Digital Brain as a Service: An Approach For Achieving Organic Web Services

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Abstract—To be able to build self-managing services, services should not be only autonomic, but also organic. This is because autonomic services can lead to services' failure when new unpredicted situations arise, as they are currently built using predefined sets of rules and policies manually tailored for specific situations and contexts. Hence, autonomic services need to support organic properties, such as self-learning and self-explanation in order to handle such unpredicted situations. Currently, all existing works focus on making services autonomic, but not organic. To overcome such limitation, this paper proposes a novel approach to build organic web services. The proposed approach aims to build digital brains as a service, which will be responsible for all cognition, thinking, learning, planning, and decision making tasks, such that any ordinary service can become organic just by plugging it to the corresponding digital brain service. The proposed approach builds the digital brain service as a composite web service, realizing the components of the adopted Starzyk-Prasad machine consciousness computational model. The proposed approach opens the doors for a new era, where digital brains for software systems can be created, trained, and rented.

Keywords-Digital Brains; Machine Consciousness; Self-Managing systems; Organic Services.

I. Introduction

The vision of organic computing [1] was introduced to create self-managing software systems, such that different organic properties (such as self-learning, self-explanation, adaptability, steady growth, and evolution) are needed to be supported. Organic computing is an extended version of the autonomic computing vision, where software systems are required to support autonomic self-managing properties (namely, self-configuration, self-optimization, self-healing, and self-protection) [2]. Currently, existing approaches for creating autonomic systems (such as the works discussed in [3][4][5]) are limited and can lead to systems' failure [5]. This is because the design of autonomous systems is mainly based on predefined static rules and policies given by service designers during design and/or run times [5]. Hence, any situation that is not covered by such predefined rules and policies will jeopardize the system, the users, and the embodying environment to all types of problems. To overcome such problems, self-managing systems should not be only autonomic, but also organic.

Being organic means the systems will be able to learn and explain unknown concepts to themselves and to others. It also means systems should be able to sense their internal states as well as their embodying environment, rationalize about the perceived facts, predict future actions and events, decide on best actions in given situations, grow their knowledge, and

able to communicate like humans. All these requirements are needed to be done without having static predefined rules and policies. The software systems after a period of training should be able to explore and learn by itself exactly as humans. This motivates the work in this paper that shows how we can create organic web services satisfying these challenging requirements.

In humans, consciousness is responsible for handling all the high-level tasks, such as cognition, thinking, learning, planning, and decision making. As these tasks are essential for having any organic property, we argue that services must have "consciousness" to be able to perform such high-level tasks. Currently, there exist many computational models for machine consciousness that try to mimic human consciousness [6][7][8]. We argue that such computational models are rich enough to model services' consciousness, as services have specific finite functionalities, and finite number of goals, which is much less complex than humans' functionalities and goals. We previously proposed to capture machine consciousness as a service (MCaaS) in [9], in which we proposed to realize the Starzyk-Prasad machine consciousness model [8]. Such MCaaS service should be able to accomplish all the cognition and thinking tasks.

In this paper, we propose a novel approach to build organic web services, as shown in Figure 1.

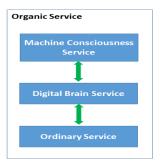


Figure 1. The proposed approach for achieving organic web services

The figure shows a digital brain service is created to directly manage the targeted services, where the digital brain service will be connected to the MCaaS service to accomplish all the cognition and thinking tasks. Adopting service-oriented computing to build software systems facilitates creation of autonomic and organic software systems, as systems' components can be encapsulated as loosely-coupled services that

can be monitored and replaced at run time, as shown in the previously proposed CRESCENT framework [3]. However, to be able to realize the proposed approach, many problems need to be solved, such as the representation problem, the memory modeling problem, the planning and thinking problem, and the motivation and learning problem. We proposed different solutions for every problem adopting a collection of existing techniques; details are given in Section IV. The proposed approach for achieving organic web services opens the doors for a new era, where digital brains for software systems can be created, trained, and rented.

The rest of the paper is organized as follows. Section II summarizes the adopted Starzyk-Prasad machine consciousness model. Section III discusses the challenges for achieving organic services. Section IV provides the proposed approach for creating digital brains for organic services and provides solutions for the discussed challenges. Section V demonstrates a use case for the proposed approach. Finally, Section VI concludes the paper and provides the directions for future work.

