TMR
DOI: 10.12032/life2018-0711-005

REVIEW

A survey of brain-inspired artificial intelligence and its engineering

Shuangming Yang[1], Xinyu Hao[1], Bin Deng[1], Xile Wei[1], Huiyan Li[2], Jiang Wang1,*

[1]*School of Electrical and Information Engineering, Tianjin University, Tianjin, China*
[2]*School of Automation and Electrical Engineering, Tianjin University of Technology and Educations, Tianjin, China*

Correspondence:
Jiang Wang, School of Electrical and Information Engineering, Tianjin University, Tianjin 300072, China
Email: jiangwang@tju.edu.cn

Exploring the human brain is perhaps the most challenging and fascinating scientific issue in the 21st century. It will facilitate the development of various aspects of the society, including economics, education, health care, national defense and daily life. The artificial intelligence techniques are becoming useful as an alternate method of classical techniques or as a component of an integrated system. They are used to solve complicated problems in various fields and becoming increasingly popular nowadays. Especially, the investigation of human brain will promote the artificial intelligence techniques, utilizing the accumulating knowledge of neuroscience, brain-machine interface techniques, algorithms of spiking neural networks and neuromorphic supercomputers. Consequently, we provide a comprehensive survey of the research and motivations for brain-inspired artificial intelligence and its engineering over its history. The goals of this work are to provide a brief review of the research associated with brain-inspired artificial intelligence and its related engineering techniques, and to motivate further work by elucidating challenges in the field where new researches are required.

Human brain

The human brain is one of the most complicated systems in the nature, which is the miracle of the biological evolution [1-3]. It has the high-level functions of cognition, memory and emotion, and it is also a significantly optimized system. Its working power consumption is only 25W, but the number of neurons in it can be up to 10^{11}. Each neuron can be connected with 10000 synapses. Such low power consumption with a considerably large neural network of human brain makes the brain have the absolute advantages when dealing with sophisticated problems. Although the neuroscience has been developed in recent years, our progress of understanding the physical structure and cognition functions of human brain is still in the initial stage. The operating mechanism of human brain is still a mystery. Recently with the development of techniques, the research in the field of neuroscience has attracted world attention. The human brain, as the center of the neural system, contains with billions of neurons that are coupled with each other by synapses. Various signals are transmitted and performed in the neural network that is made up with neurons and synapses, so that the complex biological cognition emerges [4-6]. The investigation of human brain is vital for the understanding of the neuroscience, effective treatment of the brain diseases and promoting a new generation of the artificial intelligence (AI).

Neuroscience

The long-term ambition of neuroscience is to obtain a better understanding of the anatomical, molecular and circuits bases for the logical operations in human brain. The Human Brain Project, based in Europe, plans to understand the human brain by simulating the functions by using the supercomputers [7]. In recent years, neuroscientists have proposed various kinds of new technological, molecular and computational tools that are applied in more efficient and accurate recording from many nerve cells at the same time, in

DOI: 10.12032/life2018-0711-005

correlating structure and neural activities to test the causal role of defined neural elements in behavior [8-10]. The innovation of research methods and development of new techniques provide conditions for the investigation of human brain. The high-performance computing is one of the critical supporting techniques. High-performance computing provides investigation methods and platforms for the quickly accumulated data observed from human brain and enables the neuroscience research step into the era of multi-mode, big sample and collaborative research [11-13]. The big data contains more beneficial information value, which provides important supports to the following neuroscience research. On the other hand, the current neuroscience research requires improvement of high-performance computing techniques, which facilitates the development of high-performance computing platform. Besides, the neuroscience provides new methodologies for the information technology, and facilitates the development of the high-performance computing methods and platforms including deep neural network, spiking neural network and brain-inspired computing chip. The human intelligence emerges from the large-scale, complicated connected neural network in brain [14]. Thus, it is vital for the development of AI to learn from the human brain.

