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Brain-Inspired Communication Technologies: Information Networks with Continuing Internal Dynamics and Fluctuation

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SUMMARY Computation in the brain is realized in complicated, heterogeneous, and extremely large-scale network of neurons. About a hundred billion neurons communicate with each other by action potentials called "spike firings" that are delivered to thousands of other neurons from each. Repeated integration and networking of these spike trains in the network finally form the substance of our cognition, perception, planning, and motor control. Beyond conventional views of neural network mechanisms, recent rapid advances in both experimental and theoretical neuroscience unveil that the brain is a dynamical system to actively treat environmental information rather passively process it. The brain utilizes internal dynamics to realize our resilient and efficient perception and behavior. In this paper, by considering similarities and differences of the brain and information networks, we discuss a possibility of information networks with brain-like continuing internal dynamics. We expect that the proposed networks efficiently realize context-dependent in-network processing. By introducing recent findings of neuroscience about dynamics of the brain, we argue validity and clues for implementation of the proposal.

key words: *brain, neuron, noise, sparseness, plasticity, liquid state machine*

1. Introduction

The brain consists of about a hundred billion neurons. Each of them receives synaptic inputs from several thousands of other neurons and integrates them into its membrane potential. Once the membrane potential rises to a threshold value, activation of ion channels in their membrane starts to evoke rapid transient increase of the membrane potential, called action potential or spike firing (Fig. 1A). The spike is the communication tool for neurons. Only when neurons generate spike firings, they send synaptic outputs to other several thousands of neurons (Fig. 1B). In cerebrum cortex that is the most outer area of the brain and mainly involved in our sensory perception, long-term memory, motor planning, and attention, network topology of neurons seems random at least up to sub-millimeter scale rather than completely organized [1]. In order to understand information transmission on the network of neurons that forms brain functions, we need to know spatiotemporal profiles of spike trains accurately on this random network topology.

Recent developments of experimental, and computational techniques, e.g. optogenetics [2], spike-sorting [3], large-scale modeling [4] and theoretical analysis of neural circuit [5], allow us to measure such temporal dynamics of huge numbers of neurons. Results of measurements of large population of neurons force us to reconsider a conventional view of "neural network". Despite static and homogeneous features, a real network of neurons is essentially dynamic and largely heterogeneous both in spatial and temporal structures.

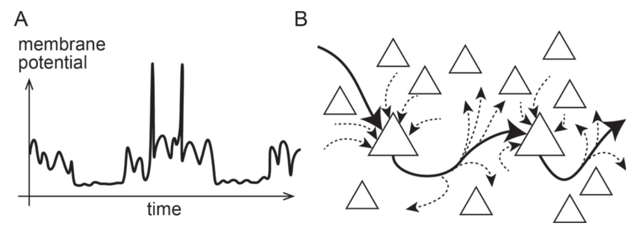

Fig. 1 (A) Membrane potential of a neuron. (B) Neurons communicate with each other by sending spike signals.

While a single neuron is a passive device and keeps silent until external stimuli evoke spike firing, networks of them are not passive. Neurons in the brain continuously generate spike firings with strong fluctuation even without sensory inputs to animals [6]. This internal activity is called "spontaneous ongoing activity" as it is neither directly evoked by stimulus to animals nor elicits actual motor movement. The spontaneous activity is generated as reverberating spike communication among neurons [7], [8]. By receiving many spikes from other neurons with small amplitude, the mean of membrane potential of each neurons dynamically changes ranging from its resting level to the firing threshold continuously in the network (Fig. 1A). Owing to the continuous modulation, the brain dynamically changes its intrinsic state, which allows the brain to respond differently even to the same stimulus depending on context around animals. It also enables the brain to anticipatory modulate susceptibility of sensory neurons and activity of motor neurons. Actually, recent studies revealed that internal dynamics engage in a wide variety of computation in the brain [9] including short-term memory [10], perception [11], inference of stimuli [12], prediction of future stimuli [13], attention [14] and motor planning and motor generation [15], [16].

