Australasian Physical & Engineering Sciences in Medicine (2019) 42:465–480
https://doi.org/10.1007/s13246-019-00743-8

SCIENTIFIC PAPER

A computationally bio-inspired framework of brain activities based on cognitive processes for estimating the depth of anesthesia

S. A. Hosseini[1] · M.-B. Naghibi-Sistani[1]

Received: 13 July 2018 / Accepted: 25 February 2019 / Published online: 23 April 2019

Abstract

This paper develops a computationally bio-inspired framework of brain activities based on concepts, such as sensory register (SR), encoding, emotion, short-term memory (STM), selective attention, working memory (WM), forgetting, long-term memory (LTM), sustained memory (SM), and response selection for estimating the depth of anesthesia (DOA) using electroencephalogram (EEG) signals. Different brain regions, such as the thalamus, cortex, neocortex, amygdala, striatum, basal ganglia, cerebellum, and hippocampus, are considered for developing a cognitive architecture and a computationally bio-inspired framework. A clinical study was managed on twenty-two patients corresponding to three anesthetic states, including awake state, moderate anesthesia, and general anesthesia. The proposed approach utilizes a multiple of dynamically reconfigurable neural networks with radial basis function (RBF) and its associated data processing mechanisms. The emotion effect in the model, dynamic RBFs in WM and LTMs, and adjusting the adaptive weights in the last layer are the main innovations of the proposed approach. In the proposed approach, various incoming information is entered into the model. The correct labeling process of EEG signals is performed by qualitative and quantitative analyses of peripheral parameters. Then, an SR is used to accumulate the pre-processed EEG segment for a period of 2.3 s. Feature extraction is performed in the encoding stage as a primary perception. The output of this stage can be transferred to STM and WM with a bottom-up involuntary attentional capture. LTM and SM are a fairly permanent reservoir for information which is passed from WM using a top-down voluntary attention mechanism. Finally, weighting factors in SM and LTMs outputs are determined and then response selection is used by winner-take-all (WTA) strategy. The results indicate that the proposed approach can classify in different anesthetic states with an average accuracy of 89.2%. Results also indicate that the combined use of the above elements can effectively decipher the cognitive process task. A final comparison between the obtained results and the previous method on the same database indicate the effectiveness of the proposed approach for estimating DOA.

Keywords Bio-inspired framework · Depth of anesthesia · Electroencephalogram · Emotion · Memory · Selective attention

Introduction

One of the key problems toward the development of a computationally bio-inspired framework of the brain activity based on memory, emotion, and attention is how to clarify the cognitive processes in terms of soft computing and mathematical approaches [1]. For instance, attention function, due to its considerable influence on many biological activities, is an important topic in engineering, neuropsychology, and cognitive neuroscience. Attention has many medical applications, such as in Attention Deficit Disorder (ADD) [2], Attention Deficit Hyperactivity Disorder (ADHD) [3], rehabilitation [4], attention-seeking personality disorder [5], and autism [6], as well as many engineering applications in Brain-Computer Interface (BCI) [7, 8], decision-making [9], learning [10], and robotics [11]. These problems have multiple challenges, such as in offline and online processing, as well as in meeting performance measures such as maximizing accuracy and minimizing computational cost at runtime and during training.

The following four major steps (adopted by [12]) should be included to perform the research activities within the context of presentation of cognitive architecture and

✉ S. A. Hosseini
sa.hosseini@mail.um.ac.ir

M.-B. Naghibi-Sistani
Mb-naghibi@um.ac.ir

[1] Department of Electrical Engineering, Ferdowsi University of Mashhad, Mashhad, Iran

computational framework of the brain activity: (1) Observing the brain activity by biomedical signal and image processing, (2) Presentation of a cognitive architecture and developing the feasible concepts, supported by different fields, such as psychology, computer science, and cognitive neuroscience, (3) Realization, validation, and implementation of a cognitive architecture by engineering approaches and mathematical tools, and (4) Investigating the obtained results by the computational framework in the third mentioned steps and in case of dissatisfaction, returning to the first step.

Several studies have been proposed for the presentation of functional models, conceptual models, and bio-inspired frameworks based on attention and memory. In one study, Atkinson and Shiffrin [13] proposed three structural components of memory, including the Sensory Register (SR), Short-Term Memory (STM), and Long-Term Memory (LTM). Sensory information (environmental stimuli) first enters SR, where it resides for a very short period of time. STM receives selected inputs from SR. Information in STM decays for a short period of time, however, a rehearsal (retrieval or recall) process can maintain a limited amount of information. LTM is a fairly permanent reservoir for information which is passed from STM [12, 14].

To date, several approaches have been proposed for estimating the Depth of Anesthesia (DOA) with different characteristics, such as the computational speed at the runtime and the training time, and the accuracy, as well as similarities and differences with the human brain [15]. Yet, there remains much to be achieved in terms of more efficient pre-processing, feature extraction, and more accurate classification. The present study tries to develop a computationally bio-inspired framework of brain activities based on memory, emotion, and selective attention with both a theoretical and applied perspectives in order to estimate DOA which can also be used in other applications as a classifier. To achieve this goal, multi-disciplinary studies in cognitive neuroscience fields, such as biomedical signal processing, cognitive architecture, soft computing, and control theory should be joined.

This paper is organized as follows. Related work is presented in "Related work". The configuration of a computationally bio-inspired framework of the brain activity based on memory, emotion, and selective attention is illustrated in "Methods and materials". The experimental results are reported in "Results". The discussion is presented in "Discussion". Finally, conclusions and future works are provided in "Conclusion and future works" section.

Related work

This section presents a detailed discussion of previous related work on modeling of brain activities based on cognitive concepts, including memory, emotion, and attention, along with different theories and approaches. To date, there are many theories of attention, such filtering [16, 17], attenuation [18, 19], dichotic listening test [20], capacity [21], pertinence (late-selection) [22], multi-mode [23], and schema [24]. In the following, several theories and models are explained in a nutshell. Broadbent [16, 17] proposed the first detailed model for attention as a filter. He explained that the human attentional system must have a limited capacity which it can only process one information source at a time. However, other researchers have proposed difficulties for this model. To address the difficulties, Treisman proposed a modification of filter theory (adapted from [18]). She propounded the *attenuation theory* to explain how unattended stimuli sometimes came to be processed in a more rigorous way than filter theory can account for [25]. She suggested that *word units* be used to detect sentences [19] and that the word units have different thresholds. Some relevant words, such as our names, have very low thresholds while irrelevant words have high thresholds [19]. Another challenge to the filter theory came from the *dichotic listening test* by Moray. He found that listeners often recognized their own names when they were presented to the unattended ear. In particular, there must be some parallel semantic processing (understand what is said) prior to conscious identification (adapted from [20]). So whatever message is sent to the unattended ear is not understood.

In another study, Kahneman [21] presented a *limited capacity framework* of attention, in which a central processor allocates attention. He introduced parallel processing in attention to two or more tasks at a time. His model attempts to account for both divided and focused attention and explains the somewhat artificial distinction between them. Deutsch and Deutsch [22] proposed a *pertinence model*, that it was revised several times by Norman [19]. In their model, selective attention part is closer to the output responses than the input senses [19]. Norman explained that a pertinence index would be assigned to each signal; therefore, only signals with a sufficiently high index would be processed more deeply [26]. Solso also explained several problems in pertinence model and thus he called uneconomical [19].

In another study, Johnston and Heinz [23] proposed a *multi-mode theory* that suggests several stages of processing for incoming information. This theory adds a new dimension called *mode of selection*, including *early mode* and *late mode*. Graziano [27] and Graziano and Kastner [28] proposed an *attention schema theory* that suggests unattended messages are not processed at all and thus they are not included in cognitive processing [24]. The total amount of sleep acquired is taken into consideration as each subject was informed well in advance that they should obtain a good night's rest [29].

In another study, Norman and Shallice [30] and Shallice [31] proposed a model in which action control depends on two distinct processes, namely, automatic and willed. They presented the *Supervisory Attentional System* (SAS), which handles complex cognitive operations and generally intervenes when routine control is insufficient. Bronzino [32] presented a framework of human information processing for multiple sources at a conscious level. This model proposes that there are memory sub-systems with bidirectional connections with the associated processor for each sensory modality.

In another study, Wickens and McCarley [33] proposed a framework of attention as a mental fuel and mental filter. In their research, filter effects of selective attention shown as limited resources for information processing. Mesulam and Posner (adapted from [34]) presented two different models of attention with neuroanatomical connectivity from the different brain regions. Both models have the same structure, while the details are different. Mesulam's model supplies greater anatomical specificity with several distinct cortical regions, such as the posterior parietal cortex, the cingulate cortex, and the frontal cortex, whereas Posner's model supplies greater weight to the cognitive functions performed by the different compartments, including an anterior attention network, a posterior attention network, and a vigilance network.

