Artificial Backbone Neuronal Network for Nano Scale Sensors

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***Abstract*—Communication between biological based nano scale devices is a crucial component of future applications in nanotechnology. This paper explores the creation of a backbone communication network for nano scale sensors using neurons. We investigate how neuron cell characteristics affect the performance of neuronal based network and highlight several key characteristics compared to conventional wire based networks. Finally, we investigate four network topologies through simulation.**

I. INTRODUCTION

In recent years Nanotechnology has received tremendous attention due to its potential application in various medical fields. The area of nano communication has recently been introduced to enable communication between nano scale devices [1]. This new capability can increase capabilities and functionalities of nano devices, in particular from perspective of their application base. As the popularity of this research area increases, a number of different solutions have been proposed. Currently, two approaches have been investigated, which includes electromagnetic wireless nano networks [8] and Molecular Communications [9] [10]. Electromagnetic based nano sensor devices resemble conventional sensor networks, and uses similar design concepts and communication capabilities. On the other hand, molecular communication is a new paradigm shift from conventional communication devices, where communication is performed on underlying biological environment. In such cases, the information is usually transformed into bio-molecules at the physical layer [6], before being propagated to the receiver. A number of different approaches have been investigated, and one potential approach is through the use of neurons.

In this paper, we aim to show how neurons can, within their intrinsic properties, form a network, to be used, for molecular communications. Neurons are specific type of cells that form highly interconnected networks, where the signaling is performed through dedicated cellular synapses (Fig. 1). The scenario we concentrated in is a fixed wireline backbone network that supports communication between distributed nano scale sensor and a sink. Given the biological nature, the physical shape and characteristics of neurons, our aim is to associate with neurons the molecular communication function of being the interconnecting links. Due to the capabilities of neurons to forms complex connections (e.g., web), we believe that this could be used to form wireline infrastructure for communication. In particular, our aim is to develop the backbone infrastructure at the basis of simple information transfer. Thus, this paper will evaluate how different geometric topologies can be used as neuronal backbone networks, and how each of these shape's influence can have diverse blocking probabilities. Therefore, the simulation work, here presented, is developed to show the associated performance for each topological shapes taken into examination.

The paper is organized as follows: Section II will present the related work, while section III will present background information on neurons and their characteristics. Section IV will describe our backbone neuronal network, while section V will present the simulation work. Lastly, section VI will be the conclusion.

II. RELATED WORK

The related work section is sub-divided into two sections, which includes current state of the art in molecular communication, and neuronal networks.

A. Molecular Communications

As described earlier, one form of communication for nano devices is through molecular communication [9], [10].

Molecular communication can be sub-divided into two propagation approaches, which are passive and active transport. Passive transport is usually associated to diffusion based propagation of molecules [11] [12]. However, in the case of passive transport, there is not an identified unidirectional path in the propagation of signals. For instance, one example is the natural occurring calcium signalling that propagates between the connexons of cells or by larger static magnetic fields [7]. Whereas an example of active transport includes the use of microtubules to connect between cells, where the molecular motors are used to transport information [13]. Another approach that has been proposed is through the use of nano scale cargoes which can be loaded onto kinesin-coated surface, that act as cargo transporters [9]. Through the use of labeling process of using single-stranded DNAs, the cargo can then selectively unload in specific locations.

The approach that we propose in this paper is availing of the active transport approach although using a different physical layer component: a neuron. While current approaches can allow directionality in transporting molecules, we believe that the process of forming interconnecting networks, similarly to conventional networks, will be difficult by using the above described approaches. Conversely, we believe that through neurons we can achieve closer characteristics to conventional communication networks.

B. Neuronal Networks

Kotsavasiloglu et al. [2] [3], studied the signaling performance of neuronal networks under varying condition. The aim of the study was to investigate the resilience of neuronal networks when synapses fail, where such failure can be due to aging or diseases. The authors performed simulations on the neuronal network of healthy neurons, and varied the synapse failure rate, refractory periods, excitation synapse ratio, as well as synapse delay. Here we show that neuronal networks are very resilient and are able to maintain high level of activity up to 70 – 80% destruction of synapses. Forming a pre-defined geometry and connectivity of neuronal networks has been investigated in a number of works. Breskin et al. [5], showed that connectivity of neural networks is based on Gaussian distribution rather than scale free network. Gabay et al. [4], developed a new approach of pre-defined geometry of neuronal network clusters using carbon nanotube clusters. In the proposed approach, neurons migrate on low affinity substrate to high affinity substrate on a lithographically defined carbon nanotube template. Once neurons have reached their destinations, they send neurites to form interconnected networks. This approach improves on previous methods, where neurons interconnecting the networks collapse during migration.