While the brain and conventional information networks share surface similarity of structures and the function, i.e. massive information transmission in a highly complicated large-scale network, their final objectives are different. The final objective of the information network is summarized as faithful and effective information transmission across net-

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works with considering fairness and demands of users. On the contrary, information is not transmitted remain intact in the brain. A network in the brain works to process information along communication rather transmits it faithfully across the network. Communication among neurons itself is a distributed computation, i.e. distributed signal processing, in the brain.

A class of information network, the wireless sensor network, shares the final objective with the brain. Users of sensor networks often do not require sensing data themselves but informative integration of them [17]. As with sensing data are processed to provide significant information to users, stimuli on receptors are processed in the brain to allow an animal recognize environment. In order to achieve efficient data integration, in-network processing has been extensively studied recently where sensed data are aggregated and processed at each relay nodes to remove redundant information before they reaches to sink nodes [18], [19]. One can also use in-network processing for query handling [20], clustering of sensor nodes [21] and compressed sensing [22], [23].

In-network processing is used for distributed inference in applications that require collaborative information processing among sensor nodes, for example, heat source detection, tracking moving objects, or estimation or classification of environmental parameters [24], [25]. In these applications, each sensor is desirable to be tasked and controlled by not only top-down queries given by users but also bottom-up information sensed by the sensor network itself i.e. context around sensors. Context-dependent active tasking and controls of sensor nodes are studied along this line [26], [27]. For a network of camera sensors used for animal monitoring, for example, a task of a sensor should automatically change from simple tracking to detection of particular behaviors of animals when sign of an infectious disease are sensed by other sensors, even without an explicit instruction by users.

Researches of information-driven control of a sensor network with reflecting context around them is still ongoing and our brain realizes this, at least some extent, by utilizing internal dynamics. In this paper, inspired by recent findings of the neuroscience, we discuss a possibility to introduce internal dynamics to information networks, typically wireless sensor networks, in order to allow a network processes information in the network with reflecting spatiotemporal context around them without centralized control. Naïve implementation, however, must extremely increase communication overhead. To suppress them, we review strategies used in the brain with discussion about possible implementation for information networks. There have been a number of studies about biologically-inspired distributed control of wireless sensor networks [28] and distributed inference in wireless sensor network [26]. However, we will see that most recent findings of the brain give us very unique insight to the subject.

In Sect. 2, we provide our scopes and outline of the proposal. We then discuss possible implementation of the proposal and validity of them in terms of communication in Sect. 3 by introducing recent findings of neuroscience, for example, sparse communication based on spikes, active roles of fluctuation, spike-timing-dependent plasticity, and computation with recurrent dynamics on local circuit called reservoir computation. Finally in Sect. 4 we summarize the paper and discuss future perspectives.

2. Brain-Inspired Wireless Sensor Network with Internal Dynamics

In this section, we describe our scopes and propose a possible solution inspired by internal dynamics of the brain.

2.1 Wireless Sensor Network

Consider a wireless sensor network consists of extremely large number ($N \gg 1$) of sensors, each of which provides huge amount of data. Let assume that while each sensor node has sufficient computational capacity to process data obtained at the node, communication capacities between nodes are largely restricted. Sensor nodes spread across a wide area largely beyond distance allowing single-hop communication. In such situations, it is not reasonable, or often actually impossible, to faithfully send all of sensed data remain intact to sink nodes to which users have direct connections. Rather, we should design the network as sensors report users only "important" parts of sensed data or extracted results of processed information that are largely reduced from original huge amount of data.

Importance of sensed data, however, is generally neither fixed in time nor homogeneous across sensors. It dynamically changes depending on context around the sensor network, i.e. sensed data measured by other sensors, and history of them. Therefore, we need a certain amount of computation for each sensor nodes with considering data at other nodes generally distributed beyond single-hop distance. Similar problems can arise widely when we need to control behavior of sensors reflecting global state of the network. For example, when we need to control duty cycle, susceptibility, and position of mobile sensors, or actuators accompanied with sensors if exist.