Although conceptual frameworks for selective attention exist, such as the *Multiple Object Recognition and attentional SELection* (MORSEL) [35, 36], the *SeLective Attention Model* (SLAM) [37], and the *Selective Attention for Identification Model* (SAIM) [38, 39], however, little research has been reported on the development of concrete frameworks of attention and its practical aspects [12, 40, 41]. For a brief description, Taylor et al. [42] proposed a *COrollary Discharge of Attention Movement* (CODAM) framework. In their framework, a forward model or predictor of the future state of the system created by a corollary discharge of the attentional control signal is used to generate speed-up in the access of the content by the earlier entry to the relevant buffer Working Memory (WM) [43]. Itti and Koch [41] proposed a plausible computational framework of bottom-up visual attention based on images. Their model was based on the two-dimensional *saliency map* that can make an efficient control strategy for the deployment of attention. Hoya [14] proposed a *Hierarchically Arranged Generalized Regression Neural Network* (HAGRNN) based on intuition and attention. His method was effective for pattern classification.

Bylinskii et al. [44] proposed a quantitative evaluation of visual attention models based on some examples of operationalizing and benchmarking different visual attention tasks. Guimaraes [45] presented an extension of the reward-attention circuit model. Her method showed that alcohol may lead to lack of attentional focus. Bays and Taylor presented [46] a neural model of retrospective attention in visual WM. Their results indicated the effects of retrospective attention on recall and demonstrated a principled approach for investigating neural representations with behavioral tasks. Wei and Luo [47] presented a biologically inspired model of spatiotemporal saliency attention using entropy value which is generated by the integration of the dynamic and the static saliency map. Their method was effective when there is noise or a change of illumination among the frames.

The proposed bio-inspired framework of the brain activity as a classifier stage is extended from [14] where the details and changes in structure are further addressed. In summary, correct labeling process of the ElectroEncephaloGraphy (EEG) signal, considering the emotion effect in the model, dynamic Radial Basis Functions (RBFs) in WM and LTMs, and adjusting the adaptive weights in the weighted layer are the main innovations of the proposed approach.

Methods and materials

A general block diagram of the proposed approach is shown in Fig. 1. This figure includes a data gathering; pre-processing by filtering, segmentation, and correct labeling process of the EEG signal by anesthesiologist comments and the analysis of peripheral parameters; feature extraction by Petrosian Fractal Dimension (PFD) [48], Approximate Entropy (ApEn) [49], Largest Lyapunov Exponent (LLE) [50], Correlation Dimension (CD) [51], and Lempel–Ziv Complexity (LZC) [52]; feature normalization in the range of 0 to 1, and classification by a computationally bio-inspired framework of the brain activity based on cognitive processes. In the following, these steps are briefly described.

Data

This section introduces the subjects, data acquisition protocol, and recording devices. The data were collected by Shamsollahi and his colleagues at Shohada-Tajrish hospital [53]. Twenty-two patients, classified as, American Society of Anesthesiologists (ASA) [54, 55] grade I or II who were undergoing elective urologic surgery participated in the study. Fourteen males and eight females with ages ranging from 15 to 75 years (mean age 44.36 ± 19.93 years) and weights ranging from 50 to 96 kg (mean weight 68.64 ± 12.99 Kg) participated. Written informed consent is achieved from all study subjects.

The anesthesia is divided into three stages, such as induction, maintenance, and recovery [53]. The patients are premedicated with 2 μg/kg fentanyl and 0.03 mg/kg midazolam. The anesthesia is induced with 5 mg/kg thiopental (4 mg/kg at the outset and 1 mg/kg before tracheal intubation). Cisatracurium besilate is used as a skeletal muscle relaxant or NeuroMuscular-Blocking Agent (NMBA) drug (0.1 mg/kg in the induction phase). After orotracheal intubation, the patients are ventilated using a mixture of Nitrous Oxide (N_2O) gas (combined with O_2), propofol, NMBA, and cisatracurium. Anesthesia is maintained with 75–100 μg/kg/h propofol with an infusion pump. Then, the recovery period begins that all drugs are discontinued.

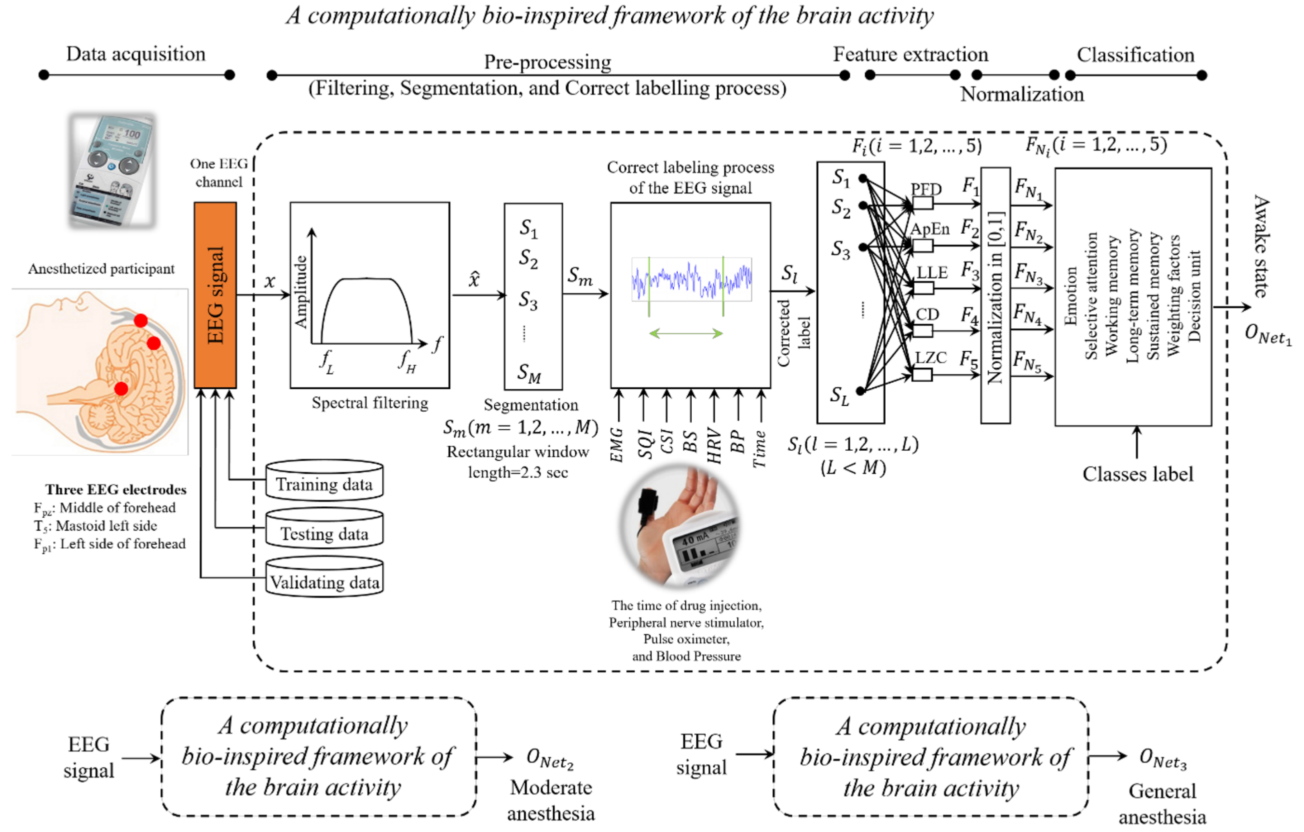


Fig. 1 A general block diagram of the proposed approach based on data gathering; pre-processing using filtering, segmentation by rectangular windows without overlap, and a correct labeling process of the EEG signal; feature extraction, normalization; and classification for estimation of different anesthetic states using EEG signals. In this model, x denotes the EEG signal, $\hat{x}$ denotes the filtered EEG signal, $S_m(m = 1, 2, \dots, M)$ are the segmented EEG, S_l $(l = 1, 2, \dots, L)$ denotes the labeled EEG, F_i $(i = 1, 2, \dots, 5)$ are the extracted features, F_{N_i} $(i = 1, 2, \dots, 5)$ are the normalized features, and $O_{Net_j}(j = 1, 2, 3)$ are the perceptual output

The patients' EEG signals are recorded using a Cerebral State Monitor (CSM, Danmeter, Odense A/S, Denmark) [56] with a sampling frequency of 100 Hz. The EEG electrodes are placed at F_{pz} (middle of forehead), T_5 (mastoid left side), and the reference electrode at F_{p1} (left side of forehead) (see Fig. 1). The EEG waveform derives from the signal recorded between the mastoid and frontal electrodes. All of the EEG signal, electrode impedances, the Burst Suppression (BS) curve, BS percent, ElectroMyoGraphy (EMG) activity percent, and the CSM calculated values, including Cerebral State Index (CSI) percent, and Signal Quality Index (SQI) percent are stored.

During the maintenance phase of anesthesia, if CSI extended the level of 60 or the anesthesiologist assessments showed a lightness of anesthesia, thiopental (0.5 mg/kg) is as an induction of anesthesia [53]. A peripheral nerve stimulator (Xavant Technology, South Africa) is utilized to quantify the muscle tone. An NMBA is repeatedly injected due to these CSI measurements. The hemodynamic parameters, such as Heart Rate Variability (HRV), Blood Pressure (BP), blood O_2 saturation (SpO_2), and the time of occurrence of movements, intubation, gagging of the patient are recorded manually by a digital pulse oximeter and non-invasive BP devices.