While a number of works have investigated neuron networks from a networking perspective, our approach taken is different. In our proposed approach presented in this paper, we aim to show from natural occurring physiological perspective.

III. NEURONS

A neuron is the basic unit of a neural network (node) and has the ability to process information packages in the form of electrical and chemical signals. The classical structure of a neuron consists of 4 specific regions including the cell body, dendrites, the axon and the axon terminal [16]. The cell body or soma contains organelle for protein synthesis while branching from it are dendritic extensions which receive incoming chemical signals from abundant neurons simultaneously. The axon transmits incoming electrical impulses or action potentials to the nerve terminal where it forms synaptic contacts with other neurons [17]. Hence, the action potential depolarizes the pre-synaptic membrane opening voltage operated channels (VOCs) and potentiates the influx of extracellular calcium [12]. Increasing intracellular calcium concentrations initiates exocytosis of synaptic vesicles containing neurotransmitters. The axon terminal is the area where a synapse occurs between the pre-synaptic neuron and the post-synaptic neuron and it is within this synaptic cleft that information of the signal is relayed via excitatory or inhibitory neurotransmitters. In this perspective, the travelling information package can be considered the action potential generated by a cascade of chemicals events that take place on the surface of the cell membrane.

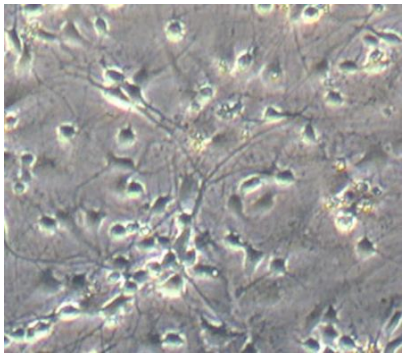

Figure 1. Examples of pattern of connections in a self organised network of neurons; please note cell bodies (or soma), axons (larger filaments) and dendrites (smaller filaments). (magnification x20).

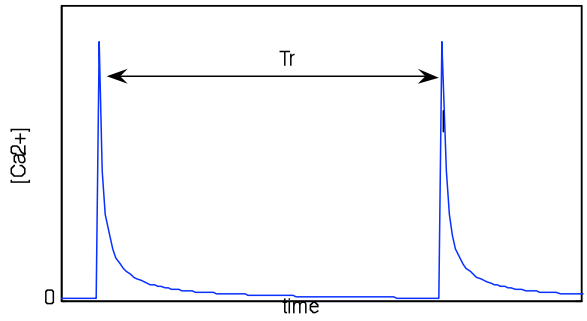

Figure 2. Intracellular Ca^{2+} concentration in a neuron. Ca^{2+} release events must be separated by at least the refractory time T_r, the time required to replenish internal Ca^{2+} stores.

In other words, the action potential can be seen as a travelling gradient of ions concentration (Na^+/K^+, Ca^{2+}) along the whole length of the cell structure. Tracking the movements of these ions may lead to a new way to interpreter the synaptic communication and dynamics within a neural network.

There are a number of inherent differences between neuron link and a wireline communication link. First of foremost, conventional communication links have specific bandwidths that are able to support multiple traffic flows. This is not the case for neurons, which are only able to transport a single flow at any one time. Secondly, once a flow is terminated within a conventional communication link, the link becomes empty and is ready again to accept a few traffic flows. However in the case of neurons, there is a refractory period, as shown in Fig. 2 which prevents the neuron-link to be used for a defined period of time. Similarities lies on the signal distribution. As signals are propagated from neuron to neuron, this could be compared to a burst-traffic behavior found in conventional communication links. At the same time, delays in intermediate nodes of a communication network (due to queuing delays) are very similar to synaptic delays found between the junctions of the neurons.