Simplest way to perform such computation is that we prepare fusion nodes collecting data from sensors distributed in a wide area to conduct integrated computation. The centralized control, however, is not a suitable solution under our assumption. Major difficulty obviously comes from limited communication capacity. Also, energy consumption at sensor nodes near fusion nodes relaying large amount of traffic and round-trip delay between sensors to fusion nodes can be deficits of the approach if quick response is required.

Distributed approach including a kind of in-network processing, however, also suffers the same problem as long as sensor nodes transmit all of its sensed data to others. This is still true even if computation on each node requires data of only restricted number of nodes. Therefore, we need to

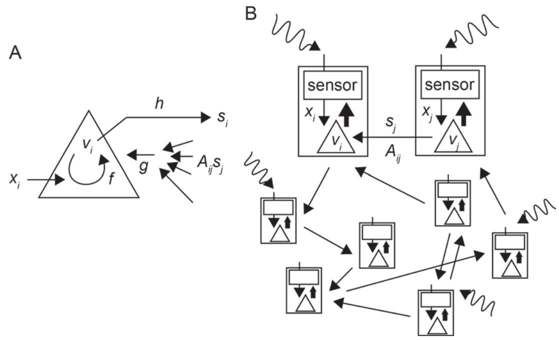

Fig. 2 (A) Wireless sensor network with virtually implemented brain-like internal dynamics. (B) v_i evolves with its internal dynamics depending on x_i and "spike" signals from other neurons.

largely reduce traffic of signals transmitted between sensor nodes in order to adaptively control sensors.

2.2 Internal Dynamics of the Brain

In the brain, we can regard susceptibility of a neuron to an input stimulus as an expression of "importance" of the input at the moment. Susceptibility of a neuron is adaptively modulated by the mean of its membrane potential. When the membrane potential of a neuron is in a high level, weak stimuli evoke output spikes on the neuron, while strong stimulus is required to evoke output spikes if the value of the membrane potential is low. Spike response of a neuron also can be stochastic if the membrane potential randomly fluctuates, and the probability of spike generation depends on variance of the membrane potential around the mean.

Membrane potential of a neuron evolves with receiving spike inputs from other neurons and external stimuli to the neuron. Internal dynamics of membrane potentials are well described by (generally nonlinear) differential equations as,

$$\begin{cases} \dfrac{dv_i}{dt} = f(v_i, x_i) + g(v_i, A_{i1}s_1, A_{i2}s_2, \cdots A_{iN}s_N) \\ s_i = h(v_i) \end{cases}, \quad (1)$$

where v_i, x_i, and s_i are the membrane potential, input stimuli, and output spike of the ith neuron respectively. $A_{\rm ij}$ is synaptic connection strength from the jth neuron to the ith neuron, that can be both positive and negative depending on whether jth neuron is excitatory or inhibitory one. Functions f and g describes intrinsic dynamics of the membrane potential and interaction mediated by spike firings, which are converted from membrane potentials using another nonlinear function h (Fig. 2A).

2.3 Sensor Networks with Virtually Implemented Internal Dynamics

Employing the relatively simple nonlinear dynamics given by Eq. (1), the brain realizes adaptive and efficient information-driven control of the network with reflecting context around animals. Inspired by the brain, here we implement virtual internal dynamics to the wireless sensor network and use them to realize information-driven control of the network (Fig. 2B). Let allow each sensor node has its own low-dimensional variable v_i that evolves with Eq. (1). Variable x_i represents generally high-dimensional, sensed data at the ith node and s_i is another low-dimensional variable that is used for interaction between nodes. $A_{\rm ij}$ is strength of interaction from jth node to ith node, that is implemented as a virtual layer network and thus can be independent from physical topology of the sensor network. This means that additional communication between sensor nodes is realized as exchange of only the low-dimensional variables s_i on the virtual network defined as $A_{\rm ij}$. Then each sensor node uses value of v_i to modulate its sensing behavior or on-site data processing, for example, an indicator of "importance" for the current measurement, duty cycle of sensing, vector indicating velocity of special movement, and input signals to actuators. Due to the interaction via s_i, variable v_i can reflect internal states of other nodes.