Pre-processing

EEG signals are usually hampered by unwanted signals or interferences from several biological or non-biological sources. These signals typically contain frequencies of up to 100 Hz and they consist of several frequency ranges, including Delta, Theta, Alpha, Beta, and Gamma. The EEG signals were filtered using a Band-Pass Filter (BPF) in the frequency band of $f_L = 1$ to $f_H = 40$ Hz to remove some noises and artifacts. To this end, Butterworth filter of order 8 with zero-phase (by *filtfilt* function) is designed.

Segmentation

In most studies, the window length of brain signals is used for a period of 1 to 4 s to distinguish among different mental states [57]. Hosseini et al. [58] determined 2.3 s time interval for segmentation. In this research, 2.3 s time intervals rectangular window without overlap, corresponding to blocks of 230 samples, is used as segmentation ($S_m, m = 1, 2, \ldots, M$, where M denotes the number of segmented signals).

Correct labeling process of the EEG signal

Correct labeling process means the assessment of the signal quality using a series of visual criteria used, including EMG, SQI, CSI, BS, HRV, BP, and the time of drug injection, by anesthesiologists and a proposed system to verify the existence of a close correlation between the signal and the different states of the subjects. The qualitative and quantitative analyses have been used to select suitable EEG segments (S_l, $l = 1, 2, \ldots, L$) for improving the efficiency of the anesthesia recognition system. For this purpose, features including standard deviation, zero crossing, average amplitude, PFD, ApEn, average frequency, and Cepstrum coefficients (with *rceps* function) are extracted from the EMG signal. The extracted features are normalized between zero to one and they are classified by Support Vector Machine (SVM) with an RBF kernel. Here, the LibSVM toolbox is used for implementation [59]. Selecting the appropriate SVM parameters (i.e., the trade-off parameter c and the kernel parameter σ) is the key to the successful application of the function. More details about the correct labeling process of the EEG signal can be found in [58, 60].

Feature extraction

Features are characteristics of a signal that are able to distinguish among different anesthetic states. In this study, a combination of five non-linear (chaotic) features (F_i, $i = 1, 2, \ldots, 5$), including PFD, ApEn, LLE, CD, and LZC, is used.

Normalization

Normalization is a necessary step to ensure that feature values with large variations are not dominated during the classifier's training. This problem is overcome by normalizing features in between zero and one by (1).

$$F_{N_i} = \frac{F_i - F_{i\text{min}}}{F_{i\text{max}} - F_{i\text{min}}}, \quad i = 1, 2, \ldots, 5. \tag{1}$$

where F_{N_i} is the relative amplitude, F_i is the original time series of features, $F_{i_{min}}$ is the minimum of features, and $F_{i_{max}}$ is the maximum of features.

Classification

The normalized features are used as inputs for the classifier based on a computationally bio-inspired framework of the brain activity. The database is arbitrarily divided into three sets; the first part for constructing a network (i.e. training set), the second part for testing (i.e. unknown to the network), and the third part for validating (see Fig. 1). In this study, 60%, 10%, and 30% of the database are selected randomly for training, validation, and testing, respectively.

Brief description of memory

Figure 2 shows a cognitive architecture based on memory and attention in the brain, which it inspired and completed from [12, 13, 61]. As depicted in Fig. 2, there are four types of connections denoted in (1) solid lines with unidirectional arrows, (2) solid lines with bidirectional arrows, (3) dashed lines with unidirectional arrows, and (4) solid lines with thick arrows, which respectively show the modules involving the unidirectional information transmission, bidirectional information transmission, extra comments, relationship between blocks. In this sections, we explain the main modules and parts of the developed and proposed cognitive architecture.

Figure 2 consists of five main modules, including SR, encoding, STM, WM, and LTM. In the following, each of them is briefly described. Sensory information first enters SR, where it resides for a very short period of time. SR does not process the information carried by the stimulus, but rather detect and hold that information, including visual, auditory, tactile, taste, and olfactory, for use in STM [13]. It automatically occurs outside of conscious control. Here, the thalamus is acted as a distributor of information, and all sensory information except the olfactory is passed through this part [62]. In this level, attention is not needed for selecting information. Then, the information entered into neocortex and cerebral cortex are interpreted and encoded [63]. The role of encoding block is to initiate the first steps of perception. The *bottom-up attentional capture* as an involuntary action is responsible for transmitting information to STM. After passing information through encoding block, STM stores a limited amount of information in SR for a short period of time. Also, a rehearsal process can maintain a limited amount of information.

Baddeley and Hitch [64] presented a new conceptual model of WM. They proposed that WM comprises a *central executive* and *top-down voluntary attention* (*attentional controller*) that supervises and coordinates a number of subsystems, including (1) The *phonological loop*, which deals with speech-based information, and (2) The *visuo-spatial sketchpad*, which deals with visually based information [64]. The central executive has a flexible structure and it is

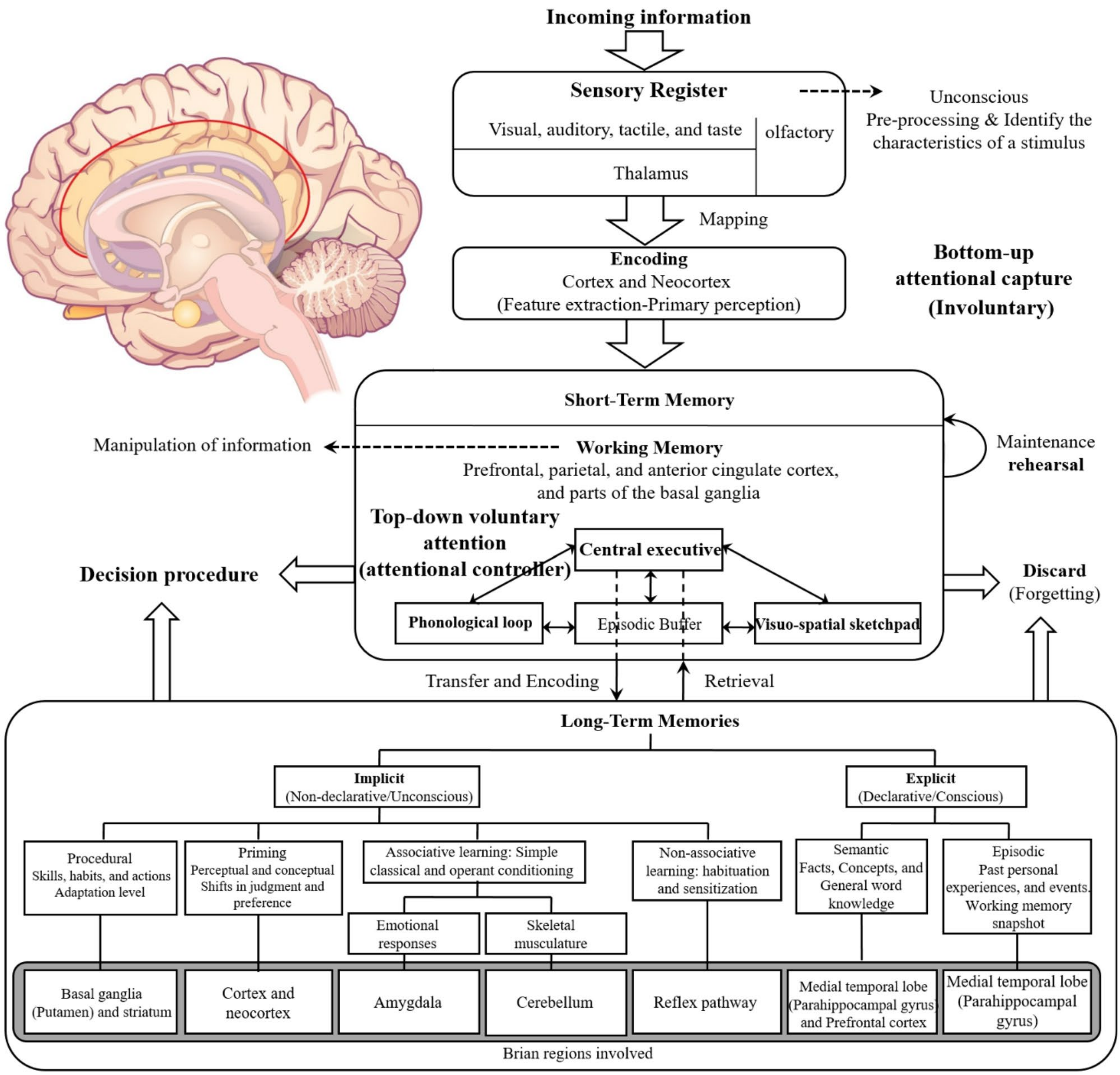


Fig. 2 A cognitive architecture of the memory and attention in the brain [12, 13, 61]

responsible for the regulation and control of cognitive processes [64]. Some studies pre-frontal cortex, large regions of the cortex (especially the parietal, frontal, and anterior cingulate), and parts of the basal ganglia are considered as WM [65, 66]. Baddeley [67, 68] equates the central executive with the SAS described by Norman and Shallice [30] and Shallice [31]. Baddeley [69] introduced the possibility of a new, fourth, component of WM called the *episodic buffer* (See Fig. 2). The episodic buffer allows information represented in different codes to be temporarily bound together [64]. It is controlled by the central executive, which can retrieve information from the episodic buffer into conscious awareness.