II. BACKGROUND

This section provides the background required for the proposed approach. It summarizes the adopted Starzyk-Prasad machine consciousness model [8], providing their definitions for machine consciousness. The work in [7] categorized existing machine consciousness models into five categories: a global workspace, information integration, an internal selfmodel, higher-level representations, and attention mechanisms. As shown in [8], the Starzyk-Prasad model characteristics explicitly and implicitly cover all the above categories. This is why we chose it to model service consciousness. The Starzyk-Prasad consciousness model follows the functionalism perspective, and sees consciousness as an emergent property resulting from "the interactions between interconnected modules with attention switching mechanism helping to select a cognitive experience and managing a sequential cognitive process." [8]. They define machine consciousness as follows:

"A machine is conscious if besides the required mechanisms for perception, action, learning and associative memory, it has a central executive that controls all the processes (conscious or subconscious) of the machine; the central executive is driven by the machine's motivation and goal selection, attention switching, semantic and episodic memory and uses cognitive perception and cognitive understanding of motivations, thoughts, or plans to control learning, attention, motivations, and monitor actions [8]."

Figure 2 depicts the architecture of the Starzyk-Prasad machine consciousness model. The figure shows that the model consists of three main modules: the sensory-motor module, the episodic memory and learning module, and the central executive module. We summarize these modules functionalities as follows:

 Sensory-Motor Module. It is the module responsible for collecting different sensory data. It uses such data for "concept formation", which will be used to build different types of associative memories. For example, semantic memory will store the gained knowledge about the environment), while a procedural memory

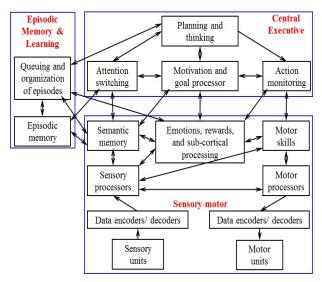


Figure 2. The Starzyk-Prasad Machine Consciousness Model [8]

will build a hierarchy of motor skills (i.e., learnt and basic actions). The module is also responsible for motor actuation, and generation of emotional and reward signals. Such signals govern the learning process and serve as an interface to other units. The sensory-motor module is composed of three parts: sensory processors integrated with semantic memory, motor processors integrated with motor skills, and sub-cortical processor integrated with emotions and rewards. In other words, it is the module responsible for the "subconscious", that automatically takes care of the actions and internal states that are previously learnt. However, it will contact the other higher consciousness modules if a conscious action is required. The sensor-motor module is connected to sensory and motor units via data encoders and decoders. Motor processor receives feedback from sensory processors. The sensory processers are the orchestrators of the sensory-motor module. They receive the inputs, contacts the semantic memory and subcortical processing modules to decide on the actions to be taken. Then, they contact the motor processors to execute the taken actions if no thinking is required.

- Episodic Memory and Learning Module. It is the module responsible for storing and recalling experiences, and responsible for recognizing the novel events/patterns in various processes and their semantic relationships. It is composed of two parts, episodic memory unit and learning unit. Episodic memory unit is a collection of smaller functional blocks, each dedicated to capture spatial and temporal semantic relationships of different data sequences. It stores and manages data as episodes collected from all the units including perceptions, motivations and interpretations of cognitive experiences and their significance from the central executive. Learning about specific events/patterns is directed by the central executive module.
- Central Executive Module. It is the module responsi-

ble for thinking, planning, coordination and selective control of all the other units. Its tasks include cognitive perception, focusing attention, attention switching, motivation, goal creation and selection, thoughts, planning, learning, etc. For this purpose, it needs the capability to dynamically select and direct execution of programs that govern attention, motivation, episodic memory and action monitoring. In addition, central executive can activate semantic memory and control emotions. Central executive module does not have a centralized decision making center. Instead, its decisions are result of competition between signals generated from units. Such signals vary in intensity based on internal or external aspects at a given moment. Once a winner is established, central executive provides cognitive interpretation of the result, providing top down activation for perception, planning, internal thought or motor functions.

The model adopts an attention switching mechanism that takes into consideration both internal and external observations. Internal observations result from changes in internal motivation, planning tasks, and components status. External observations result from opportunities, threats, and failures of the embodying environment. The cognitive realization of internal processes states decides the central executive s decision of what is observed, planning how to respond, and evaluating the created action plans. Once an action is selected to be performed, its consequences must be taken into consideration before the actual execution of the action. The model implements both attention focusing and attention switching. Selection between signals is not via a competition rather than via a conscious decision to select the signal that fulfills the current goals, based on their priorities (e.g., survival is considered the highest priority goal). Once an attention switching occurs, the system focuses its cognitive attention on the selected issue.

