Neuron Inspired Collaborative Transmission in Wireless Sensor Networks

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Abstract. We establish a wireless sensor network that emulates biological neuronal structures for the purpose of creating smart spaces. Two different types of wireless nodes working together are used to mimic the behaviour of a neuron consisting of dendrites, soma and synapses. The transmission among nodes that establish such a neuron structure is established by distributed beamforming techniques to enable simultaneous information transmission among neurons. Through superposition of transmission signals, data from neighbouring nodes is perceived as background noise and does not interfere. In this way we show that beamforming and computation on the channel can be powerful tools to establish intelligent sensing systems even with minimal computational power.

Keywords: computational neuroscience, neuronal networks (NN), distributed adaptive beamforming, artificial intelligence (AI), collaborative communication, superimposed signals, context recognition.

1 Introduction

Smart spaces are spaces equipped with sensing systems consisting of sensor nodes of different types linked in a wireless sensor network, which collaboratively provides intelligent systems applications. For installing smart spaces, it is essential to address questions of scalability and cost reduction. One idea is to use lightweight sensor node platforms and employ algorithms for self-organization of sensor networks. In particular, bio-inspired solutions are promising candidates, as many biological systems are able to produce complex global behaviour from simple only locally interacting identical components. Smart spaces fit this description very well: they consist of a large number of low-cost computing nodes enabled to sense environmental parameters and to communicate locally so as to keep transmission power low.

While the number of required nodes can be huge for scenarios such as the massive deployment of RFID tags for item level tagging, the limited computing power and physical constraints to the transmission reduce the amount of useful

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computation feasible in such scenario. In particular, the constrained communication and computational power of individual nodes lower the employment of algorithms that can be executed on the nodes directly. In addition, the available low power hinders long distanced transmission and thus the far-range exchange of information in larger areas.

A biological system that matches these constraints is the nervous system of the brain. Neurons communicate "wirelessly" locally. Through a complex electrochemical process the synapse of a neuron bridges the gap to the dendrites of other neurons. Each dendrite in turn is connected to a main cell body, the soma, where the neuron performs a single, very simple computational task: an addition of the weighted input signals from all dendrites. The result is sent, through the axon, a possibly far distance to the synapse of the neuron, where again it is transmitted to the dendrites of other neurons. This very simple distributed sensing and processing platform is able to perform astonishingly complex computational tasks in a wide range of biological systems. In this paper, we explore whether an extremely cost efficient WSN would be able to perform the basic steps of this process: the transmission from synapse to dendrite, the addition of weighted signals, and the transmission of the result from soma to synapse.

Our system consists of two types of sensor nodes, which we call dendrite nodes and synapse nodes. A neuron is a distributed system. It consists of several dedrite nodes and one synapse node. The dendrite nodes of a neuron obtain signals from their immediate surroundings and send them collaboratively, using a technique called beamforming, to the synapse node of the neuron. Beamforming can bridge farther distances and the overlay of signals at the receiving synapse can be used to compute the addition function [3].

We thus extended the understanding of smart spaces by considering the space itself as "alive", i. e. the installed wireless sensor network including sensory information processing is functioning as a biological neural system cooperating with the user.

After discussing the related work in section 4, we detail this structure in section 2 and explain how neuronal structures can evolve in wireless networks. Section 3 verifies it in mathematical simulations. In section 5 we draw our conclusion.

2 From Collaborative Transmission to Neuronal Structures

The following sections briefly introduce the biological neuron system, distributed adaptive transmit beamforming and their joint application to wireless sensor networks.