Experiences and knowledge in LTM are stored permanently [61] and LTM is divided into two types of modules, (1) Explicit (declarative or conscious), and (2) Implicit (non-declarative or unconscious) as shown in Fig. 2 (Modified from [70]). Explicit memory involved the medial temporal lobe, hippocampus, and pre-frontal structures of the brain [71]. According to Fig. 2, explicit memory is divided into two types of modules, (1) Episodic and (2) Semantic. Episodic memory is responsible for past personal experiences and events [71] and semantic memory is responsible for facts, concepts, and general knowledge about the world [71].

Implicit memory refers to non-conscious forms of LTM that are expressed as a change in behavior without any conscious recollection [71] and It is divided into four parts, including procedural, priming, associative learning, and non-associative learning. *Procedural* is responsible for motor skills, habits, and actions. *Priming*, including *perceptual priming* and *conceptual priming*, is defined as a change in performance with a stimulus due to the prior presentation of that stimulus or a related stimulus. Also, Priming is responsible for encoding and retrieval. *Associative learning* is responsible for *simple classical conditioning* and *operant conditioning* that also called *instrumental conditioning*, including emotional responses and skeletal musculature. *Non-associative learning* is responsible for skill learning, habituation, and sensitization. Implicit memory involved the basal ganglia, striatum, cortex, neocortex, amygdala, cerebellum, reflex pathway structures of the brain.

A system for storing information must be able to (1) Encode, (2) Store, (3) Consolidate, and (4) Access or retrieve information [61, 72]. Encoding is the initial information processing to be learned or memorized. "Memory consolidation refers to the transformation over time of experience-dependent internal representations and their neurobiological underpinnings [73]." Retrieval "is the process of reactivating knowledge in a way that will allow it to become an image in consciousness or translated into a motor output [74]."

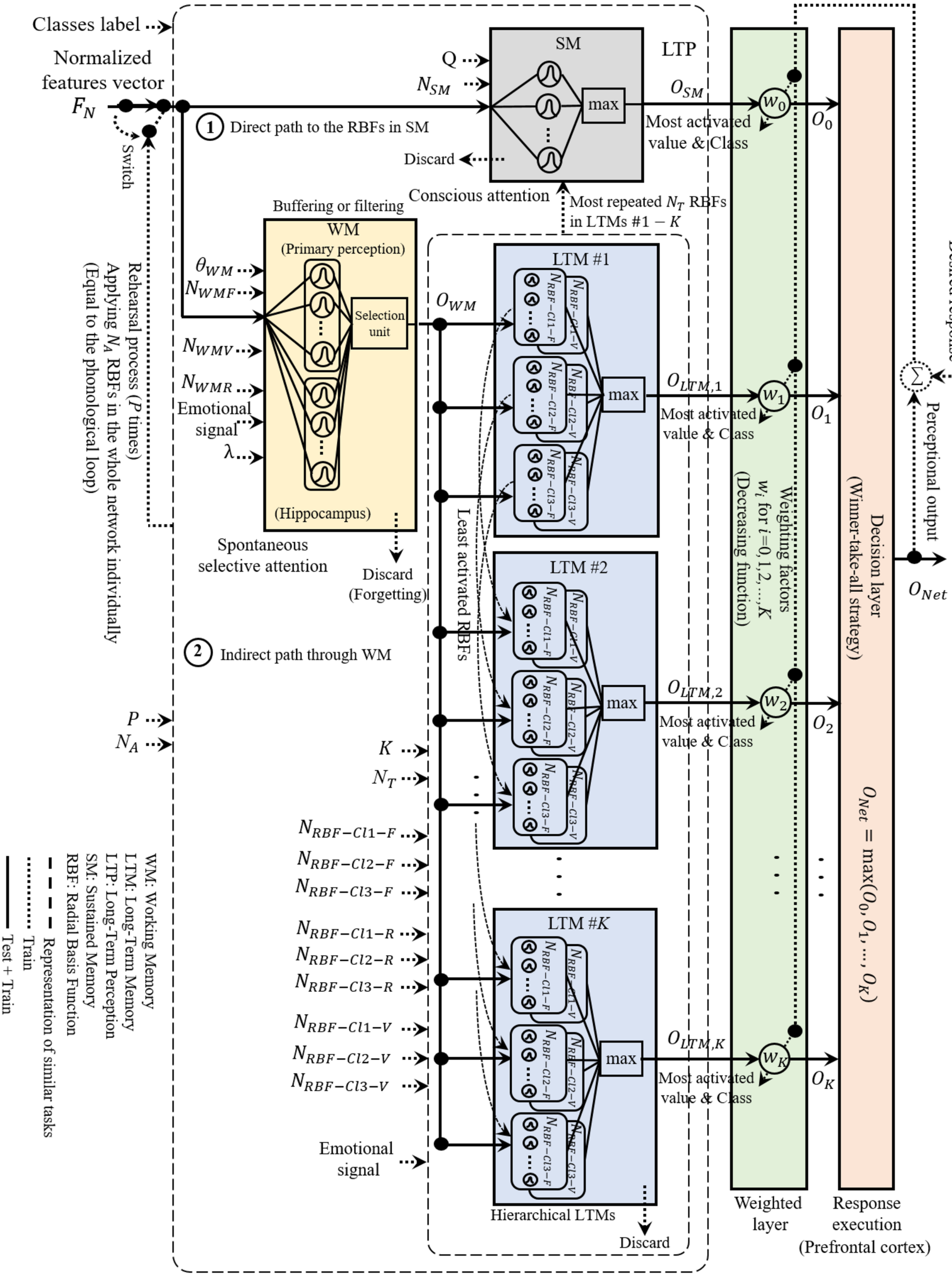
Brief description of the bio-inspired framework

The structure of a computationally bio-inspired framework of the brain activity is proposed based on the more perceptual aspects of memory, emotion, and selective attention, which some of its parts inspired from previous studies [12, 67, 68, 75–78].

This framework consists of a multiple of dynamically reconfigurable neural networks with RBF and its associated data processing mechanisms. The following steps must be performed to develop the framework: (1) Evaluation of emotional signal, (2) Configuration of WM, (3) Configuration of LTMs #1 to K which K denotes the number of hierarchical LTM (here, $K=6$), (4) Configuration of the Sustained Memory (SM), (5) Reconstruction of LTMs, (6) Reconstruction of SM, (7) Applying RBFs in the whole network individually, (8) Determining of weighting factors in SM and LTMs outputs, and (9) Response execution as a decision unit with Winner-Take-All (WTA) strategy.

Evaluation of emotional signals The emotional signal is checked in the first stage. Emotional states are usually divided into three categories: positive, calm, and negative. There are various positive emotional states, such as happiness, love, joy, passion, interest, curiosity, pride, optimism, wonder, hope and satisfaction. Also, there are various negative emotional states, such as fear, guilt, insecurity, jealousy, hatred, malice, revenge, anger, hostility, blame, shame, sadness, worry, doubt, disappointment, reproach feelings of inferiority, lack of interest, and regret. These states play an important role in memory, learning, and attention. Human's usually in positive and negative emotional states are not used from all parts of WM and LTM, but they focus on a particular part. In this study, the emotional signal range is between -5 to $+5$, where the number of zero indicates a calm state, numbers above zero indicate positive emotion, and numbers less than zero indicate negative emotion.

The maximum of RBFs in WM are divided into two groups, (1) fixed (N_{WMF}), and (2) non-fixed (N_{WMV}). The maximum of RBFs in each sub-network of LTMs are also divided into two groups, (1) fixed (N_{RBF-Cl_i-F}), and (2) non-fixed (N_{RBF-Cl_i-V}), where Cl_i is the number of classes (here, $i = 1, 2, 3$). It should be noted that $N_{WM} = N_{WMF} + N_{WMV}$ and $N_{RBF-Cl_i} = N_{RBF-Cl_i-F} + N_{RBF-Cl_i-V}$ when the emotional signal is zero. When the emotional signal is non-zero, the number of non-fixed RBFs in WM and LTM are N_{WMR} and N_{RBF-Cl_i-R} (R denotes the reduced version), respectively, which $N_{WMR} < N_{WMV}$ and $N_{RBF-Cl_i-R} < N_{RBF-Cl_i-V}$. The number of RBFs in sub-networks can be different, in other words, $N_{RBF-Cl_1} \neq N_{RBF-Cl_2} \neq N_{RBF-Cl_3}$. In this study, the values of N_{WMF}, N_{WMV}, and N_{WMR} are considered 20, 20, and 15, respectively. Pseudo-code for evaluating the emotional signal is shown in Algorithm 1.