While both v_i and s_i are scalar values in the brain, we can use vector variables for information networks if necessary because computational power of our node will generally be much higher than a single neuron. Dimensions of v_i and s_i generally can be different. Dimension of v_i is limited by computational power of each sensor node whereas dimension of s_i is mainly restricted by communication capacity between nodes as we will discuss details in the next section.

How to design f, g, h, A_{ij}, and dependency of sensor nodes on v_i is obviously the most significant subject. We can take various approaches for the subject. The simplest way is that we preprogram them based on previous knowledge of objective of the sensor network. For tracking of tiny objects in noisy circumstance, for example, we use $v_i(t)$ as an indicator of the prior probability that a target object is sensed at ith node at time t. The prior probability generally depends on history of sensed data measured not only at the node, x_i, but also at other nodes. We design g and A_{ij} as they reflect typical movement of target objects. Actually, by using nonlinear filtering theory [29], we will obtain Eq. (1) that approximates a continuous time filter of the subject. However, this preprogramming approach requires enough knowledge of targets in advance. Lack of flexibility to queries of users and target behaviors are other major drawbacks of the approach. More flexible way to design the internal dynamics is that we allow they to change by themselves on site and on the fly using heuristic learning algorithms including genetic algorisms, self-organization, particle filters, and various machine learning techniques. We will discuss a kind of approach at the next section by introducing synaptic plasticity of the brain.

3. Clues from Neuroscience for Valid Implementations of the Proposal

In terms of communication, the most significant issue is the communication overhead added by the proposal. Because nodes exchange only variables s_i on A_{ij}, design of them is crucial for the issue. We will review clues for possible implementations of the proposal by referring strategies used in the brain.

3.1 Spike-Based Sparse Communication

Communication is expensive even in the brain. Significant proportion of brain's energy is consumed by communication between neurons [30] and significant volume of the brain is used for dendrites, or wires, between neurons that use valuable biological resources. Brain's strategy to reduce communication demands is sparse spatiotemporal structure in spike-based communication. While communication variable s_i in Eq. (1) can be an arbitral low-dimensional variable, the brain uses spikes, which is just a binary variable. Because spike firing are a transient event, the value takes zero for most of the time. Moreover, experiment reveals that firing rate of spikes kept very low in the brain [31], or s_i vanishes most of the time. If we can use such sparsely nonzero signals as s_i, while binary representation is not necessarily required, we can implement this as transmission of a packet with extremely small size only when s_i is not zero, which can largely reduce traffic required for s_i exchange.

Another sparseness can be seen in network topology of the brain. While the numbers of neurons in the brain is extremely large, each neuron sends spikes only to small portion of them. Moreover, recent experiments reveal that most connections are very weak and only a few connections are significantly strong to directly influence to downstream neurons [32]. This kind of sparseness also often improves performance of machine learning and clearly reduces overhead communication. Therefore, choosing sparse s_i and A_{ij} will be an effective design principle for us.

3.2 Active roles of Fluctuation

Remarkably, internal dynamics of the brain is highly fluctuating. A temporal profile of membrane potentials is well described by the Ornstein-Ulhenbeck process. This large fluctuation is not a result of thermal or chemical fluctuations of a single neuron. Rather, it is sustained by reverberating spike communication between neurons. Noise in nonlinear dynamics is not always obstacle for computation but it can help to realize effective and reliable results if its strength are suitably tuned [7], [33], [34]. Examples include efficient dynamic routing utilizing fluctuation [35], [36].