Artificial intelligence

Recently, rapid progress has been made in the fields of neuroscience and AI. AI is a critical application of simulating brain. Building the human-level general AI (or "Turing-powerful" intelligent systems) is a difficult task because the search space of possible solutions is huge. Studying human cognition and its neural implementation can also have a critical meaning that provides various vital aspects of higher-level general intelligence. In summary, the benefits to developing AI by closely relating with biological intelligence have two reasons. Firstly, the neuroscience provides a rich amount of inspiration for the development of new types of algorithms and architectures. Secondly, neuroscience can provide validation of the existed AI techniques. If a known algorithm is realized in human brain, then that is strong support for its plausibility as an overall general intelligence system. The investigation of the cognitive system structure is the foundation of the brain-like cognitive model investigation. Recently the researchers have combined the mechanisms of human memory, inference and attention with general AI [15-17]. Besides, the investigation of collaborative cognition model across different brain areas has been presented, aiming at the brain-like cognition computing model of the general AI. For example, the SPAUN brain simulator from Waterloo University of Canada realizes the cognition functions including working memory and visual information processing by divide 2.5 million neurons into several brain areas modularly [18]. The hierarchical temporal memory model further considers the information processing mechanisms of human brain, which uses the information processing principle across various brain areas [19-20].

Brain-machine interface

Another critical technique in the field of brain-inspired AI is the brain-machine interface (BMI) engineering [21-24]. It can obtain the human thoughts of behaviors via the neural decoding, which can be divided to invasive and non-invasive BMI techniques. The invasive BMI is majorly used to rebuild special cognition such as vision and motor functions of movement-disorders patients, which is planted into gray matter in brain. The representative work is from the research group led by John Donoghue [25]. They put a microelectrode into the brain cortex of a paralyzed patient. The patient can control TV, prosthetic or send email based on his thought. The non-invasive BMI uses multiple electrodes to obtain the EEG signals of human brain. In the last decades, most works are focusing on the decoding of EEG signals from brain cortex. Mason *et al.* divides the existing BMI techniques into three types, which are signal transducer system, demonstration system and assistive device control system [26]. Besides, the interact control between brain and machine is significantly necessary.

On one hand, the information such as voluntary cognition or emotion can be output based on the BMI platform. On the other hand, the external information such as sounds or some kinds of electrical stimulation can be sent into human brain directly [27-30]. By using the BMI techniques, we can control external devices based on brain signals directly, and control animal behaviors by stimulating the animal nervous system directly, i.e., the animal robots. The final ambition is to obtain the valuable products with practical values. The accurate decoding of brain information is the most critical factor for the BMI system. Previous studies have proposed various methods of signal processing and pattern classification [31-32]. However, not all of these methods can be applied in the practical systems, because the practical application requires online computation in real time, and should solve the problems of individual parameter optimization, interact adaption between brain and machine, and testing of the rest state. In addition, the practical system should consider the convenience of the product and the economic cost. Thus, there still requires more efforts and focuses on this field.

Spiking neural networks

The spiking neural network (SNN) is called as the third generation of neural network [33]. It uses the discrete neural spikes-based coding method to simulate the timing feature of the neural network and to make the network to own stronger ability of information processing [34-39]. The computing process of the SNNs is similar with the human brain, which receives the stimulation generated from the external environment and gradually accumulates. When the power is accumulated to a degree, the electrical signals are generated and the stimulation information can be shared and processed based on the transition of the electrical signals. The weights and delay of the SNNs can be changed based on learning, whose mechanisms are more closed to human brain. The modeling and parameter selection of the SNNs are based on the biological neural network in human brain in the field of neuroscience. In comparison with the general artificial neural network, the SNNs have the superior advantages in terms of versatility, parallel computation, hardware implementation, computational speed and computational capability [40-42]. The major structures of SNNs contain feedforward and recurrent type. In summary, the models of SNNs are constituted by differential equations with timing properties. The classical neuron model is the Leak and Fire model, which can be regarded as a circuit with capacitance. When the membrane potential arrives at a threshold, a spike is generated and the membrane potential is reset to the resting voltage. Besides, a refractory period occurs in which no response is generated and the membrane potential keeps in the resting value even if there is an input stimulation. The major model of the recurrent SNN is the liquid state machine (LSM), which refers to a kind of reservoir computing. It has a sophisticated structure and is used to deal with the high-dimension timing problem [43-44]. The presentation of LSM is based on the memory capability for the timing problem based on the recurrent connection. The structure of LSM contains three levels, which are input level, reservoir level and output level. The input level is responsible for the coding of input data trains into spike trains and input them into the reservoir level based on a certain ratio. The reservoir level contains 80% excitatory neurons and 20% inhibitory neurons, which is based on the ratio of neural type in biological brain. The connection is stochastic recurrent. The output level is responsible for the neural state of each reservoir level and linear classification based on some algorithms such as logistic regression. From the view of machine learning, the application of SNNs contains two tasks, which are classification and regression, which refers to the organization and processing of data. Thus, data should be coded into spiking trains before it is input into the SNN. The classical coding methods include rate-based, binary-based and rand-based [45-46].