2.1 Biological Neuron Systems

The fundamental processor units of a central nervous system represent biological neurons interlinked together in a complex manner and providing a biological

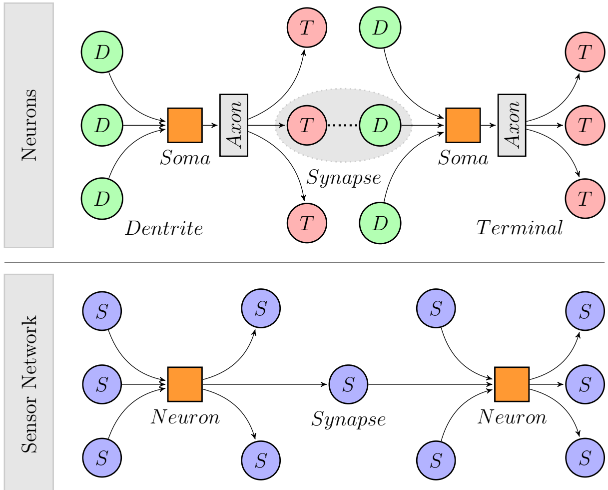


Fig. 1. Schematic representation of neuronal structures into WSN

organism with cognitive capabilities. The communication between neurons and thus the information processing of, for instance, a sensed environment is accomplished by permanently sending out electrical pulses called action potentials or spikes. The form of an action potential has no encoding information because all emitted pulses show the same shape. The information is rather encoded in the number and firing time points of the action potentials. A series of pulses emitted consecutively by a neuron is called a spike train. The spiking neurons interact in a dynamic way, so that the degree of firing pulses depends on exciting or inhibiting the neuron by its connected adjacent neurons. The physiology of a neuron is divided into three inherent components: dendrites, soma and axon (cf. figure 1). The dendrites collect signals sent out from other neurons. These signals pass through to the soma, the cell body containing the cell nucleus, where the processing of the signals take place. The output signal of the intrinsic processing consisting of an emitting spike train is relayed along the axon to other neurons. The connection between two neurons is called synapse which describes an actual gap, also known as the synaptic cleft. Here, the signal transmission is carried out in a complex manner, whereby the pre-synaptic neuron is exciting a post-synaptic neuron electro-chemically.

For mapping biological neuronal structures onto wireless sensor networks in order to create smart spaces we adapted wireless communication to neuronal functioning phenomenologically. Two types of transceiver nodes[1] α and β are working together to emulate the functioning of a neuron and neural networks, respectively. In particular, neuronal components such as dendrites are realized by nodes of type α and for the functioning of synapses the nodes of type β are used. Through collaborative transmission of signals between different types of

[1] Applied for different tasks although they feature the same functionality.

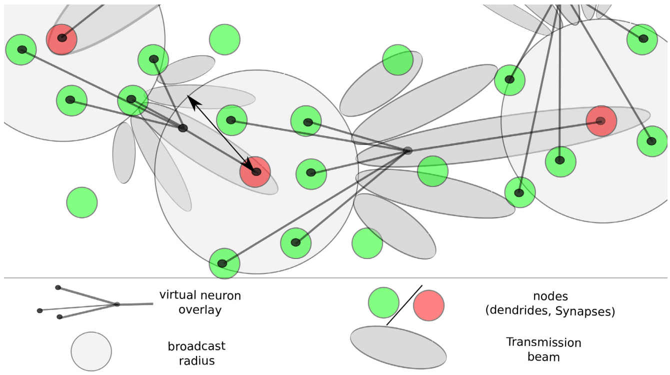


Fig. 2. Schematic illustration of a neuron overlay in a network of wireless nodes utilising distributed adaptive beamforming techniques

nodes, the soma and axon of a neuron are recreated implicitly. In the modeling of smart spaces the nodes of type α have the function primarily of sensing and transmitting the sensory information to an assigned node of type β, which in turn can transmit a processed information to further nodes. Based on our previous work in [3] sensor values and other entities can be assigned to binary sequences initialised randomly, and transmitted to an associated receiver node. In terms of neuronal encoding the randomly drawn binary sequences correspond to spike trains a neuron is emitting. The simultaneous transmission of binary sequences and thus the occurring superposition of signals on the channel corresponds to behaviour of the dendrites and soma. For extracting the data in superimposed signals refer to [3]. The characterization so far, a neuronal network can be engineered to achieve reasoning in a spatial distributed sensor network.