The brain realizes the suitable strength fluctuation by using the simplest g in Eq. (1) as,

$$g(v_i, A_{i1}s_1, A_{i2}s_2, \cdots, A_{iN}s_N) = \sum_j A_{ij}s_j, \tag{2}$$

probably in order to reduce computational demand at each neuron. Because most of nonzero values of A_{ij} is very small and are almost independent for different j, due to central limit theorem, the sum has negligible amount of fluctuation that depending on values of s_j.

In information networks under our subject, however, computational capacity of each node is not so small. We can thus use more explicit implementation of fluctuation if necessary by extending Eq. (1) to stochastic differential equations,

$$\begin{cases} \dfrac{dv_i}{dt} = f(v_i, x_i) + g_1(v_i, \{A_{ij}s_j\}) + g_2(v_i\{A_{ij}s_j\})\xi_i, \\ s_i = h(v_i) \end{cases} \tag{3}$$

where ξ_i is the white Gaussian noise whose strength g_2 generally depends on v_i and input s_j from other nodes.

As in the brain and other nonlinear systems, noise term in Eq. (2) stabilizes internal dynamics by avoiding abnormally synchronized communication that can cause excess communication overhead. It also enhances susceptibility to input signals and helps the system to escape from local solutions. Also because it makes v_i as an internal random variable, it naturally allows us to use Eq. (3) for stochastic inference i.e. sequential Bayesian inference.

3.3 Spike-Timing-Dependent Plasticity

As we have discussed, design of connection matrix A_{ij} is an important subject and distributed adaptive algorithms are preferable. In order to suppress excess overhead associated with implementation of these algorithms, A_{ij} should be varied depending only on the low-dimensional communication signals s_i and s_j.

In the brain, A_{ij} corresponds to strength of synaptic connection. It dynamically changes depending on spike signals s_i and s_j, and results in distributed learning of the network. Spike-timing-dependent plasticity (STDP) is the recently found principle of plasticity of A_{ij} [37], [38]. The plasticity based on the traditional Hebb's rule where A_{ij} is strengthened when s_i and s_j almost simultaneously take nonzero value (Fig. 3A) [39]. The traditional rule, however, results in only a symmetric connection matrix and cannot generate rich internal dynamics required for various subjects. In the STDP, A_{ij} is strengthened or weakened depending on relative spike timings reflecting causality of spikes (Fig. 3B). If s_j is shortly advances in s_i, A_{ij} is strengthened while it is weakened if s_j is shortly delayed from s_i.

Enhancing causal relationships between neurons, STDP can induce Bayesian computation to the network [40]. Also the learning rule organizes the network to produce motor sequences [41], which can be used to generate

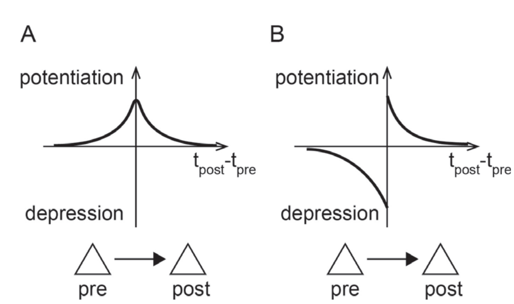

Fig. 3 (A) Hebb's rule. (B) Spike-timing dependent plasticity (STDP).

orchestrated spatial movement for mobile sensors or actuators. Objectives of the sensors/actuators network, however, are not limited to inference and motor control for which we can directly apply achievements of theoretical neuroscience. Therefore, we should develop novel distributed learning rules for spike-like communication to answer more general class of queries for information networks.

3.4 Internal Dynamics with Parallel Readout Neurons

So far, we have implicitly assumed that a single user uses the network with a query. Here, we discuss multi-users scenario where many users use the network to obtain answers to their own queries. For example, while a user requires anomaly detection within a certain area, another user wants to know correlated events between two specific nodes, and another asks the mean of a measurement at a node over a certain period.