Classes label
Normalized features vector
F_N
Switch
SM
LTP
Q
N_{SM}
max
O_{SM}
w_0
O_0
Most activated value & Class
① Direct path to the RBFs in SM
Discard
Conscious attention
Most repeated N_T RBFs in LTMs #1 − K
Buffering or filtering
WM
(Primary perception)
Selection unit
(Hippocampus)
θ_{WM}
N_{WMF}
N_{WMV}
N_{WMR}
Emotional signal
λ
O_{WM}
Rehearsal process (P times)
Applying N_A RBFs in the whole network individually
(Equal to the phonological loop)
Spontaneous selective attention
Discard (Forgetting)
② Indirect path through WM
Least activated RBFs
LTM #1
LTM #2
LTM #K
$N_{RBF-Cl1-F}$
$N_{RBF-Cl1-V}$
$N_{RBF-Cl2-F}$
$N_{RBF-Cl2-V}$
$N_{RBF-Cl3-F}$
$N_{RBF-Cl3-V}$
$O_{LTM,1}$
$O_{LTM,2}$
$O_{LTM,K}$
w_1
w_2
w_K
O_1
O_2
O_K
P
N_A
K
N_T
$N_{RBF-Cl1-R}$
$N_{RBF-Cl2-R}$
$N_{RBF-Cl3-R}$
Emotional signal
Hierarchical LTMs
Discard
Weighting factors
w_i for $i = 0, 1, 2, \ldots, K$
(Decreasing function)
Weighted layer
Decision layer
(Winner-take-all strategy)
$O_{Net} = \max(O_0, O_1, \ldots, O_K)$
Response execution
(Prefrontal cortex)
Desired response
Perceptional output
Σ
O_{Net}
WM: Working Memory
LTM: Long-Term Memory
LTP: Long-Term Perception
SM: Sustained Memory
RBF: Radial Basis Function
Representation of similar tasks
Train
Test + Train

◂**Fig. 3** A computationally bio-inspired framework of the brain activity based on emotional states, bottom-up attentional capture, WM, LTM, top-down attention, SM, forgetting, weighting factors, and a decision unit. In this framework, F_N denotes the incoming information pattern vector, O_{WM} is the WM output vector, O_{SM} is the SM output, $O_{LTM,k}$ $(k = 1, 2, \ldots, K)$ are LTM outputs, $W_k (k = 0, 1, 2, \ldots, K)$ are the weighting factors in SM and LTM outputs, $O_k (k = 0, 1, 2, \ldots, K)$ are the weighted outputs, and O_{Net} is the final perceptional output

following steps: if the intensity of activation of the least activated RBF ($Value_{min}$) is less than the threshold of WM (here, $\theta_{WM} = 0.1$), in other words, $Value_{min} < \theta_{WM}$, replace it with a new RBF with $C_i = F_N$ and set $O_{WM} = F_N$. Otherwise, O_{WM} is given as the filtered version of F_N as shown in (3).

$$O_{WM} = \lambda C_{Index_{\max}} + (1 - \lambda) F_N \tag{3}$$

Algorithm 1. Algorithm for evaluating of emotional signals

$\boldsymbol{if}$ $EmotionalSignal = 0$ $\boldsymbol{then}$
$N_{WM} = N_{WMF} + N_{WMV}$
$N_{RBF-Cl_1} = N_{RBF-Cl_1-F} + N_{RBF-Cl_1-V}$
$N_{RBF-Cl_2} = N_{RBF-Cl_2-F} + N_{RBF-Cl_2-V}$
$N_{RBF-Cl_3} = N_{RBF-Cl_3-F} + N_{RBF-Cl_3-V}$
$\boldsymbol{else}$
$N_{WMV} = N_{WMR}$
$N_{WM} = N_{WMF} + N_{WMV}$
$N_{RBF-Cl_1-V} = N_{RBF-Cl_1-R}$
$N_{RBF-Cl_1} = N_{RBF-Cl_1-F} + N_{RBF-Cl_1-V}$
$N_{RBF-Cl_2-V} = N_{RBF-Cl_2-R}$
$N_{RBF-Cl_2} = N_{RBF-Cl_2-F} + N_{RBF-Cl_2-V}$
$N_{RBF-Cl_3-V} = N_{RBF-Cl_3-R}$
$N_{RBF-Cl_3} = N_{RBF-Cl_3-F} + N_{RBF-Cl_3-V}$
$\boldsymbol{endif}$
$\boldsymbol{if}(-5 \le EmotionalSignal < -3)$ or $(3 < EmotionalSignal \le 5)$ $\boldsymbol{then}$
$K = K - 2$
$\boldsymbol{else}$
$K = K - 1$
$\boldsymbol{endif}$

Configuration of WM WM is responsible for temporarily stores input pattern vector as buffering or filtering. The configuration of WM consists of a series of RBF with a selection unit for selecting one of the most activated RBFs (see Fig. 3). This single layer structure does not have any subnetworks. Each RBF is introduced using activation value and index by (2).

$$[Value, Index] = Value_i\left(F_N, C_i, \sigma_i\right) = \frac{1}{2\sigma_i^2} \exp\left(-\frac{\left\|F_N - C_i\right\|_2^2}{2\sigma_i^2}\right), \tag{2}$$

where σ_i denotes RBF radius, C_i denotes the center of RBF, and $\| \|_2$ denotes the squared Euclidean norm. The WM is firstly formed by the following procedure [14]. The learning mechanism of WM is summarized in the following. If the number of RBFs in WM (M_{WM}) is less than the number of maximum RBFs (N_{WM}), in other words, $M_{WM} < N_{WM}$, add an RBF with an activation intensity $Value_i\left(F_N, C_i, \sigma_i\right)$ calculated by (2) and RBF vector $C_i = F_N$ in the WM. Then, set $O_{WM} = F_N$ and terminate. Otherwise, execute the

where $C_{Index_{max}}$ is the RBF vector of the most activated RBF and λ (0 ≤ λ ≤ 1) is a smoothing factor (here, λ = 0.7). The parameter λ is a measure to determine how quickly WM is evolved by a new incoming pattern vector and switches its focus to the patterns in other domains. This may relate to the spontaneous selective attention of a particular event [14]. If λ is small, θ_{WM} becomes more likely to F_N itself, which can be regarded as a sign of carelessness. In contrast, if λ is large, WM becomes sticky to only a particular pattern. In other words, the output is a combination of F_N with the maximum output value according to (2) as computed in (4).

$$\left[Value_{\max}, Index_{\max}\right] = \max_{i=1,2,\ldots,N_{WM}} \left(Value_i\right). \tag{4}$$

Pseudo-code for the configuration of WM is shown in Algorithm 2.

Algorithm 2. Algorithm for configuration of WM

```
if M_WM < N_WM then
  [Value_min, Index_min] = min_{i=1,2,...,N_WM} (Value_i)
  //C_i = F_N
  //t denotes class label
  AddNewRBF = CreateRBF(F_N, F_N, σ_i, t)
  O_WM = F_N
  elseif Value_min < θ_WM then
    //C_i = F_N
    ReplaceNewRBF = CreateRBF(F_N, F_N, σ_i, t)
    O_WM = F_N
   else
    [Value_max, Index_max] = max_{i=1,2,...,N_WM} (Value_i)
    //0 ≤ λ ≤ 1
    O_WM = λC_{Index_max} + (1 − λ)F_N
  endif
endif
if M_WM > N_WM then
  [Value_min, Index_min] = min_{i=1,2,...,N_WM} (Value_i)
  Discard RBF with Value_min
endif
```

Also, if M_{WM} to reach N_{WM} (WM is full), there is no capacity to store the new vector, so RBF with the lowest value in WM according to Algorithm 2 is discarded. In the test phase, O_{WM} is introduced by (5).

$$O_{WM} = \max_{i=1,2,\ldots,N_{WM}} \left(\frac{1}{2\sigma_i^2} \exp\left(-\frac{\|F_N - C_i\|_2^2}{2\sigma_i^2} \right) \right). \tag{5}$$

If more than one maximum for RBFs is found, then one of them is randomly chosen as O_{WM}. The role of SM and LTMs #1 to K is to realize a hierarchical classification system based on the importance or attractiveness of information [14]. SM and LTMs are usually described into two parts, including (1) SM for generating *intuitive output*, which is illustrated in Fig. 3, and (2) LTMs #1 to K for the regular (ordinary) outputs, which they illustrated in Fig. 3 and have the same structure with each other [14]. Each of these parts is briefly described below.

Configuration of LTMs #1 to *K* LTMs #1 to K have several sub-networks and each part has one decision unit. As a result, the iterative learning of weight vectors is not necessary at all; and the network can be flexibility formed for giving tasks. LTM #1 is constructed by directly assigning O_{WM} to RBF vectors in it. Information transfer from WM to LTM is known as consolidation. RBFs within LTM #1 are distributed into the respective sub-networks according to the classes label, which is given by the target vector consisting of a series of indicator functions [14]; associated with each RBF vectors. Formation of LTMs #1 to K is summarized as follows: Provided that O_{WM} belongs to class i, then, for $j = 1$ to $K - 1$, execute the following steps: If the number of RBFs in sub-network i of LTM j ($M_{LTM_{j,Cl_i}}$) reaches a maximum $N_{LTM_{j,Cl_i}}$, move the least activated RBF within sub-network i of LTM j to LTM $j + 1$. If the number of RBFs in sub-network i of LTM K ($M_{LTM_{K,Cl_i}}$) reaches a maximum $N_{LTM_{K,Cl_i}}$, (i.e., if all the ith sub-networks of LTMs #1 to K are filled), there is no entry for store a new O_{WM} (here, $N_{LTM} = 18$). Therefore, execute the following steps: Forgetting (discard) the least activated RBF in sub-network i of LTM #K. Pseudo-code for the formation of LTMs #1 to K is shown in Algorithm 3.