2.2 Distributed Adaptive Beamforming for Neuron Overlays

To create a neuron overlay in a wireless sensor network, we map the structures described above for the neuron system to wireless nodes. As described above, it generally suffices to identify two types of nodes as α-nodes and β-nodes. With these nodes we model the information transfer from dendrites.

Generally, we assume that each type β node (synapses) is associated with a group of type α nodes (dendrites) as depicted in figure 2.

These dendrites are located in the proximity of other type β nodes. Information in this network can then be disseminated from type β nodes to nearby type α nodes associated with other synapses. The dendrites then forward these stimuli to their synapses which are possibly activated by this process and then further disseminate information to activate other synapses over their dendrites.

Information dissemination from type β nodes to dendrites in close proximity can be interpreted as normal omnidirectional broadcast transmission. A problem that might occur for the information transfer from dendrites to their respective synapses in this scheme, however, is that due to the omnidirectional information transfer among wireless nodes and since dendrites likely transmit simultaneously, collisions will occur during transmission. Also, we would have to employ a sophisticated protocol to identify the correct synapses for each transmission.

However, we can overcome both problems elegantly by utilising distributed beamforming transmission. When dendrites associated with specific synapses are synchronised for their carrier phase and frequency, they can act as a distributed beamformer in their transmission. A signal received from a distributed beamformer has an improved signal strength at a specific spatial location but fades into background noise at most other locations [6]. The reason for this property is that the identical signals transmitted from various transmitters constructively overlay only at a spatially sharply restricted region since signal path lengths are mostly unique from the various locations of distributed transmitters. At most other locations the signals interfere destructively and fade to background noise provided that a sufficient count of signals is transmitted simultaneously.

We propose to utilise an iterative distributed adaptive beamforming mechanism for wireless sensor networks which was discussed in [6,8,14] to establish the connection between dendrites and their respective synapses.

Generally, in order to establish a transmission beam from a set of distributed devices to a remote receiver, carrier phases of transmit signals have to be synchronised with respect to the receiver location and the phase and frequency offset of the distributed local oscillators. After synchronisation, a message $m(t)$ is transmitted simultaneously by all transmit devices $i \in [1..n]$ as

$$\zeta_i(t) = \Re\left(m(t)e^{j(2\pi(f_c+f_i)t+\gamma_i)}\right) \tag{1}$$

so that the receiver observes the superimposed signal

$$\begin{aligned}&\zeta_{\text{sum}}(t) + \zeta_{\text{noise}}(t) = \\ &\Re\left(m(t)e^{j2\pi f_c t}\sum_{i=1}^{n}\text{RSS}_i e^{j(\gamma_i+\phi_i+\psi_i)}\right) + \zeta_{\text{noise}}(t)\end{aligned} \tag{2}$$

with minimum phase offset between carrier signals:

$$\begin{aligned}&\min\left(|(\gamma_i+\phi_i+\psi_i) - (\gamma_j+\phi_j+\psi_j)|\right) \\ &\qquad \forall i,j \in [1..n], i \neq j.\end{aligned} \tag{3}$$

In equation (1) and equation (2), f_i denotes the frequency offset of device i to a common carrier frequency f_c. The values γ_i, ϕ_i and ψ_i represent the carrier phase offset of node i as well as the phase offset in the received signal component due to the offset in the local oscillators of nodes (ϕ_i) and due to distinct signal propagation times (ψ_i). $\zeta_{\text{noise}}(t)$ denotes the noise and interference in the received sum signal. We assume additive white Gaussian noise (AWGN) here. With RSS_i we describe the received signal strength of device i.

3 Results

To show the feasibility of the proposed neuronal overlay, we utilised a matlab-based numerical simulation environment in which collaborative nodes are synchronised for their phase and simultaneous transmission of various neighbouring and interleaved neuron structures is demonstrated.