IV. Backbone Neuronal Network

As described earlier, our aim is to create an active molecular communication transport network using neurons. Mazzatenta et al. [15], showed that electrical signals delivered via single-wall carbon nanotubes can directly activate neuronal signaling. This approach could provide a physical interface mechanism for nano scale sensors and neurons. In our work, we design the neuron networks for specific applications and these can be illustrated in Fig. 3, where we have a number of sensors that are connected via a network of neurons to transmit information to a receiving sink (targeted-neuron for communication actuation). Therefore, the key issue here is the ability to maximize the coverage and enable collection of information from majority of sensors to send information to the receiver sink. Therefore, in order to ensure, the geometric shape of the backbone is crucial. Fig. 4 illustrates the three types of topologies that we are considering for our investigation, which consists of a simple Bus (Fig. 4 (a)), Star topology (Fig. 4 (b)), Spiral shaped topology (Fig. 4(c)), and a Tree shaped topology (Fig. 4 (d)).

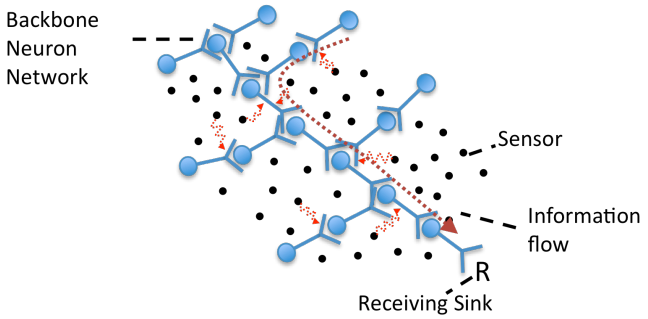

Figure 3. Sensor connected through Neuron Network

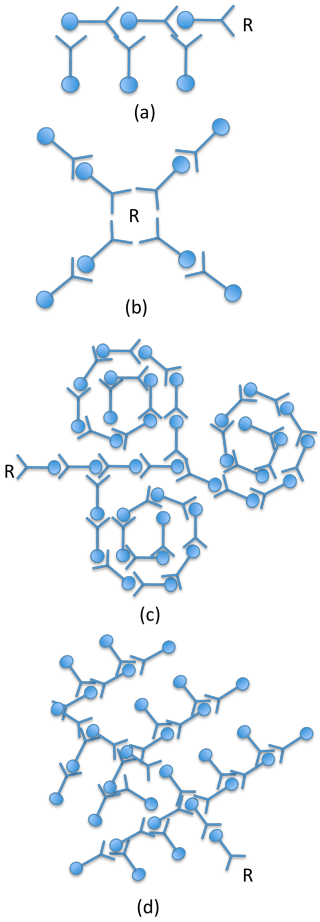

Figure 4. Topologies for Neuron Network Backbone (a) simple Bus topology, (b) Star topology, (c) Spiral shape, (d) Tree topology

For the latter two topologies, our aim is to build on the bus topology structure to develop other types of topologies that can maximize the information coverage. On this, one crucial characteristic that will influence the performance of each topology is the timing processes within a neurons. This timing issue ranges from the timing for the action-potential to induce the electrical signalling to the refractory period of Ca^{2+} as well as associated delay of signaling in the synapses. Therefore, by taking these into account our work provides an opportunity to allow multiple devices to transmit on the same bus link, provided the delays of transmission are properly triggered. For example in Fig. 5, four neurons are connected to a single receiver *R*. This example shows how multiple neurons within the bus can fire without leading to signaling interference. If neuron *A* first fires, neuron *D* will be able fire no later that d_{Delay} to minimize interference at *D*. This is provided that sum of d_{Delay}, the signal propagation of D ($t_{p,D}$) and the refractory time of D ($T_{r,D}$) is less than the sum of propagation time of A ($t_{p,A}$), B ($t_{p,B}$) and C ($t_{p,C}$).

An example illustration of Ca^{2+} disruption caused by two neurons firing close to each other is illustrated in Fig. 6. In this illustration, 16 neurons are connected in a bus topology configuration. Fig. 6 (a) illustrates when two neurons are fired, without any collision events, where the Ca^{2+} in each neuron are fired sequentially. This is when neuron 1 fires at t=0, and this is

followed by neuron 3 firing at t=15. There is no collision leading to no disruption in Ca^{2+} signalling since the firing of neuron 1 occurs way before d_{Delay}, which allows the neurons, down the bus line, to recover from the refractory process; this allow for both transmissions to successfully propagate. On the other hand, Fig. 6 (b) illustrates when two neurons are closely firing to each other and thus leading to collisions which disrupts the firing of Ca^{2+}. As we can see from the figure, the firing of Ca^{2+} in each neuron is terminated after neuron 6 due to the collision (please note that the Ca^{2+} is not the signal that propagates between the cells, but the signal used to invoke the neurotransmitters).