Algorithm 3. Algorithm for configuration of LTMs

$\boldsymbol{for}\ j \leftarrow 1\ \boldsymbol{to}\ K\ \boldsymbol{do}$
  $NewRBF = CreateRBF(O_{WM}, O_{WM}, \sigma_i, t)$
  $\boldsymbol{for}\ i \leftarrow 1\ \boldsymbol{to}\ 3\ \boldsymbol{do}$
    $\boldsymbol{if}\ M_{LTM_{j,Cl_i}} > N_{LTM_{j,Cl_i}}\ \boldsymbol{then}$
      $[Value_{min}, Index_{min}] = \min_{i=1,2,\ldots,N_{LTM_{j,Cl_i}}} (Value_i)$
      $\boldsymbol{if}\ j < K\ \boldsymbol{then}$
        $Move\ RBF\ j^{th} with\ Value_{min}\ to\ RBF\ (j+1)^{th} belongs\ to\ Cl_i$
      $\boldsymbol{else}$
        $Discard\ RBF\ with\ Value_{min}$
      $\boldsymbol{endif}$
    $\boldsymbol{endif}$
  $\boldsymbol{endfor}$
$\boldsymbol{endfor}$

Shift all the least activated RBFs in sub-network i of LTMs #$(K-1)$ to 1 into LTMs from #K to 2, respectively. Store a new O_{WM} in the sub-network i of LTM #1. In the test phase, $O_{LTM,k}$ is introduced by (6).

$$O_{LTM,k} = \max_{\substack{t=1,2,\ldots,N_{RBF-Cl_1}\\ r=1,2,\ldots,N_{RBF-Cl_2}\\ e=1,2,\ldots,N_{RBF-Cl_3}}} \begin{pmatrix} \frac{1}{2\sigma_t^2}\exp\left(-\frac{\|O_{WM}-C_t\|_2^2}{2\sigma_t^2}\right), \\ \frac{1}{2\sigma_r^2}\exp\left(-\frac{\|O_{WM}-C_r\|_2^2}{2\sigma_r^2}\right), \\ \frac{1}{2\sigma_e^2}\exp\left(-\frac{\|O_{WM}-C_e\|_2^2}{2\sigma_e^2}\right) \end{pmatrix}, \quad k = 1,2,\ldots,K \tag{6}$$

Configuration of SM Input pattern vector is also directly entered into the SM network for Long-Term Perception (LTP). SM have RBFs not having a summing operation unit at the output. Therefore, O_{SM} is the mostly activated RBF chosen by the WTA strategy. The number of RBFs in SM varies due to the following reasons. The framework of WM and SM are similar to each other, but the associated data processing within WM is different from SM. O_{WM} is also given as an RBF vector by the associated LIFO stack-like mechanism (queuing system), whilst that O_{SM} is a scalar value. Also, WM is not a pattern classifier, unlike SM and LTMs #1 to K.

Formation of SM is summarized as follows. The number of RBFs in LTM #1 to K, which are most activated based on their activation counters (here, $N_T = 4$) is sorted in a descending list and chosen for transferring to SM in a certain period here, $Q = 360$, Q where denotes time period to fill or update SM with most activated RBF in LTM #1 to K. In this study, the value of N_{SM} is assumed to be 12, by trial and error. Pseudo-code for the formation of SM is given in Algorithm 4.

Algorithm 4. Algorithm for configuration of SM

$\boldsymbol{for}\ k \leftarrow 1\ \boldsymbol{to}\ Q\ \boldsymbol{do}$
  $Sort\ RBFs\ in\ LTMs\ in\ a\ decreasing\ order\ based\ on\ their\ activation\ counters$
  $Select\ N_T\ RBFs$
  $\boldsymbol{if}\ M_{SM} \le N_{SM} - N_T\ \boldsymbol{then}$
    $Add\ all\ N_T\ RBFs\ to\ existing\ RBFs\ in\ SM$
  $\boldsymbol{else}$
    $Replace\ N_T\ RBFs\ with\ the\ least\ activation\ counters\ with\ new\ RBFs$
  $\boldsymbol{endif}$
$\boldsymbol{endfor}$

Table 1 A summary of results of the proposed approach with the considered parameters, including $\theta_{WM} = 0.1$, $\lambda = 0.7$, $N_T = 4$, $Q = 360$, $P = 3$, and $N_A = 6$

Number of RBFs	Emotional signal (K value)					
	0 ($K = 6$)		2($K = 5$)		4($K = 4$)	
	Average accuracy (%)	Highest accuracy (%)	Average accuracy (%)	Highest accuracy (%)	Average accuracy (%)	Highest accuracy (%)
$N_{WMF} = 20$ $N_{WMV} = 20$ $N_{WMR} = 15$ $N_{LTM} = 18$ $N_{SM} = 12$	89.2	91.6	85.1	90.7	82.7	85.2
$N_{WMF} = 25$ $N_{WMV} = 25$ $N_{WMR} = 20$ $N_{LTM} = 23$ $N_{SM} = 17$	90.2	91.4	87.2	89.7	83.3	86.3

This process is like a strong persistence in memory due to repetition and practice. At the end stage of the training phase, a number of RBFs in WM, SM, LTMs #1 to K which are most activated based on their activation counters (N_A), are entered as incoming information pattern to the network (here, $N_A = 6$). This process is repeated P times (here, $P = 3$), which is equivalent to a phonological loop in the cognitive architecture of memory. Pseudo-code for the feedback of RBFs according to their decreasing activation function is shown in Algorithm 5.

In the test phase, O_{SM} is introduced by (7).

$$O_{SM} = \max_{i=1,2,\ldots,N_{SM}} \left(\frac{1}{2\sigma_i^2} \exp\left(-\frac{\|F_N - C_i\|_2^2}{2\sigma_i^2} \right) \right). \tag{7}$$

Configuration of weighted layer and response execution The final perceptual output (O_{Net}) is given by (8) as the maximum value amongst the weighted O_{SM} and $O_{LTM,k}$ ($k = 1, 2, \ldots, K$) with the WTA strategy.

Algorithm 5. Algorithm for the rehearsal process

```
for p ← 1 to P do
  Sort RBFs in WM, SM, and LTMs in a decreasing order based on their activation counters
  Select N_A RBFs
  if M_WM ≤ N_WM − N_A then
    Add all N_A RBFs to existing RBFs in WM
  else
    Replace the N_A RBFs with the least activation counters with new RBFs
  endif
  if M_SM ≤ N_SM − N_A then
    Add all N_A RBFs to existing RBFs in SM
  else
    Replace N_A RBFs with the least activation counters with new RBFs
  endif
endfor
```

$$\begin{aligned} O_{Net} &= \max(W_0 \times O_{SM}, W_1 \times O_{LTM,1},\ W_2 \times O_{LTM,2}, \ldots,\ and\ W_K \times O_{LTM,K}) \\ &= \max(O_0, O_1, \ldots, O_K) \end{aligned} \tag{8}$$

where $W_0 \gg W_1 > W_2 > \cdots > W_K$. Note that the weight value W_0 for O_{SM} is relatively given greater than the others. An adaptive algorithm is used for determining W_k ($k = 0, 1, 2, \ldots, K$) by comparing the output with the desired output in the training phase. If the output with the corrected label is observed, then the related weighting factor is increased by one and the other weighting factors are decreased by 0.1. In the test phase, the value of weighting factors is determined as constant, e.g., when the emotional signal is zero, the values of $W_i s (i = 0, 1, 2, \ldots, 6)$ are 5.8, 3.3, 3.1, 2.7, 2.6, 2.4, and 1.9.

Results

In this section, results are presented and the outcomes are analyzed on the basis of literature, with the numerical representation of the proposed approach. The described anesthesia recognition was used as a benchmark to validate our proposed approach based on a cognitive architecture and a computationally bio-inspired framework of the brain activity. The experimental simulations were implemented in MATLAB on a workstation with 8 GB of RAM and 2.40 GHz processor.

The input of the proposed approach is the EEG signal collected by the sensors in different anesthetic states. We used a 2.3 s time intervals rectangular window without overlap, corresponding to blocks of 230 samples of EEG signals for data segmentation. Correct labeling process of the EEG signal means the assessment of the signal quality using a series of visual criteria used, including EMG, SQI, CSI, BS, HRV, BP, and the time of drug injection, by anesthesiologists and a proposed system to verify the existence of a close correlation between the signal and different anesthetic states. The results showed that the awake state, the moderate anesthesia, and the general anesthesia are distinguished using the EMG signal with the accuracy of 83.4%, 87.28%, and 86.12%, respectively. Then, according to the obtained accuracy and the expert opinion in the field of anesthesia, the EEG signal is correctly labeled in different anesthetic states.