In these simulations, 180, 240, 300 or 500 type α transmit nodes are placed uniformly at random on a $30m \times 30m$ square area. These nodes are randomly allocated to 2, 3, 4 or 5 type β receiver nodes – the synapses – which are additionally placed in this area. Receiver and transmit nodes are stationary. Frequency and phase stability are considered perfect.

In these simulations, the groups of nodes first synchronise their carrier phase in 6000 iterations to their synapses with the iterative carrier synchronisation described in [6,8,14]. Afterwards, the nodes simultaneously transmit an amplitude modulated binary sequence. Although all sequences are then superimposed at the type β nodes, we can show that due to the beamforming transmission the signal designated for a specific type β node is dominant at this node while the superimposition of other signals results in less dominant background noise.

Nodes transmit at a base band frequency of $f_{base} = 2.4$ GHz with a transmit power of $P_{tx} = 1$ mW and a transmission gain of $G_{tx} = 0$ dB. The type β nodes have an antenna gain of $G_{rx} = 0$ dB. Random noise power was -103 dBm as proposed in [1]. For the pathloss between transmit and receive nodes we utlised the Friis free space equation [10]

$$P_{tx}\left(\frac{\lambda}{4\pi d}\right)^2 G_{tx}G_{rx}. \tag{4}$$

We derived the median and standard deviation from 10 identical simulation runs for each distinct configuration. Signal quality is measured by the Root of the Mean Square Error (RMSE) of the received signal to an expected optimum signal as

$$RMSE = \sqrt{\sum_{t=0}^{\tau} \frac{\left(\zeta_{\text{sum}} + \zeta_{\text{noise}} - \zeta_{\text{opt}}\right)^2}{n}}. \tag{5}$$

Here, τ is chosen to cover several signal periods.

The optimum signal is calculated as a perfectly aligned and properly phase shifted received sum signal from all transmit sources. For the optimum signal, noise is disregarded. In the following sections we detail the impact of several environmental parameters on the performance of the transmission.

3.1 Count of Neurons

We altered the count of type β nodes utilised in the simulations from 2 over 3 and 4 to 5 nodes. Figure 3 illustrates the relative BER for changing number of neuron overlay groups. The figure depicts the improvement of the median BER normalised on the lowest BER achieved in the simulations with only two synapses. The value 1 represents the lowest BER transmission achieved. We observe that the beamforming transmission quality gradually deteriorates with increasing number of neurons. This is not surprising since for each neuron overlay,

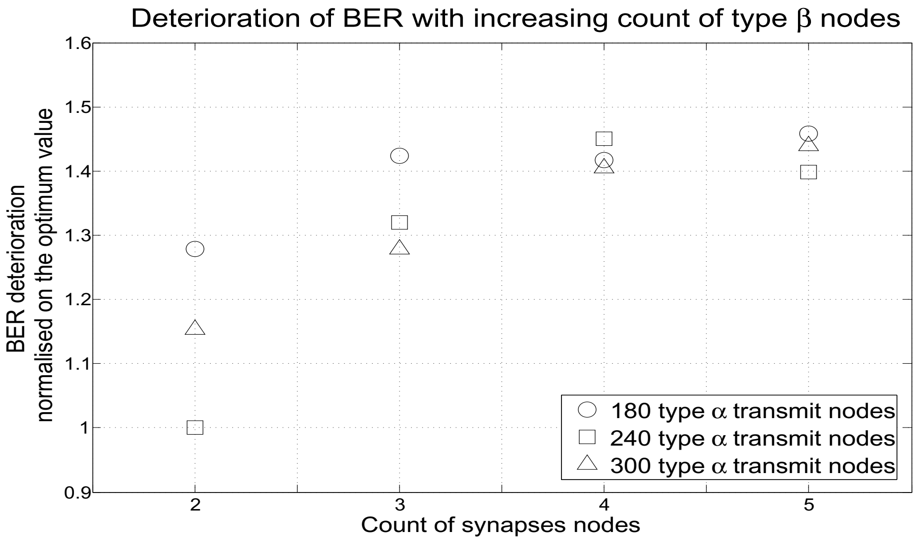


Fig. 3. Relative improvement of the median BER for increasing count of neuron groups