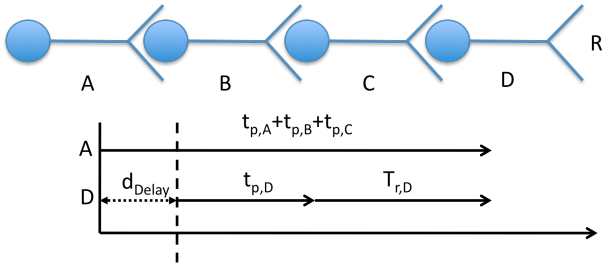

Figure 5. Propagation timing between neurons

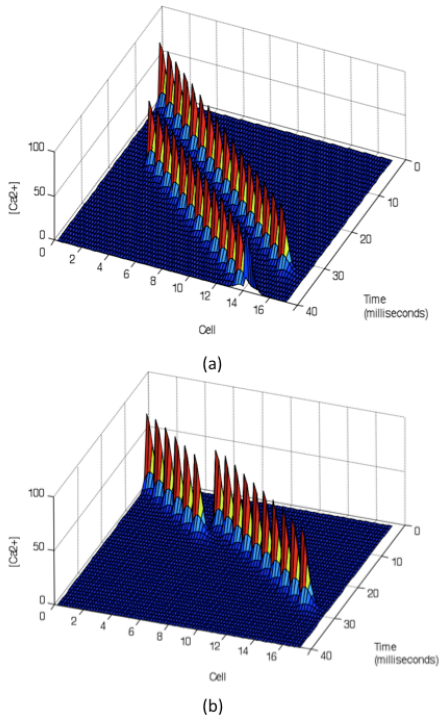

Figure 6. (a) Ca^{2+} signalling in straight bus topology for firing from neuron 1 and 3, (b) Ca^{2+} disruption caused by collision caused by close firing from neuron 1 and 7

V. SIMULATION

This section will present the simulation work conducted on the different topological shapes shown in Fig. 4.

A. Single Bus topology results

The first set of simulation is based on evaluating the performance of the bus topology as we vary the number of devices on the bus and the transmission rate. The parameters for the simulation environment are shown in Table I. The transmission events are performed for $\tau = 0.005$ s, in agreement with the neuron physiology.

TABLE I. SIMULATION PARAMETERS

Simulation Time	5 s
Transmission window	4.5 s
Device Transmission rate	0.1 – 2 ms

Fig. 7 and 8 shows the performance of the bus topology with varying transmission rates and number of devices.

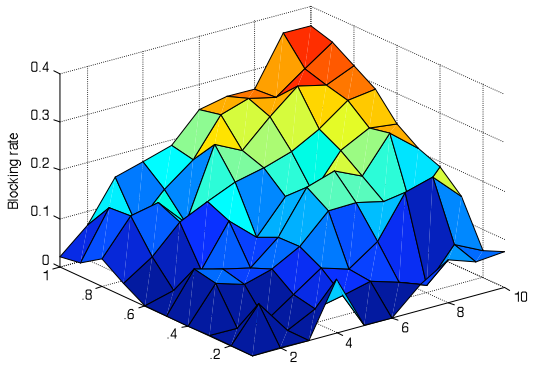

Figure 7. Performance of bus topology for varying number of devices and transmissions per second (0.1 – 1)

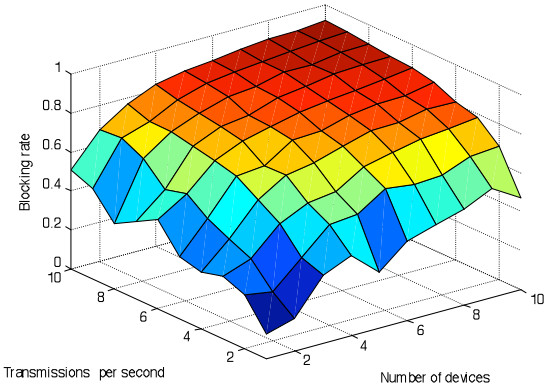

Figure 8. Performance of bus topology for varying number of devices and transmissions per second (1 – 10)

In the case of Fig. 7, the transmission rate is between 0 – 1/ s, while in Fig. 8, this rate change between 2 – 10/s; and this is

in line with what we expected when increasing the number of transmission, when the number of collisions increases. There is, however, very little difference between the highest number of devices and low number of devices, when the transmission rate is low. We believe this may be caused by the close proximity of devices which led to a larger number of collisions. Obviously in the case of Fig. 8, with very high transmission rates correspond a very high rate of collision.