While a single owner, or an animal, uses the brain at the most macroscopic scale, a local network of neurons in the brain is shared to answer different requirements to multiple users. A local network of neurons receives various stimuli from many sensory neurons and processes them to send different outputs to different readout neurons in parallel. A basic mechanism of the parallel computation in the brain is called "reservoir computing", also known as "liquid state machine" and "echo state network", that is tightly linked to internal dynamics of the brain [13], [42].

In the framework, input signals are fed into a recurrent network or a dynamical system called reservoir. Signals are transformed into high-dimensional spatiotemporal sequences due to the internal dynamics of the network. Then, readout neurons that read states of the reservoir are trained to generate their own desired outputs (Fig. 4). Advantages of the method are that both training and signal processing at each readout neuron are performed in parallel and independently with reservoir topology remains intact. Because readout neurons receive only spikes from reservoir neurons, it also suppresses communication demand. Regarding a sensor network and users as a reservoir and readout neurons respectively, we can apply the framework of reservoir computation to allow users simultaneously ask different queries to a sensor network.

The reservoir computing is similar to the network coding [43], especially to the random linear network coding where input information is fed into a random, typically acyclic, network and allow each nodes encode received signal with random linear coding [44]. Major differences between them are that reservoir computing employs nonlinear signal transformations at each node and cycles in network at the expense of faithful information transmission. For applications where users do not require raw data, reservoir computing can be a valuable option. Design principles of the internal dynamics that are suitable for reservoir computing are important future subjects.

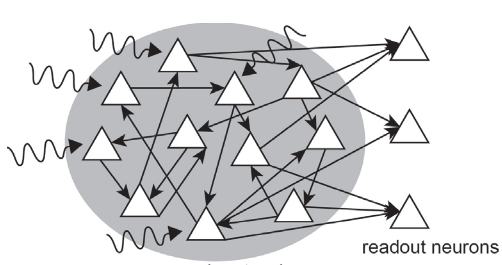

Fig. 4 Reservoir computing. Reservoir network is a, often randomly connected, recurrent network.

4. Conclusion

In the paper, based on recent findings of neuroscience, we discuss possible communication on wireless sensor/actuator networks with internal dynamics. The internal dynamics is implemented as virtual layer network with low-dimensional variable assigned to each sensor node. Sensors and the internal variable interact bi-directionally in order to actively modulate the sensor network and finally realize adaptive control of sensing and reduce total required communication on the network. To reduce communication overhead of the internal dynamics we can use spike-based sparse representation for communication signals that has nonzero value only transiently. We also discussed possible roles and implementation of fluctuation and plasticity. Both neuroscience and communication engineering are rapidly developing fields sharing similar but bit different problems. Active exchange of ideas and problems between them must bring fruitful results in both fields.

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References

[1] N. Kalisman, G. Silberberg, and H. Markram, "The neocortical microcircuit as a tabula rasa," P. Natl. Acad. Sci. USA, vol.102, no.3, pp.880–885, 2005.
[2] S. Peron and K. Svoboda, "From cudgel to scalpel: Toward precise neural control with optogenetics," Nat. Methods, vol.8, no.1, pp.30–34, 2011.
[3] K.D. Harris, D.A. Henze, J. Csicsvari, H. Hirase, and G. Buzsáki, "Accuracy of tetrode spike separation as determined by simultaneous intracellular and extracellular measurements," J. Neurophysiol., vol.84, no.1, pp.401–414, 2000.
[4] E.M. Izhikevich and G.M. Edelman, "Large-scale model of mammalian thalamocortical systems," P. Natl. Acad. Sci. USA, vol.105, no.9, pp.3593–3598, 2008.
[5] L.F. Abbott, "Theoretical neuroscience rising," Neuron, vol.60, no.3, pp.489–495, 2008.
[6] A. Destexhe, M. Rudolph, and D. Paré, "The high-conductance state of neocortical neurons in vivo," Nat. Rev. Neurosci., vol.4, no.9, pp.739–751, 2003.