a distinct signal sequence is modulated onto the mobile carrier. With increasing count of synapses nodes, therefore the count of different signals which are superimposed rises. Similarly, the interference rises at all respective synapses nodes.

3.2 Count of Transmit Nodes

Also, we altered the count of transmit nodes. Generally, we expect that the BER decreases with increasing node count, since then more interference signals are superimposed from an increased count of locations so that potentially the superimposed sum signal ζ_{sum} better approximates random noise. Figure 4 depicts the results from these simulations. The figure depicts the situation for three type β nodes with 180, 240, 300 and 500 type α transmit nodes. For this scenario we could not observe a significant trend with the count of nodes utilised. This means that already groups of about 60 nodes are sufficient to significantly perturb the superimposed sum signal at non-correlated receive nodes in order to allow simultaneous transmission of neuron overlays.

3.3 Location of Receivers

The location of receivers might impact the signal quality for simultaneous transmission. Since type α transmit nodes are synchronised in phase to achieve the most coherent superimposition in the proximity of the respective type β node, the interference also increases for nearby nodes. We study the impact of this property on the BER of the transmitted signal sequences by comparing the signal quality achieved for random placement of synapses nodes with simulations in which the synapses nodes are spatially maximally separated. Figure 5 depicts the results from this simulation. We altered the count of type β nodes from 2 over 3 and 4 to 5. The count of transmit nodes in distinct simulations was set to 180, 240 and 300 respectively.

We observe that generally, the normalised median BER for the scenarios with fixed locations of synapses nodes achieve an improved BER. Occasionally, however, the performance in the scenarios with random receiver placement is slightly better. This is due to the random positioning of receivers which also allows for optimum positioning of type β nodes and receiver nodes. With increasing count of simulations, however, this effect becomes less significant. We can see this for instance from figure 5d that shows the average performance over all simulations.

3.4 Transmission Data Rate

Finally, we studied the impact of the data rate at which the symbol sequences are modulated onto the wireless carrier by transmit nodes. Naturally, we expect the BER to rise with increasing data rate [13]. Figure 6 confirms this expectation. The figure shows the normalised median BER for various data rates with respect to the count of transmit nodes or the count of neuron overlays. In both cases we observe that the BER increases with increasing data rate. Consequently, it is possible to counter an increasing BER due to other environmental effects by decreasing the transmission data rate.