B. Comparisons between Bus, Star, and Spiral topology

In this sub-section we present the result of comparison between the Bus, Spiral, Tree and Star topology. The parameters used in the simulation are presented in Table II. Configurations for the listed topologies are as follows: the number of devices was fixed to 10 devices, while the number of transmissions events varied. The Bus topology contains 13 neurons connected in a line, with the sensors connected in fixed locations of [1, 2, 3,4, 5, 6, 7, 8, 9, 10], while the Receiver is located at neuron 13. The Spiral topology is based on Fig. 4 (c), where three spirals are connected to a single bus line. Each spiral has 13 neurons connected where the location of sensors connected to the neurons for each spirals are located at Spiral-1: [1, 5, 8, 10], Spiral-2: [1, 3, 9], and Spiral-3: [2, 6, 9]. Furthermore, the tree topologies have six short branches connected to a shared media with nodes distributed across the branches as illustrated in Fig. 4(d). In the case of the Star topology, this consists of 3 buses connected to a receiver at the centre. Even in this case, each bus line has a length of 13 neurons.

TABLE II. SIMULATION PARAMETERS

Simulation Time	0 to 1000 * τ (10 sec)
Transmission window	0 to 900 * τ (9 sec)
Probability of device transmitting at time *nτ*	$1x10^{-3}$ - $1x10^{-2}$
Device Transmission rate	0.1 – 1/second

Similarly to previously reported simulation, the calcium model used in our work is based on Fire-Diffuse-Fire model [14]. In order to make the simulation more efficient, it is assumed that the transmissions (transmission event) only take place at time *nτ*, integer multiples of the calcium release time constant *τ*. For our simulation, we took τ = 0.01s. Interestingly, the blocking rate between the Bus and Spiral are very close, as shown in Fig. 9, since the Spiral topology is essentially a bus topology with a Donut shape. The tree topology shows a marginal improvement compared to Bus and Spiral due to the increased length of the communication network. This increases the average distance (in nodes) between transmission events and, therefore reduces the likelyhood of blocking the transmission during the initial stages of the simulation. Furthermore, the Star topology has a lower blocking probability. This is mainly due to the fact that the star topology does not have a single shared media like the bus, which minimizes collissions during the transmission.

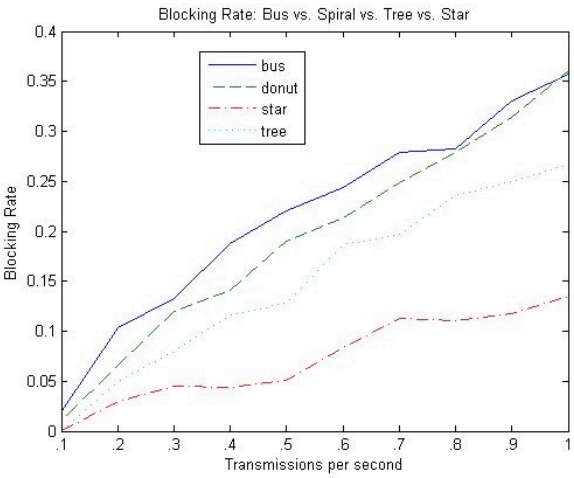

Figure 9. Comparison between Bus, Star, and Spiral topology

VI. CONCLUSION

Molecular communication is one form of communication between nano- machines (devices, organisms), and therefore represents a new paradigm shift from conventional communication systems. In this paper, we have proposed the use of neurons to form interconnected networks for the active transport of defined action-potential events in a molecular communication model. The aim of our proposed approach is to create a communication network from biological components. We believe that this could be best achieved through neurons that are able to form web of interconnection similar to conventional wireline networks. Four topologies of neuron interconnection were modelled and their performances of blocking rate under varying number of devices and transmission were evaluated. This allowed us to determine if the patterns of transmitted events can be influenced by the topological shapes with an increased success rate in transmission.

While this work is the first step towards enabling the creation of artificial neuronal networks, we believe that this could create a new form of active transport of events across molecular networks. Our future work will focus at creating more refined communication network design based on physiologically relevant neuronal networks to address, or resolve, specific signalling demand.

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