[7] J.-N. Teramae, Y. Tsubo, and T. Fukai, “Optimal spike-based communication in excitable networks with strong-sparse and weak-dense links,” Scientific Reports, vol.2, pp.00485-1–6, 2012.
[8] Y. Ikegaya, T. Sasaki, D. Ishikawa, N. Honma, K. Tao, N. Takahashi, G. Minamisawa, S. Ujita, and N. Matsuki, “Interpyramid spike transmission stabilizes the sparseness of recurrent network activity,” Cereb. Cortex, vol.23, no.2, pp.293–304, 2013.
[9] D.V. Buonomano and W. Maass, “State-dependent computations: Spatiotemporal processing in cortical networks,” Nat. Rev. Neurosci., vol.10, no.2, pp.113–125, 2009.
[10] G. Mongillo, O. Barak, and M. Tsodyks, “Synaptic theory of working memory,” Science, vol.319, no.5869, pp.1543–1546, 2008.
[11] T. Kenet, D. Bibitchkov, M. Tsodyks, A. Grinvald, and A. Arieli, “Spontaneously emerging cortical representations of visual attributes,” Nature, vol.425, no.6961, pp.954–956, 2003.
[12] P. Berkes, G. Orbán, M. Lengyel, and J. Fiser, “Spontaneous cortical activity reveals hallmarks of an optimal internal model of the environment,” Science, vol.331, no.6013, pp.83–87, 2011.
[13] W. Maass, T. Natschläger, and H. Markram, “Real-time computing without stable states: A new framework for neural computation based on perturbations,” Neural Comput., vol.14, no.11, pp.2531–2560, 2002.
[14] K.D. Harris and A. Thiele, “Cortical state and attention,” Nat. Rev. Neurosci., vol.12, no.9, pp.509–523, 2011.
[15] D. Sussillo and L.F. Abbott, “Generating coherent patterns of activity from chaotic neural networks,” Neuron, vol.63, no.4, pp.544–557, 2009.
[16] R. Laje and D.V. Buonomano, “Robust timing and motor patterns by taming chaos in recurrent neural networks,” Nature Publishing Group, vol.16, no.7, pp.925–933, 2013.
[17] I. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, “Wireless sensor networks: A survey,” Comput. Netw., vol.38, no.4, pp.393–422, 2002.
[18] E. Fasolo, M. Rossi, J. Widmer, and M. Zorzi, “In-network aggregation techniques for wireless sensor networks: A survey,” IEEE Wireless Commun., vol.14, no.2, pp.70–87, 2007.
[19] J.N. Al-Karaki and A.E. Kamal, “Routing techniques in wireless sensor networks: A survey,” IEEE Wireless Commun., vol.11, no.6, pp.6–28, 2004.
[20] Y. Yao and J. Gehrke, “The cougar approach to in-network query processing in sensor networks,” ACM SIGMOD Record, vol.31, no.3, pp.9–18, 2002.
[21] A.A. Abbasi and M. Younis, “A survey on clustering algorithms for wireless sensor networks,” Comput. Commun., vol.30, no.14, pp.2826–2841, 2007.
[22] J. Haupt, W.U. Bajwa, M. Rabbat, and R. Nowak, “Compressed sensing for networked data,” IEEE Signal Process. Mag., vol.25, no.2, pp.92–101, 2008.
[23] S. Li, L. Da Xu, and X. Wang, “Compressed sensing signal and data acquisition in wireless sensor networks and internet of things,” IEEE Trans. Industrial Informatics, vol.9, no.4, pp.2177–2186, 2013.
[24] F. Zhao, J. Shin, and J. Reich, “Information-driven dynamic sensor collaboration,” IEEE Signal Process. Mag., vol.19, no.2, pp.61–72, 2002.
[25] J.B. Predd, S.R. Kulkarni, and H.V. Poor, “Distributed learning in wireless sensor networks,” IEEE Signal Process. Mag., vol.23, no.4, pp.56–69, 2006.
[26] F. Zhao and L.J. Guibas, Wireless sensor networks: An information processing approach, Elsevier, New York, 2004.