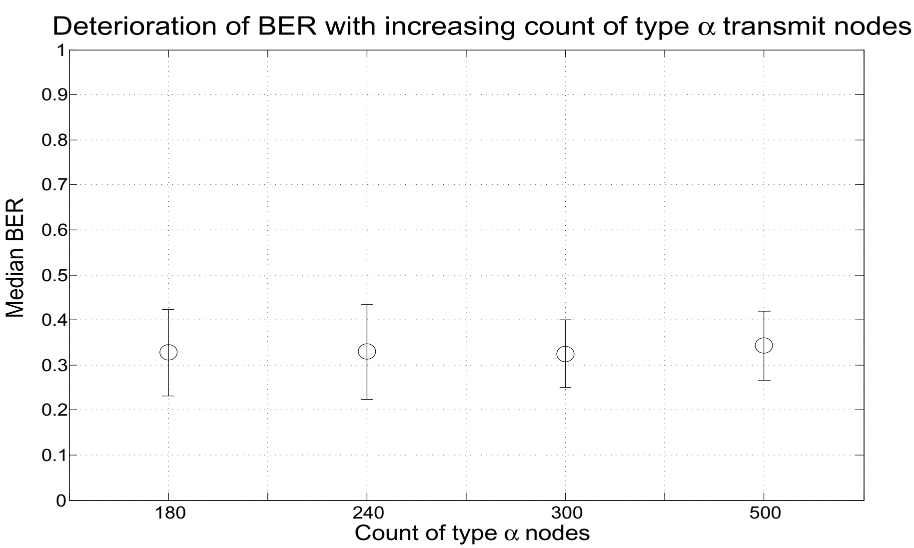
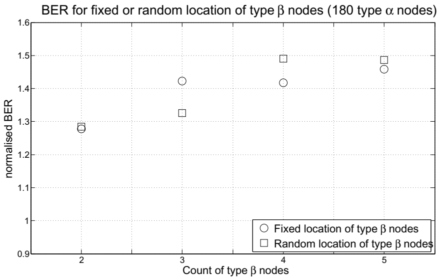
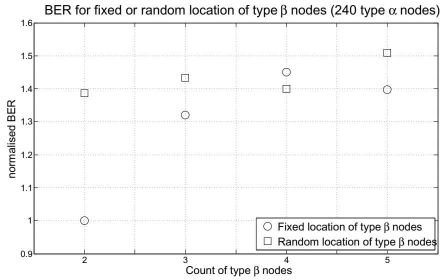


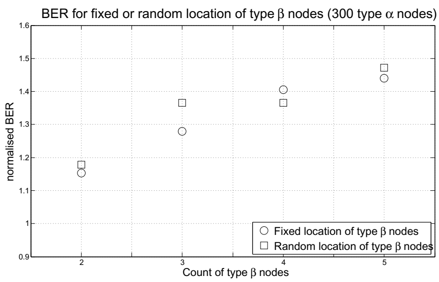
Fig. 4. BER for increasing node count



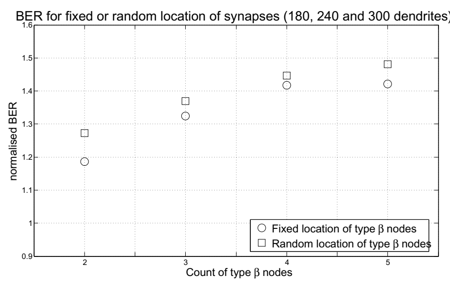
(a) BER for different count of neuron overlays; 180 transmit nodes.



(b) BER for different count of neuron overlays; 240 transmit nodes.



(c) BER for different count of neuron overlays; 300 transmit nodes.



(d) BER for different count of neuron overlays; average of all counts of transmit nodes.

Fig. 5. BER for different count of neuron overlays for deterministic and randomly placed synapses nodes and various counts of transmit nodes

4 Related Work

Traditional neural models are distinguished mainly into three different generations [4], i. e. the McCullouch-Pitts neurons referred also as perceptrons or threshold gates (first generation), the feedforward and recurrent sigmoidal neural nets assigned to the second generation and the spiking neural networks (SNN) termed as the third generation. While the first generation of neural models features binary input and output signals, and calculate every boolean function, the neural models of the second generation are able to compute beside arbitrary boolean functions, as well to approximate any continuous mathematical function. In addition, these kind of neural networks are characterized by employing learning algorithms such as the backpropagation. The third class of neuronal models represent spiking neural networks, which simulate real biological neural systems. The common feature of all described generations is that all neuron models are applied on computer hardware of the von Neumann architecture. In contrast, we simulated biological neuronal structures in wireless sensor networks