III. CHALLENGES FOR ACHIEVING ORGANIC WEB SERVICES

There are four main challenges for achieving organic web services, namely, the representation problem, the memory modeling problem, the motivation and learning problem, and the planning and thinking problem. We summarize these problems as follows.

A. The Representation Problem

Representation is one of the most controversial problems in machine consciousness [10]. How do we represent a concept? How do we get its meaning knowing the physical world cannot possess any semantics? How to assign meaning to mental states?

In neuroscience, empirical evidence demonstrates that every region of the neocortex represents a given piece of information using a specific sparse activity pattern of large collection of neurons. This sparse activation pattern is grounded, which means the same group of neurons are activated every time the same symbol/concept is identified. This indicates that the current best way forward of the representation problem is to adopt distributed sparse encoding techniques [11]. Finding the suitable data representation is crucial for building the encoders/decoders, memory modules, the learning and thinking units. Currently, there exist many sparse autoencoders (SAE),

for example, the work in [12] proposed different generic SAEs, for scalar data, categorical data, and date-time data. However, the work in [13] proposed a sparse encoder that learns sparsity connections rather than enforcing them as in traditional SAEs. Currently, there does not exist an SAE that performs well in all applications domains, hence the question of which sparse encoding technique should be chosen for a given application domain is left for empirical research.

B. The Memory Modeling Problem

The Starzyk-Prasad model uses different types of associative memories (e.g., semantic, episodic, and procedural). Every associative memory type is different in terms of its purpose, functionality, and architecture. Hence, a different model is needed for every memory type. In what follows, we provide a quick overview of the existing models.

- For semantic memory modeling, we can find models, such as the ones proposed in [14][15][16]. For example, the work in [14] proposed a well-known simple model for semantic memory adopting a feed-forward neural network, in which activation propagates from the inputs (concepts and relations) to the outputs (attributes) with hidden layers in between. Each unit in the input layer corresponds to an individual concept in the environment. Each unit in the relation layer represents contextual constraints on the kind of information to be retrieved. The network is trained to turn on all those units that represent correct completions of the input query. The work in [15] proposed a more complex neural model using pain networks, where sensory data, biases, pains, and actions are connected via neural network, such that each pain neuron is associated with its corresponding pain detection and learning unit, and motivates the machine to act. It adopts both forward and backward connections to determine the weights of the connections. While, the work in [16][17] proposed a new model known as hierarchial temporal memory (HTM), which is a hierarchical deep neural model adopting the human cortex structure.
- For episodic memory modeling, the work in [18]. is one of the recent proposed model, it propose to use a neural model based on fusion adaptive resonance theory. The proposed model learns episodic traces in response to a continuous stream of sensory input and feedback received from the environment. It extracts key events and encodes spatial and temporal relations between events by dynamically creating cognitive nodes. It also supports a mechanism of gradual forgetting.
- For procedural memory modeling, the work in [19] adopts a contention scheduling model that uses discrete, hierarchically-organized goal and action representations.

As we can see, each memory type has its own model that facilitate its purpose. Hence, we need to decide on the suitable model for each needed memory type, encapsulate it as service, and let it accessed via a suitable memory manager service to store and retrieve information.

C. The Motivation and Learning problem

Motivations are related to either cognitively recognized or unconscious needs and desires, emotional changes, and internally set abstract goals, hence motivation is essential for determining attention focus and attention switching tasks. Learning is essential to achieve two major tasks:

- Concept identification: Concept identification learning is a process that aims to extract the space-temporal relations from different internal and external sensory data. Then, it uses such information to identify different concepts and their relationships.
- Action selection: Action selection learning is about choosing the suitable actions to optimize different objectives originated by the adopted motivation model. Reinforcement learning is a very well known and established scheme for action selection that is only motivated by making gains (rewards). However, the work in [20] showed that the motivational learning (ML) approach proposed in [15] outperformed many of the well-known reinforcement learning approaches.