For each EEG segment, five different features are extracted. The results showed that the ApEn and PFD values of general anesthesia state are less as compared to those of the awake state. The performance over the validating set is achieved after the consideration of perceptual output. The experiment is carried out in three different states, including when the emotional value is zero, when it is between zero and three, and when it is between three and five. The confusion matrix is obtained by the proposed approach. The proposed approach with zero, two, and four as emotional values is used for recognizing of different anesthetic states which yield average accuracies of 89.2%, 85.1%, and 82.7%, and with highest accuracies of 91.6%, 90.7%, and 85.2%, respectively. The proposed approach with zero, three, and five emotional values is used for recognizing of different anesthetic states which yield average accuracies of 89.2%, 83.8%, and 80.1%, and with highest accuracies of 91.6%, 86.4%, and 83.2%, respectively.

When five RBFs were added to each module, the proposed approach with zero, two, and four emotional values is used for recognizing of different anesthetic states which yield average accuracies of 90.2%, 87.2%, and 83.3%, and with highest accuracies of 91.4%, 89.7%, and 86.3%, respectively. As a result, the average accuracy is increased with the addition of RBFs and vice versa. A summary of the obtained results of the proposed approach is shown in Table 1.

Discussion

Current computational cognitive architectures lack a comprehensive representation of human physiology. Therefore, the aim of the present study is to propose an efficient computationally bio-inspired framework of brain activities based on the cognitive architecture for estimating DOA using EEG signals. We developed a cognitive architecture to complete a version of the HAGRNN model carried out by [14]. To this end, Algorithm 1 evaluated values for emotional signals related to different emotional states, including positive, calm, and negative; Algorithm 2 constructed the configuration for WM; Algorithm 3 established the configuration of LTMs; and Algorithm 4 constructed the configuration of SM. Finally, Algorithm 5 presented a process for the rehearsal. The rationale of each step of algorithmic development was discussed in detail and the proposed approach was analyzed on EEG signals for recognizing different anesthetic states. Study of variations of the anesthetic EEG signal is a unique tool for considering consciousness and for confirming or ignoring conceptual theories about that state. The main contribution and advantages of this paper can be summarized as follows.

First, the proposed approach develops a cognitive architecture and a computationally bio-inspired framework of brain activities based on concepts, such as SR, encoding, emotion, STM, selective attention, WM, forgetting, LTM, SM, and response selection. The main innovations of the proposed approach include considering the emotion effect in the model, dynamic RBFs in WM and LTMs, and adjusting weights in the weighted layer.

Second, this study is able to evaluate the quality of EEG signals according to different anesthetic states using a series of visual criteria used by an anesthesiologist and the proposed system.

Third, the chaotic dynamics of EEG signals were examined for discrimination of different anesthetic states. Non-linear features can successfully extract small variations in non-stationary signals like EEG. Therefore, quantitative measures of non-linear features are convenient descriptive tools to characterize the main information from complex EEG signals.

Fourth, one of the advantages of the proposed approach is its ability to yield considerable results even when a small proportion of the segments was selected as the training data set. This particularly accelerates the process of training the classifier and, thus, reduces the total processing time and computational cost [15]. The purpose of this paper is to design a simple learning mechanism for the proposed framework.

Fifth, the average accuracy obtained from a previous study with zero emotional value [58] for recognizing different anesthetic states is 87.6%. In comparison with that study, the proposed approach provides better accuracy and lower computational complexity as well as load. The average accuracy obtained from another study [15] for recognizing the different anesthetic states is 93.89% (a 2.7 s interval is selected for segmentation). Although the accuracy of the proposed approach is less than [15], the proposed approach may provide a computationally simple as well as practically implementable way for processing data. According to the results, the average accuracy is increased with the addition of RBFs and vice versa.

Sixth, the proposed layered-memory concept is not limited to pattern classification-oriented tasks and it can be widely applicable where the tasks and the goals are known or given, e.g., various planning tasks for autonomous robotics, and cognitive controllers. In such applications, the incoming input vectors are considered as a set of sequential data points, e.g., sensory data to know the position of the robot or the internal states, and to interact with other robots. This can alternatively be represented by the attentive states while the output sequence from the proposed approach can directly or indirectly change or set parameters to actually control the movement of the robot or the response to other robots by built-in communication facilities, according to the current situations.

Conclusion and future works

This paper proposes a computationally bio-inspired framework of the brain activity based on memory, emotion, and selective attention for estimating DOA by EEG signals. This study considers five main parts, including (1) Elaboration of the concept of attention and memory phenomena, (2) Designing and developing a cognitive architecture, (3) Developing a computationally bio-inspired framework of the brain activity, (4) Simulation of the model, and (5) Its application in recognition of different anesthetic states.

A clinical study was carried out on 22 patients corresponding to three anesthetic states, including the awake state, moderate anesthesia, and general anesthesia. The hybrid strategy proposes data gathering, pre-processing, feature extraction, normalization, and classification. Different brain regions, such as the thalamus, temporal cortex, parietal cortex, neocortex, amygdala, striatum, basal ganglia, hippocampus, and pre-frontal cortex, have functions based on primary perception, SR, encoding, STM, WM, LTM, SM, forgetting, behavioral inhibition, and response selection. This paper the first proposes a cognitive architecture of memory, emotion, and attention, and then it provides a computationally bio-inspired framework. The proposed framework has been applied due to its simplicity and its further adaptation to the biological aspect of the memory and attention concepts. It also has the ability to add many high-level cognitive concepts, including positive and negative emotional states and forgetting to the framework.

In the proposed approach, various incoming information is entered into the model. Then, the correct labeling process of the EEG signal is performed by qualitative and quantitative analyses of peripheral parameters. Then, an SR is used to accumulate the pre-processed EEG segment for a period of 2.3 s using a rectangular window without overlap. Feature extraction is performed in the encoding stage as a primary perception. The output of this stage can be transferred to STM and WM with a bottom-up involuntary attentional capture as the perception stage. An important part of brain modeling is attention allocation based on conscious or unconscious decisions. Finally, LTM and SM as fairly permanent reservoirs for information are passed from WM with a top-down voluntary attention mechanism.

The important proposes of this study are to more explain concepts, such as memory, emotion, and attention to develop a computationally bio-inspired framework of the brain activity, and model simulation to classify three different anesthetic states. The results show that the proposed approach can classify different anesthetic states with an average accuracy of 89.2%. Results also indicate that the combined use of the above elements can effectively decipher the cognitive process task. A final comparison between the obtained result and the previous method on the same database is presented to show the effectiveness of the proposed approach for estimating DOA.

There are some concerns that merit further consideration. First of all, it is better to propose a computationally bio-inspired framework of the brain activity closer to the brain function. Therefore, with electrophysiological and intuitive studies, other parts of the computational model can be intelligently added. Second, different parts of the framework, based on memory and attention, were modeled in more detail based on a comprehensive cognitive architecture. Third, the universal approximation property was proved for this framework. Fourth, this framework can be used as a cognitive controller for solving complex engineering problems. Fifth, the role of various types of emotion in the computational framework is added. To this end, it is possible to determine the type of emotion with regard to the level of arousal and valence, and how its impact on attention and memory can be evaluated.

Acknowledgements The authors would like to acknowledge Prof. M.-B. Shamsollahi (Sharif University of Technology, Tehran, Iran) for providing access to EEG signals in our experiments.

Funding This work is supported by the cognitive sciences and technologies council in Iran (Grant No. 774, approved on 07/08/2014).

Compliance with ethical standards

Conflict of interest There is no conflict of interest that could inappropriately influence this research work.

Ethical approval This study was approved by the local ethics committee and written informed consent was obtained from all subjects included in the study.