The brain-like computing is the essential evolution of the current computational system on the levels of hardware, software and algorithm, which is based on the neural network structure of the human brain and its operation mechanism of the information

TMR
DOI: 10.12032/life2018-0711-005

storage, combining modern information technology and theory. Its ambition is to build a brain-like supercomputer and realize more sophisticated artificial general intelligence. The investigation of brain-like computing is based on the SNNs, which can simulate the cognitive functions of human brain such as face recognition. Currently, the major trend of the investigation in the field of brain-like computing is divided into three parts. The first aspect is the modeling of the neurons, synapses and their corresponding mechanisms including memory and attention in biological brain. The second one is the learning algorithm of the biologically inspired neural networks and their application in the machine learning task including pattern recognition. The third one is the biologically inspired algorithm and the investigation of the hardware system for SNNs. Besides, the combination of multiple techniques is helpful for the development of the brain-like computing. For example, previous works have combined deep neural networks with Bayesian-based AI methods [47]. The deep neural network can learn the nonlinear dynamics from data and output high-dimension vectors, and Bayesian inference can finally obtain the results based on these high-dimension vectors. The improvement of Bayesian inference algorithm is also needed to adapt to the inference of high-dimension vectors.

Neuromorphic engineering

The conventional Von Neumann computer has two major features: using the separated CPU and memory; sequential operating based on program. Because the memory and calculator is separated with each other, the frequent data transition limits the efficiency of the conventional computer significantly, which induces the so-called "Von Neumann" bottleneck and leads to high power consumption consequently. Besides, the conventional computer has limited ability of self-adaption, which further constrains the application of the AI on conventional computers. The human brain can realize the high-level intelligence with 20W power consumption and 10Hz low frequency, which is significantly superior to the computers. It can also be the example of the high-performance and low-power-consumption hardware. Besides, the human brain has huge and highly connected neural loop. It processes the information in energy-efficient, highly parallel, event-driven architectures. They are able to self-repair, self-adapt and learn from the environmental interaction. The memory function in human brain is distributed throughout the architecture based on local biological organization for efficient storage and recall. Although the signal transmission between neurons is slow, the distributed and parallel computation in human brain accelerates the signal processing significantly. The human brain can interact with the external environment and has the ability of self-learning, which has the advantages of low power consumption, high fault tolerance, high parallelism and unsynchronized information processing. Thus, building the brain-like supercomputing machine is the final target of the intelligence technology and engineering. Under this background, the brain-inspired AI computing occurs. In this field, the conventional computational mode is abandoned thoroughly, and the parallel spiking neural network architecture is used to realize the higher level of intelligence, which will be the critical technique in the field of computer science and AI science.

In the field of brain-inspired AI computation, the neuromorphic engineering is a vital aspect which combines the neuroscience with engineering [48-55]. Neuromorphic engineering is a promising interdisciplinary field that obtains inspiration from biology, physics, computer science, mathematics and engineering to implement artificial neural systems including vision systems, head-eye systems, autonomous robots and auditory processors, whose physical structure and design principles are based on the biological nervous systems. Neuromorphic VLSI systems are the bridging technology between the biological neural systems models and VLSI-based engineering, which is the term to describe full custom-designed integrated circuits or silicon chip. It is also a methodology of building biologically inspired elements and systems, including individual neurons, density to the point where it is probable to develop large-scale neural network on a single FPGA-based neuromorphic system. The spiking neural networks inspired by biological brain have been implemented by using FPGA device based on various digital architectures [57, 60, 63, 64, 66]. Since the optimization of digital realization method for a single neuron is useful for the implementation of large-scale SNN, previous works have also focused on this target [62, 65, 67, 69]. Besides, the digital neuromorphic systems based on FPGA have also applied in the intelligent control and dynamics identification of nonlinear systems [58, 59, 61, 70]. Though it is limited by larger area, higher power consumption and lower throughput than the customized analog VLSI implementations, previous works have proposed interesting neuromorphic signal processing systems based on FPGA technology, which have advantages over analog VLSI circuit, including shorter design and fabrication time, more roust to power supply, temperature and transistor mismatch variations than analog systems, high reconfigurability and reuseability for many applications, arbitrarily high dynamic range and signal-to-noise ratios, more convenience to interface with a host computer.