D. The Planning and Thinking Problem

One of the possible signs of having consciousness is the ability to switch attention to attend to emerging situations. Response to emerging situation depends on the adopted motivation and goal models. As per the Starzyk-Prasad model, the digital brain service needs to determine the attention spotlight in every situation in a way that reduces its pains and increases its rewards. An object/concept in the spotlight needs to be determined (usually, it is the one with the most salient features), and the most suitable action (retrieved from the corresponding associative memories) should be performed. If there is lack of certain resources needed to execute the action, the digital brain service has to search for it and plan to get it, which creates sub-goal(s) for the current goal. Hence, a suitable action plan needs to be created to fulfill the current goal and its subgoals.

IV. THE PROPOSED APPROACH FOR ACHIEVING ORGANIC WEB SERVICES

This section first summarizes the proposed approach for achieving organic web services, then it introduces solutions for the discussed challenges, and finally it proposes a road map for the approach realization.

To make an ordinary service "organic", the proposed approach aims to build a digital brain service, which will be plugged into the ordinary targeted service in order to directly manage it, provided that the digital brain service will be plugged into a machine consciousness service in order to accomplish all the cognition and thinking tasks, as shown in Figure 1. We require any service that wants to use the digital brain service, to expose the suitable interfaces that enable reading the sensory data and executing the required actions. Like any machine learning approach, digital brains require some training first, before releasing them to real-life. Hence, once the digital brain is created, it should be attached to the embodying service to learn from the service interactions.

To create digital brain as a service, every module in the Starzyk-Prasad model needs to be realized and encapsulated as a service. The high-level components will be added to the machine consciousness service such as the central executive unit and different memory units, while the low-level components will be added to the digital brain service such as the sensory and motor units, as seen in Table I. Hence, we need first to create encoder/decoder services, different memory services (i.e., episodic, semantic, and procedural), sensory and motor services, monitoring service, sub-cortical and emotion management services, attention switching service, motivation management service, and planning service. Then, we need to compose the brain and machine consciousness services from these components. We believe choreography is the suitable coordination style for these components services, as central orchestration will degrade the overall performance and limits possibilities for parallelization. We summarize the approach realization as follows:

- For building decoders/encoders services, different sparse encoders should be adopted for each data type such as the ones discussed in [12]. Decoders/encoders services pass the data from sensory units to sensory processors, and the decoders will pass the data from the motor processors to the motor units.
- For building memory services, we propose to build the episodic memory service adopting the model proposed in [18], and the procedural memory service adopting the model proposed in [19] (which realizes the motorskills component in the Starzyk-Prasad model). This is because these models represent the state of the art for modeling episodic and procedural memories. The work in [21] showed that HTM outperformed many of the well-known neural models, such as ELM, ESN and LSTM. Additionally, HTM requires little or no hyperparameter tuning. HTM is very suitable for concept identification and predictions. Hence, we propose to build the semantic memory service using HTM to represent learnt concepts/beliefes. Then, we need to integrate such concepts/beliefes with the pain-network to be able to learn the action suitable for every learnt concept/belief.
- For building the motivation service, we propose to adopt the motivation model of the the Starzyk-Prasad model [22], in which motivation is modelled via a pain network (i.e., connections between different sets of sensory, pains, biases, and actions neurons). The painnetwork model is always changing according to the responses of different actions. We also propose to use ML as the digital brain action selection approach [15] because ML compromises between making gains and relieving pains using the pain network model. ML extends the well-known reinforcement learning approach, and use it when curiosity-based learning is needed. A current goal is selected based on a dominant pain signal, and it represents an intended action that the agent wants to perform.
- For building the planning and thinking service, we propose to use the attention switching approach proposed in [22] that is based on mental saccade mechanism. A "mental saccade is a concept created to mimic the well-established concept of "visual saccade [22]. The mental saccade identifies the object with the most salient features from all the collected information and makes it the attention spotlight. Then, it retrieves all

THE ROADMA		

Implementing Service	Component	Realizing Solution
Digital Brain Service	Decoders/Encoders Services Sensory Processing Service Motor Processing service	Adopt different sparse encoders for each data type such as the ones discussed in [12]. Handle the reflexive actions (retrieved from semantic and procedural memories). Execute action plans over different motor units (i.e., straightforward operations calls).
Machine Consciousness Service	Episodic Memory Service Procedural Memory Service Semantic Memory Service Sub-Cortical Service Action Monitoring Service Central Executive Service	Adopt the most recent model proposed in [18]. Adopt the well-known model proposed in [19]. Integrate the cortical earning algorithm (CLA) of HTM model [21] with the pain network model [15]. Adopting the pain-network and ML mechanism proposed in [15]. Compare between predicted and actual actions' responses. Adopt the mental saccade, attention switching, and cognition techniques discussed in [22].