References

1. Hosseini SA (2017) Introductory chapter: emotion and attention recognition based on biological signals and images. In: Intech
2. Chabot RJ, Serfontein G (1996) Quantitative electroencephalographic profiles of children with attention deficit disorder. Biol Psychiatry 40(10):951–963
3. Loo SK, Makeig S (2012) Clinical utility of EEG in attention-deficit/hyperactivity disorder: a research update. Neurotherapeutics 9(3):569–587
4. Loetscher T, Lincoln NB (2013) Cognitive rehabilitation for attention deficits following stroke. The Cochrane Library
5. Skodol AE, Morey LC, Bender DS, Oldham JM (2015) The alternative DSM-5 model for personality disorders: a clinical application. Am J Psychiatry 172(7):606–613
6. Stroganova TA et al (2007) Abnormal EEG lateralization in boys with autism. Clin Neurophysiol 118(8):1842–1854
7. Hosseini SA, Naghibi-Sistani MB, Akbarzadeh-T MR (2015) A two-dimensional brain-computer interface based on visual selective attention by magnetoencephalograph (MEG) signals. Tabriz J Electr Eng 45(2):65–74
8. Kallenberg M (2006) Auditory selective attention as a method for a brain computer interface. Masters thesis, Radboud University Nijmegen, Nijmegen,
9. Studer B, Cen D, Walsh V (2014) The angular gyrus and visuospatial attention in decision-making under risk. NeuroImage 103:75–80
10. Chen H-R, Chen JH (2015) Design of attention-based recommendation learning mechanism in the cloud computing environment. In: Advanced Learning Technologies (ICALT), IEEE 15th International Conference on 2015, pp. 456–457
11. Begum M, Karray F, Mann GK, Gosine RG (2010) A probabilistic model of overt visual attention for cognitive robots. IEEE Trans Syst Man Cybern Part B 40(5):1305–1318
12. Hoya T (2005) Artificial mind system: Kernel memory approach, vol. 1. Springer Science & Business Media, New York
13. Atkinson RC, Shiffrin RM (1968) Human memory: A proposed system and its control processes. Psychol Learn Motiv 2:89–195
14. Gazzaniga MS (2000) The new cognitive neurosciences. The MIT Press, Cambridge
15. Hosseini SA (2018) A computational framework to discriminate different anesthesia states from EEG signal. Biomed Eng 30(03):1850020
16. van der Heijden AH (2003) Selective attention in vision. Routledge, London
17. Broadbent DE (2013) Perception and communication. Elsevier, Amsterdam
18. Ward A (2004) Attention: a neuropsychological approach. Psychology Press, London
19. Lund N (2002) Attention and pattern recognition. Routledge, London
20. Styles E (2006) The psychology of attention. Psychology Press, London
21. Kahneman D (1973) Attention and effort. Citeseer, Princeton
22. Deutsch JA, Deutsch D (1963) Attention: some theoretical considerations. Psychol Rev 70(1):80
23. Johnston WA, Heinz SP (1978) Flexibility and capacity demands of attention. J Exp Psychol Gen 107(4):420
24. Galotti KM (2013) Cognitive psychology in and out of the laboratory. SAGE, Thousand Oaks
25. Treisman A (1964) Monitoring and storage of irrelevant messages in selective attention. J Verbal Learn Verbal Behav 3(6):449–459
26. Leclercq M, Zimmermann P (2004) Applied neuropsychology of attention: theory, diagnosis and rehabilitation. Psychology Press, London
27. Graziano MS (2010) God soul mind brain: a neuroscientist's reflections on the spirit world. Leapfrog Press, Fredonia
28. Graziano MS, Kastner S (2011) Human consciousness and its relationship to social neuroscience: a novel hypothesis. Cognit Neurosci 2(2):98–113
29. Venter H (2011) The effect of the tempo of music on concentration in a simulated driving experience. Doctoral dissertation
30. Norman DA, Shallice T (1986) Attention to action. Springer, Berlin
31. Shallice T (1982) Specific impairments of planning. Philos Trans R Soc Lond B 298(1089):199–209
32. Bronzino JD (2000) The biomedical engineering handbook. CRC Press LLC, Boca Raton
33. Wickens CD, McCarley JS (2007) Applied attention theory. CRC Press, Boca Raton
34. Parasuraman R, Yantis S (1998) The attentive brain. MIT Press, Cambridge
35. Mozer MC (1991) The perception of multiple objects: A connectionist approach. MIT Press, Cambridge
36. Mozer MC, Sitton M (1998) Computational modeling of spatial attention. Attention 9:341–393
37. Phaf RH, Van der Heijden AHC, Hudson PT (1990) SLAM: a connectionist model for attention in visual selection tasks. Cognit Psychol 22(3):273–341
38. Heinke D, Humphreys GW (2003) Attention, spatial representation, and visual neglect: simulating emergent attention and spatial memory in the selective attention for identification model (SAIM). Psychol Rev 110:29
39. Heinke D, Humphreys GW (2005) Computational models of visual selective attention: a review. Connect Models Cognit Psychol 1(4):273–312
40. Taylor J, Fragopanagos N, Korsten N (2006) Modelling working memory through attentional mechanisms. In: *Artificial Neural Networks–ICANN 2006*, Springer, pp 553–562

41. Itti L, Koch C (2001) Computational modelling of visual attention. Nat Rev Neurosci 2(3):194–203
42. Taylor JG (2007) CODAM model: Through attention to consciousness. Scholarpedia 2(11):1598
43. Tsotsos JK (2011) A computational perspective on visual attention. MIT Press, Cambridge
44. Bylinskii Z, DeGennaro EM, Rajalingham R, Ruda H, Zhang J, Tsotsos JK (2015) Towards the quantitative evaluation of visual attention models. Vis Res 116:258–268
45. Guimarães K (2018) Extension of reward-attention circuit model: alcohol's influence on attentional focus and consequeces on autism spectrum disorder. Neurocomputing. https://doi.org/10.1016/j.neucom.2018.10.034
46. Bays PM, Taylor R (2018) A neural model of retrospective attention in visual working memory. Cognit Psychol 100:43–52
47. Wei L, Luo D (2014) A biologically inspired spatiotemporal saliency attention model based on entropy value. Optik 125(21):6422–6427
48. Petrosian A (1995) Kolmogorov complexity of finite sequences and recognition of different preictal EEG patterns. In: Computer-Based Medical Systems, ., Proceedings of the Eighth IEEE Symposium on 1995, pp 212–217
49. Pincus SM (1991) Approximate entropy as a measure of system complexity. Proc Natl Acad Sci USA 88(6):2297–2301
50. Rosenstein MT, Collins JJ, De Luca CJ (1993) A practical method for calculating largest Lyapunov exponents from small data sets. Phys. D 65(1):117–134
51. Grassberger P, Procaccia I (2004) Measuring the strangeness of strange attractors. In: Hunk BR et al. (eds) The theory of chaotic attractors. Springer, Berlin, pp 170–189
52. Lempel A, Ziv J (1976) On the complexity of finite sequences. IEEE Trans Inf Theory 22(1):75–81
53. Esmaeili V, Assareh A, Shamsollahi MB, Moradi MH, Arefian NM (2008) Estimating the depth of anesthesia using fuzzy soft computation applied to EEG features. Intell Data Anal 12(4):393–407
54. Daabiss M (2011) American Society of Anaesthesiologists physical status classification. Indian J Anaesth 55(2):111
55. "American Society of Anesthesiologists–American Society of Anesthesiologists. http://www.asahq.org/ (Accessed 14 Aug 2015)
56. CSM Monitor. http://www.danmeter.dk/products/neuromonitoring/csmmonitor/ (Accessed 14 Aug 2015)
57. Hosseini SA, Khalilzadeh MA, Changiz S (2010) Emotional stress recognition system for affective computing based on bio-signals. J Biol Syst 18(spec01):101–114
58. Hosseini SA (2016)A computationally inspired model of brain activity in selective attentional state and its application for estimating the depth of anesthesia. PhD Thesis, Ferdowsi University of Mashhad
59. Chang C-C, Lin C-J (2011) LIBSVM: A library for support vector machines. ACM Trans Intell Syst Technol 2(3):27
60. Hosseini SA, Khalilzadeh MA (2010) Emotional stress recognition system using EEG and psychophysiological signals: using new labelling process of EEG signals in emotional stress state. In: 2010 International Conference on Biomedical Engineering and Computer Science (ICBECS), pp. 1–6
61. Kandel ER, Schwartz JH, Jessell TM, Siegelbaum SA, Hudspeth AJ (2014) Principles of neural science. McGraw-hill, New York
62. Snell RS (2010) Clinical neuroanatomy. Lippincott Williams & Wilkins, Philadelphia
63. Tse D et al (2011) Schema-dependent gene activation and memory encoding in neocortex. Science 333(6044):891–895
64. Styles EA (2005) Attention, perception and memory: An integrated introduction. Psychology Press, London
65. Baddeley A (1992) Working memory: the interface between memory and cognition. J Cognit Neurosci 4(3):281–288
66. Constantinidis C, Procyk E (2004) The primate working memory networks. Cognit Affect Behav Neurosci 4(4):444–465
67. Baddeley A (1986) Oxford psychology series, No. 11. Working memory. Clarendon Press/Oxford University Press, New York
68. Baddeley AD (1997) Human memory: theory and practice. Psychology Press, London
69. Baddeley A (2000) The episodic buffer: a new component of working memory? Trends Cognit Sci 4(11):417–423
70. Squire LR, Knowlton BJ (1995) Memory, hippocampus, and brain systems. MIT Press, Cambridge
71. Smith EE, Kosslyn SM (2006) Cognitive psychology: mind and brain. Pearson, London
72. Melton AW (1963) Implications of short-term memory for a general theory of memory. J Mem Lang 2(1):1
73. Dudai Y, Karni A, Born J (2015) The consolidation and transformation of memory. Neuron 88(1):20–32
74. Basar E (2004) Memory and brain dynamics: oscillations integrating attention, perception, learning, and memory. CRC Press, Boca Raton
75. Baddeley AD, Hitch G (1974) Working memory. Psychol of Learn Motiv 8:47–89
76. Baddeley A, Wilson B (1985) Phonological coding and short-term memory in patients without speech. J Mem Lang 24(4):490–502
77. Malhotra RP, Yufik YM, (1999) Virtual associative networks: a new paradigm for sensor fusion. AeroSense 99:43–50
78. Squire LR (1987) Memory and brain. Oxford University Press, New York.

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.