Modern investigation in biological brain enables better understanding of form, structure and biological behaviors of neural systems to develop algorithms implemented on a neuromorphic circuit, which is realized in parallel-distributed architectures with functions of adaption and learning by using low power and high integration density techniques. As the technology being mature, the neuromorphic engineering is expected to become more efficient for the clinical industrial field such as neuroprosthetic replacement. Effective interdependence collaborations among several critical fields of biology, neuroscience, electrical engineering, computer science and physiology are essential to develop this promising filed of engineering neural systems.

Conclusions

In the era of big data and AI, the brain research faces challenges and chances for the development. The combination of the brain research and high-performance computing techniques will be the effective approach towards the investigation of the efficient information processing. The brain-inspired AI will finally make significant influence on science, society and economics. Besides, the engineering of brain-inspired AI will combine the high performance of supercomputer with high intelligence of human and present "brain-like machine", so as to open new perspective of various applications including machine vision, speech recognition and big data mining.

Reference

[1] Lumer E.D., *et al.* Neural dynamics in a model of the thalamocortical system. I. Layers, loops and the emergence of fast synchronous rhythms. Cereb Cortex. 1997; 7:207–227.

[2] Lumer E.D., *et al.* Neural dynamics in a model of the thalamocortical system. II. The role of neural synchrony tested through perturbations of spike timing. Cereb Cortex. 1997; 7:228–236.

[3] Markram H. The blue brain project. Nat. Rev. Neurosci. 2006; 7:153–160.

[4] Jones A.R., *et al.* The Allen brain atlas: 5 years and beyond. Nat. Rev. Neurosci. 2009; 10:821-828.

[5] Mikula S., *et al.* Internet-enabled high-resolution brain mapping and virtual microscopy. Neuroimage. 2007; 35:9-15.

[6] Mi Y. T., *et al.* Interactive brain atlas with the visible human project data: development methods and techniques. Radiographics. 1996; 16:1201-1206.

[7] Amunts K., *et al.* The human brain project: creating a European research infrastructure to decode the human brain[J]. Neuron. 2016; 92(3): 574-581.

[8] Markram, H., *et al.* Reconstruction and simulation of neocortical microcircuitry. Cell. 2015; 163: 456–492.

[9] Hansen, E.C.A., *et al.* Functional connectivity dynamics: modeling the switching behavior of the resting state. Neuroimage. 2015; 105: 525–535.

[10] Zenke, F., Agnes, E.J. & Gerstner, W. Diverse synaptic plasticity mechanisms orchestrated to form and retrieve memories in spiking neural networks. Nat. Commun. 2015; 6: 6922.

[11] Yu T., *et al.* in Biomedical Circuits and Systems Conference (BioCAS). 2012; 21–24.

[12] Schemmel J., *et al.* in 2012 IEEE International Symposium on Circuits and Systems. 2012; 702.

[13] Benjamin B. V., *et al.* Proc. IEEE. 2014; 102: 699–716.

[14] Izhikevich E.M. & Edelman G.M. Large-scale model of mammalian thalamocortical systems. PNAS. 2008; 105(9): 3593-3598.