the corresponding information about this object to start the cognition and identification processes. This is done by adopting the well-established concept of a global workspace (summarized in [7]), where all the information of the activated processes are collected in one global space (i.e., an associative memory). This space is known as the "mental workplace. The operation of searching this mental workspace is known as a "mental saccade. Once the perceived input activates an object in the mental workspace, its corresponding information in the episodic memory and semantic memory are activated and uploaded to the mental workspace. Such updated mental workspace will be researched for a new mental saccade. The mental saccade mechanism adopts a simple winner-take-all approach to choose the attention spotlight among competing signals. A successful execution of a given action triggers the memorization of the discovered solution in the procedural memory, which in turn train itself to remember the best performing actions. This is needed to create rhythmic actions to avoid future planning for the same situations appeared before [15].

Table I indicates the major components of the machine consciousness model, and their proposed realizing solutions. It also shows the suggested implementing service for every component. This table provides the roadmap for building organic web services. By realizing the components indicated in this table, we can easily build the digital brain and the machine consciousness services from those components, as shown in the use case discussed in Section V.

V. A USE CASE

This sections shows how the proposed approach could be adopted in real-life, and discusses a corresponding use case.

In our previous work in [3], we proposed the CRESCENT framework for managing composite web services. CRESCENT aimed to be autonomous, so it is designed to be self-healing, self-optimizing, and self-organizing. Therefore, it has modules for SLA management, workflow management, adaptive composition, capacity planning management, components provisioning, components discovery, dispatchers and monitors. Figure 3 depicts the main modules of the CRESCENT framework and their interactions. Unfortunately, CRESCENT is designed based on pre-defined rules and policies for detecting and replacing bad performing components. Hence, CRESCENT can ensure the managed composite web service to be autonomous, but not organic.

Given that we have a composite web service that realizes a given real-life business process, and we want to make this composite web service organic using the proposed approach, the CRESCENT framework should be extended to to create the digital brain service. This should be done by adding all the low-level components of the machine consciousness model (shown in Table I) to CRESCENT, where the other CRESCENT modules appear as different functional units in the digital brain service. Then, we need to create the machine consciousness service, which will have all high-level components of the machine consciousness model. Once the digital brain and the machine consciousness services are created, we connect the composite web service to be managed into the digital brain service, as in Figure 1. Then, we start the training process until all neural models converge. Finally, we release the digital brain and machine consciousness services to manage the composite web service in real-life situations, and let them grow and evolve.

VI. CONCLUSION AND FUTURE WORK

This paper argued that to be able to build self-managing services, services are needed to be autonomic and organic. Therefore, this paper proposed a novel approach for building organic web services, in which a digital brain service is created to transform any ordinary service into an organic service. This is done by connecting the ordinary service to the digital brain service, which in turn is connected into a machine consciousness service to accomplish all cognition, thinking, learning, planning, and decision making tasks. The paper proposed to adopt the Starzyk-Prasad machine consciousness model to build both the digital brain and machine consciousness services, showing the mapping between the model's modules and the implementing services. The paper also discussed different problems that create obstacles for building the digital brain service (i.e., the representation problem, the memory modeling problem, the planning and thinking problem, and the motivation and learning problem), then it proposed solutions for every problem, creating a roadmap for building digital brains for software systems.

Future work will focus on implementing a prototype for the digital brain service, then training different instances of the digital brain service for different application domain business services. We believe extending the CRESCENT framework to include machine consciousness components is the way forward to build a digital brain prototype.

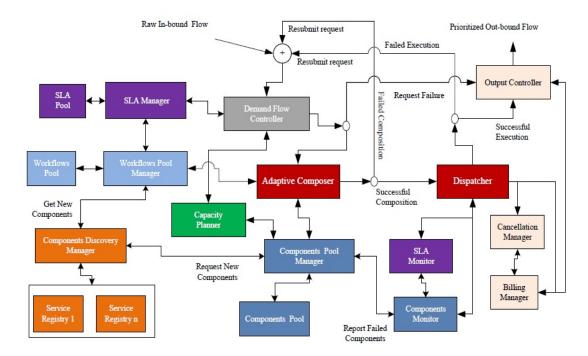


Figure 3. CRESCENT Architecture [3]

