program product as set forth in claim **16**, wherein the system controls intervention that applies to the specific memory such that consolidation of other memories is also allowed to occur.

20. The computer program product as set forth in claim **16**, wherein the neural model comprises a short-term memory store and a long-term memory store, wherein each memory store comprises a plurality of items, each item having an activation level that evolves dynamically over time, wherein while an item is active, it forms links with other items that are active at the same time, wherein the links are directional to represent an order in which the linked items are experienced.

21. The computer program product as set forth in claim **20**, wherein the links are represented as weight values, and wherein weight values are updated based on the activation levels of the linked items.

22. The computer program product as set forth in claim **20**, wherein recall is a function of the activation level of each item, wherein an item is considered recalled if its activation level rises above the other activations going on at the same time.

* * * * *

专利名称(译)	基于神经模型的控制器		
公开(公告)号	US20180146916A1	公开(公告)日	2018-05-31
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申请(专利权)人(译)	HRL实验室，LLC		
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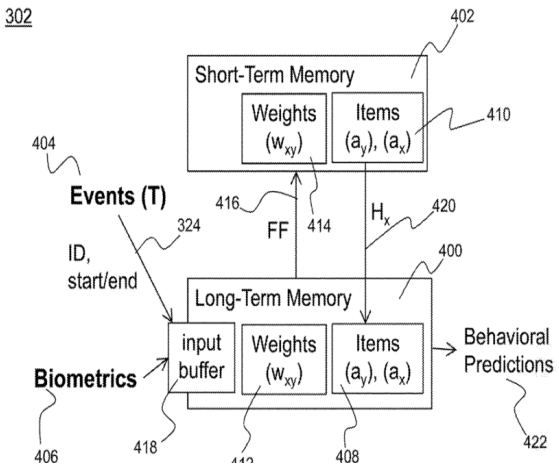
描述了一种用于记忆改善干预的系统。基于实时EEG数据和神经模型，系统模拟在睡眠状态期间人的特定记忆的重放。使用神经模型，生成对特定存储器的重放的行为表现的预测。如果预测低于第一阈值，则使用存储器增强干预系统，系统在睡眠状态期间应用干预以改善特定存储器的合并。如果预测低于第二阈值，则系统减少使用存储器增强干预系统执行的干预。