[15] Riesenhuber M. & Poggio T. Hierarchical models of object

DOI: 10.12032/life2018-0711-005

recognition in cortex. Nature Neurosci. 1999; 2(11): 1019-1025.
[16] Serre T., Oliva A. & Poggio T. A feedforward architecture accounts for rapid categorization. PNAS. 2007; 104(15): 6424-6429.
[17] Rivest F., *et al.* Brain inspired reinforcement learning. Advances in Neural Information Processing Systems. Cambridge, USA: The MIT Press. 2004; 1129-1136.
[18] Eliasmith C., *et al.* A large-scale model of the functioning brain. Science. 2012; 338(6111): 1202-1205.
[19] Hawkins J. & Blakeslee S. On intelligence: How a new understanding of the brain will lead to the creation of truly intelligent machines. Macmillan, 2007.
[20] George D. & Hawkins J. Towards a mathematical theory of cortical micro-circuits. PLoS Comput. Biol. 2009; 5(10): e1000532.
[21] Nicolelis M.A. Actions from thoughts. Nature. 2001; 409: 403–407.
[22] Wessberg J., *et al.* Real-time prediction of hand trajectory by ensembles of cortical neurons in primates. Nature. 2000; 408: 361–365.
[23] Laubach M., *et al.* Cortical ensemble activity increasingly predicts behaviour outcomes during learning of a motor task. Nature. 2000; 405: 567–571.
[24] Chapin J.K., *et al.* Real-time control of a robot arm using simultaneously recorded neurons in the motor cortex. Nat. Neurosci. 1999; 2: 664–670.
[25] Hochberg L.R., *et al.* Neuronal ensemble control of prosthetic devices by a human with tetraplegia. Nature. 2006; 442(13):164-171
[26] Mason S.G., *et al.* A comprehensive survey of brain interface technology designs. Ann. Biomed. Eng. 2007; 35: 137-169.
[27] Birbaumer N., *et al.* A spelling device for the paralysed. Nature. 1999; 398: 297–298.
[28] Bouton C.E., *et al.* Restoring cortical control of functional movement in a human with quadriplegia. Nature. 2016; 533: 247–250.
[29] Collinger J.L., *et al.* High-performance neuroprosthetic control by an individual with tetraplegia. Lancet. 2013; 381: 557–564.
[30] Hochberg L.R., *et al.* Reach and grasp by people with tetraplegia using a neurally controlled robotic arm. Nature. 2012; 485: 372–375.
[31] Bashashati A., *et al.* A survey of signal processing algorithms in braincomputer interfaces based on electrical brain signals. J. Neural Eng. 2007; 4: R32-R57.
[32] Lotte F., *et al.* TOPICAL REVIEW: A review of classification algorithms for EEG-based brain-computer interfaces. J. Neural Eng. 2007; 4: R1-R13.
[33] Falah Y.H., Ahmed B.Y., & Haza N.A.H. Computing with Spiking Neuron Networks-A Review. Appl. Soft Comput. 2014; 6(1): 1-21.
[34] Hodgkin A. L. & Huxley A. F. A quantitative description of ion currents and its applications to conduction and excitation in nerve membranes. J. Physiol. 1952; 117: 500–544.
[35] Ermentrout G. B. Type I membranes, phase resetting curves, and synchrony. Neural Comput. 1996; 8: 979–1001.
[36] Izhikevich E. M. Simple model of spiking neurons, IEEE Trans Neural Netw. 2003;14(6): 1569–1572.
[37] Rinzel J. & Ermentrout G. B. Analysis of neuronal excitability and oscillations. Methods in Neuronal Modeling. 1989; 135–169.
[38] Hopfield J. Pattern recognition computation using action potential timing for stimulus representation. Nature. 1995; 376: 33–36.
[39] Maass W. and Natschlager T. Networks of spiking neurons can emulate arbitrary Hopfield nets in temporal coding. Network. 1997; 8(4): 355–372.
[40] Adeli H. & Kumar S. Concurrent structural optimization on a massively parallel supercomputer. J. Struct. Eng. 1995; 121(11): 1588–1597.
[41] Hung S. L. & Adeli H. Parallel backpropagation learning algorithms on Cray Y-MP8/864 supercomputer. Neurocomputing. 1993; 5(6): 287–302.
[42] Hung S. L. & Adeli H. A parallel genetic/neural network learning algorithm for MIMD shared memory machines. IEEE Trans Neural Netw. 1994; 5(6): 900–909.
[43] Maass W. Liquid state machines: motivation, theory, and applications. Computability in context: computation and logic in the real world. 2010; 275-96.
[44] Maass W., *et al.* Real-time computing without stable states: A new framework for neural computation based on perturbation. Neural Comput. 2002; 14(11): 2531-60.
[45] Paugam-Moisy H. & Bohte S. Computing with Spiking Neuron Networks. Springer Berlin Heidelberg. 2012.
[46] Dayan P. Theoretical neuroscience. Cambridge, MA: MIT Press. 2001.
[47] Zoubin G. Probabilistic machine learning and artificial intelligence, Nature. 2015; 521(7553): 452-459.
[48] Mead C.A. Neuromorphic electronic systems. Proceedings of the IEEE. 1990; 78(10): 1629-1639, 1990.
[49] Boahen K. Point-to-Point connectivity between neuromorphic chips using address events. IEEE Trans Circuits Syst. II Express Briefs. 2000; 47(5): 416-434.
[50] Strukov, D. B., *et al.* The missing memristor found. Nature. 2008; 453: 80–83.
[51] Schemmel J., *et al.* A wafer-scale neuromorphic hardware system for largescale neural modeling," in Circuits and Systems