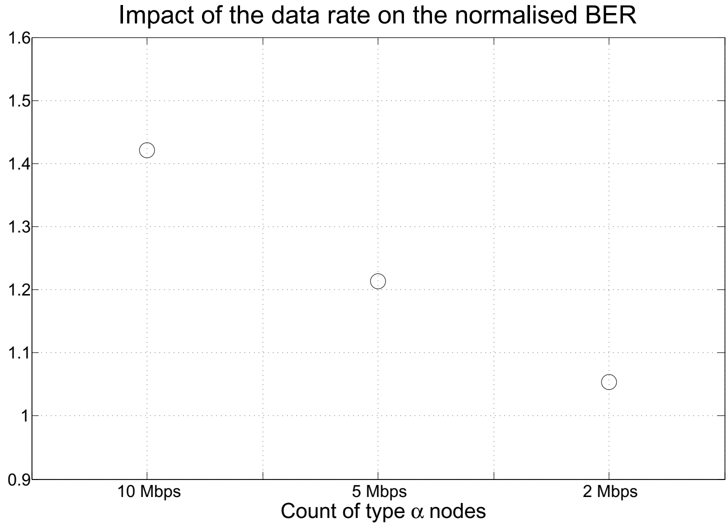


Fig. 6. Normalised median BER for different data rates

using simple transceiver nodes to emulate behavior of biological neurons. The communication and processing of spiking neural signals is based on collaborative transmission and simple on-off-shift-keying.

Algorithms for distributed adaptive beamforming are distinguished by closed-loop phase synchronisation and open-loop phase synchronisation techniques [6]. Closed-loop carrier synchronisation can be achieved by a master-slave approach [15]. Transmit nodes then send a synchronisation sequence simultaneously on code-divisioned channels to a destination node. The destination calculates the relative phase offset of the received signals and broadcasts this information to all transmitters that adapt their carrier signals accordingly.

Due to the high computational complexity burden for the source node to derive the relative phase offset of all received signals, this implementation is not suggestive in some applications for wireless sensor nodes.

Alternatively, a Master-slave-open-loop synchronisation can be applied [5]. In this method, however, the generally high complexity for the nodes is shifted from the receiver node to one of the transmit nodes. Therefore, this approach also suffers from its high computational load.

A simpler and less resource demanding transmit beamforming scheme to synchronise carrier signal components in phase and frequency was proposed in [9]. This computationally cheap carrier synchronisation utilises a one-bit feedback on the achieved synchronisation quality that is transmitted in each iteration from a remote receiver [6,7]. The central optimisation procedure of this process consists of n devices $i \in [1, \dots, n]$ randomly altering the phases γ_i of their carrier signal $\zeta_i(t)$ in each iteration. The carrier synchronisation process for distributed adaptive transmit beamforming is then generally described by a random search method [8,11,12]. Since a decreasing signal quality is never accepted the method eventually converges to the optimum with probability 1 [8]. The authors of [11] demonstrated in a case study that the method is feasible to synchronise frequency as well as phase of carrier signal components. In [8] it was determined that the expected optimisation time of this approach for a network of n transmit nodes is linear in n when in each iteration the optimum probability distribution is chosen for the random decision taken by the nodes. For a fixed uniform distribution over the whole optimisation process, a sharp asymptotic bound of $\Theta(n \cdot k \cdot \log n)$ was derived for the expected optimisation time [14]. Here, k denotes the maximum number of distinct phase offsets a physical transmitter can generate.

5 Conclusion

We presented a method to build a neural network overlay over a wireless sensor network. In particular, we utilised an iterative, computationally cheap method for carrier synchronisation among distributed nodes to establish a synchronised transmission beam among nodes allocated to one neuron in the neural network overlay. Due to beamforming, communication can be established simultaneously in several neurons in the overlay network. With this construction we are able to establish smart spaces capable of executing complex computations on computationally limited wireless nodes. In mathematical simulations, we demonstrated how a cost efficient wireless sensor network is able to perform the transmission from synapse to dendrite, the addition of weighted signals and the transmission of the result from the soma to synapse. In particular, the impact of the count of synapses, the count of dendrites, the location of dendrites and the transmission data rate impacts the bit error rate of the simultaneous superimposed transmission from dendrites to several respective synapses.

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