REFERENCES

- [1] C. Müller-Schloer, "Organic computing: On the feasibility of controlled emergence," in Proceedings of the 2nd IEEE/ACM/IFIP International Conference on Hardware/Software Codesign and System Synthesis, 2004, pp. 2–5.
- [2] J. O. Kephart and D. M. Chess, "The vision of autonomic computing," Computer, vol. 36, no. 1, Jan 2003, pp. 41–50.
- [3] I. Elgedawy, "CRESCENT: A reliable framework for durable composite web services management," Computer Journal, vol. 58, no. 2, Feburary 2015, pp. 280–299.
- [4] A. Lam, J. J. Q. Yu, Y. Hou, and V. O. K. Li, "Coordinated autonomous vehicle parking for vehicle-to-grid services: Formulation and distributed algorithm," IEEE Transactions on Smart Grid, vol. PP, no. 99, 2017, pp. 1–1.
- [5] S. Singh and I. Chana, "Qos-aware autonomic resource management in cloud computing: A systematic review," ACM Comput. Surv., vol. 48, no. 3, Dec. 2015, pp. 42:1–42:46.
- [6] D. Gamez, "Progress in machine consciousness," Consciousness and Cognition, vol. 17, no. 3, 2008, pp. 887 – 910.
- [7] J. A. Reggia, "The rise of machine consciousness: Studying consciousness with computational models," Neural Networks, vol. 44, 2013, pp. 112 131.
- [8] J. A. Starzyk and D. K. Prasad, "A computational model of machine consciousness," International Journal of Machine Consciousness, vol. 03, no. 02, 2011, pp. 255–281.
- [9] I. Elgedawy, "Machine consciousness as a service (MCaaS): a roadmap," to appear, Iran Journal of Computer Science, Oct 2017.
- [10] A. Chella and R. Manzotti, "Machine consciousness: A manifesto for robotics," International Journal of Machine Consciousness, vol. 01, no. 01, 2009, pp. 33–51.
- [11] S. Ahmad and J. Hawkins, "Properties of sparse distributed representations and their application to hierarchical temporal memory," CoRR, vol. abs/1503.07469, 2015.
- [12] K. Gupta and A. Majumdar, "Sparsely connected autoencoder," 2016 International Joint Conference on Neural Networks (IJCNN), 2016, pp. 1940–1947
- [13] S. Purdy, "Encoding data for htm systems," CoRR, vol. abs/1602.05925, 2016.

- [14] T. T. Rogers and J. L. McClelland, "Prcis of semantic cognition: A parallel distributed processing approach," Behavioral and Brain Sciences, vol. 31, no. 6, 2008, p. 689714.
- [15] J. A. Starzyk, J. T. Graham, P. Raif, and A.-H. Tan, "Motivated learning for the development of autonomous systems," Cognitive Systems Research, vol. 14, no. 1, 2012, pp. 10 25.
- [16] J. Hawkins and D. George, "Hierarchical temporal memory concepts, theory, and terminology," in Technical report, Numenta, 2006.
- [17] J. Hawkins, D. George, and J. Niemasik, "Sequence memory for prediction, inference and behaviour." Philosophical transactions of the Royal Society of London. Series B, Biological sciences, vol. 364 1521, 2009, pp. 1203–9.
- [18] W. Wang, B. Subagdja, A. H. Tan, and J. A. Starzyk, "Neural modeling of episodic memory: Encoding, retrieval, and forgetting," IEEE Transactions on Neural Networks and Learning Systems, vol. 23, no. 10, Oct 2012, pp. 1574–1586.
- [19] F. P. Tamborello, "A computational model of routine procedural memory," Ph.D. dissertation, 2009. [Online]. Available: https://search.proquest.com/docview/304989696?accountid=13014, [re-trieved: 12, 2017]
- [20] J. Graham, J. A. Starzyk, Z. Ni, H. He, T. H. Teng, and A. H. Tan, "A comparative study between motivated learning and reinforcement learning," in 2015 International Joint Conference on Neural Networks (IJCNN), July 2015, pp. 1–8.
- [21] Y. Cui, C. Surpur, S. Ahmad, and J. Hawkins, "A comparative study of htm and other neural network models for online sequence learning with streaming data," 2016 International Joint Conference on Neural Networks (IJCNN), 2016, pp. 1530–1538.
- [22] J. A. Starzyk, "Mental saccades in control of cognitive process," in The 2011 International Joint Conference on Neural Networks, 2011, pp. 495–502.