[27] R.V. Kulkarni, A. Forster, and G.K. Venayagamoorthy, “Computational intelligence in wireless sensor networks: A survey,” IEEE Communications Surveys & Tutorials, vol.13, no.1, pp.68–96, 2011.
[28] S. Barbarossa and G. Scutari, “Bio-inspired sensor network design,” IEEE Signal Process. Mag., vol.24, no.3, pp.26–35, 2007.
[29] A.H. Jazwinski, Stochastic processes and filtering theory, Academic Press, New York, 2007.
[30] P. Lennie, “The cost of cortical computation,” Curr Biol., vol.13, no.6, pp.493–497, 2003.
[31] T. Hromádka, M.R. DeWeese, and A.M. Zador, “Sparse representation of sounds in the unanesthetized auditory cortex,” PLoS Biol., vol.6, no.1, e16, 2008.
[32] S. Lefort, C. Tomm, J.-C. Floyd Sarria, and C.C. H. Petersen, “The excitatory neuronal network of the C2 barrel column in mouse primary somatosensory cortex,” Neuron, vol.61, no.2, pp.301–316, 2009.
[33] L. Gammaitoni, P. Hanggi, P. Jung, and F. Marchesoni, “Stochastic resonance,” Rev. Mod. Phys., vol.70, no.1, pp.223–287, 1998.
[34] J.-N. Teramae and D. Tanaka, “Robustness of the noise-induced phase synchronization in a general class of limit cycle oscillators,” Phys. Rev. Lett., vol.93, no.20, 204103, 2004.
[35] N. Asvarujanon, K. Leibnitz, N. Wakamiya, and M. Murata, “Concurrent multipath traffic distribution in ad hoc networks based on attractor perturbation,” Proc. IEEE INFOCOM, 2013.
[36] K. Leibnitz, N. Wakamiya, and M. Murata, “Resilient multi-path routing based on a biological attractor selection scheme,” Biologically Inspired Approaches to Advanced Information Technology, vol.3853, no.7, pp.48–63, Springer Berlin Heidelberg, Berlin, Heidelberg, 2006.
[37] G.Q. Bi and M.M. Poo, “Synaptic modifications in cultured hippocampal neurons: Dependence on spike timing, synaptic strength, and postsynaptic cell type,” J. Neurosci., vol.18, no.24, pp.10464–10472, 1998.
[38] S. Song, K.D. Miller, and L.F. Abbott, “Competitive Hebbian learning through spike-timing-dependent synaptic plasticity,” Nat. Neurosci., vol.3, no.9, pp.919–926, 2000.
[39] N. Caporale and Y. Dan, “Spike timing-dependent plasticity: A Hebbian learning rule,” Annu. Rev. Neurosci., vol.31, pp.25–46, 2008.
[40] B. Nessler, M. Pfeiffer, L. Buesing, and W. Maass, “Bayesian computation emerges in generic cortical microcircuits through spike-timing-dependent plasticity,” PLoS Comp. Biol., vol.9, no.4, e1003037, 2013.
[41] I.R. Fiete, W. Senn, C.Z. H. Wang, and R.H.R. Hahnloser, “Spike-time-dependent plasticity and heterosynaptic competition organize networks to produce long scale-free sequences of neural activity,” Neuron, vol.65, no.4, pp.563–576, 2010.
[42] H. Jaeger and H. Haas, “Harnessing nonlinearity: Predicting chaotic systems and saving energy in wireless communication,” Science, vol.304, no.5667, pp.78–80, 2004.
[43] R. Ahlswede, N. Cai, S.Y. R. Li, and R.W. Yeung, “Network information flow,” IEEE Trans. Inf. Theory, vol.46, no.4, pp.1204–1216, 2000.
[44] T. Ho, M. Medard, R. Koetter, D.R. Karger, M. Effros, J. Shi, and B. Leong, “A random linear network coding approach to multicast,” IEEE Trans. Inf. Theory, vol.52, no.10, pp.4413–4430, 2006.

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