(ISCAS). IEEE. 2010; 1947–1950.
[52] Irizarry-Valle Y., *et al.* A cmos neuromorphic approach to emulate neuro-astrocyte interactions," in Neural Networks (IJCNN). IEEE, 2013; 1–7.
[53] Irizarry-Valle Y., *et al.* An astrocyte neuromorphic circuit that influences neuronal phase synchrony. IEEE Trans Biomed. Circuits Syst. 2015; 9(2): 175–187.
[54] Livi P., *et al.* A current-mode conductance-based silicon neuron for address-event neuromorphic systems. in Circuits and systems,. IEEE, 2009; 2898–2901.
[55] Ambrogio S., *et al.* Neuromorphic learning and recognition with one-transistor-one-resistor synapses and bistable metal oxide rram. IEEE Trans Electron. Devices, 2016; 63(4): 1508–1515.
[56] Catherine B., *et al.* Neuromorphic hardware databases for exploring structure-function relationships in the brain. Phil. Trans. R. Soc. Lond. B. 2001; 356: 1249-1258.
[57] Yang S., *et al.* Cost-efficient FPGA implementation of basal ganglia and their Parkinsonian analysis. Neural Netw. 2015; 71: 62-75.
[58] Yang S., *et al.* Digital implementations of thalamocortical neuron models and its application in thalamocortical control using FPGA for Parkinson's disease. Neurocomputing, 2016; 177: 274-289.
[59] Yang S., *et al.* Efficient implementation of a real-time estimation system for thalamocortical hidden Parkinsonian properties. Scientific Rep. 2017; 7: 40152.
[60] Luo J., *et al.* Real-Time Simulation of Passage-of-Time Encoding in Cerebellum Using a Scalable FPGA-Based System. IEEE Trans Biomed. Circuits Syst. 2016; 10(3): 742-753.
[61] Yang S., *et al.* Efficient hardware implementation of the subthalamic nucleus–external globus pallidus oscillation system and its dynamics investigation. Neural Netw. 2017; 94: 220-238.
[62] Yang S., *et al.* Efficient digital implementation of a conductance-based globus pallidus neuron and the dynamics analysis. Physica A. 2018; 494: 484-502.
[63] Yang S., *et al.* FPGA implementation of hippocampal spiking network and its real-time simulation on dynamical neuromodulation of oscillations. Neurocomputing. 2018; 282: 262-276.
[64] Yang S., *et al.* Real-Time Neuromorphic System for Large-Scale Conductance-Based Spiking Neural Networks. IEEE Trans Cybern. 2018; in press.
[65] Yang S., *et al.* Cost-efficient FPGA implementation of a biologically plausible dopamine neural network and its application. Neurocomputing. 2018; in press.
[66] Yaghini S., *et al.* FPGA implementation of a biological neural network based on the Hodgkin-Huxley neuron model. Front. Neurosci. 2014; 8: 379.
[67] Korkmaz N., *et al.* The investigation of chemical coupling in a HR neuron model with reconfigurable implementations. Nonlinear Dyn. 2016; 86(3): 1841-1854.
[68] Rahimian E., *et al.* Digital Implementation of the Two-Compartmental Pinsky–Rinzel Pyramidal Neuron Model. IEEE Trans Biomed. Circuits Syst. 2018; 12(1): 47-57.
[69] Lin Q., *et al.* The dynamical analysis of modified two-compartment neuron model and FPGA implementation. Physica A. 2017; 484: 199-214.
[70] Chen Q., *et al.* A real-time FPGA implementation of a biologically inspired central pattern generator network. Neurocomputing. 2017; 244: 63-80.

Competing interests: The authors declare no competing financial interests. Readers are welcome to comment on the online version of this article at www.tmrliferes.com

Received: 15 July 2018; **Accepted:** 21 July 2018; **Published online:** 25 July 2018