Biologically Inspired Distributed Sensor Networks: Collective Signal Amplification via Ultra-Low Bandwidth Spike-Based Communication

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***Abstract*— Wireless networks of biologically inspired distributed sensors (BIDS) are hypothesized to enable improved overall detection accuracy using ultra-low power and low bandwidth spike-based communication between nodes. Unlike traditional sensor networks, in which nodes communicate via digital protocols that require precise decoding of binary signal packets, BIDS nodes communicate by broadcasting generic radio frequency pulses, or spikes. Individual BIDS nodes are modeled after leaky integrate-and-fire (LIF) neurons, in which both filtered sensory signals and inputs from other BIDS nodes are accumulated as capacitive charge that decays with a characteristic time constant. A BIDS node itself broadcasts a spike whenever its internal state exceeds a threshold value. Here we present detailed simulations of a BIDS network designed to detect a moving target–modeled as a pure acoustic tone with a translating origin–against a background of 1/f noise. In the absence of a target, the average internal state is well below threshold and noise-induced spikes recruit little additional activity. In contrast, the presence of a target pushes the average internal state closer to threshold, such that each spike is now able to recruit additional spikes, leading to a chain reaction. Our results show that while individual BIDS nodes may be noisy and unreliable, a network of BIDS nodes is capable of highly reliable detection even when the signal-to-noise ratio (SNR) on individual nodes is low. We demonstrate that collective computation between nodes supports improved detection accuracy in a manner that is extremely robust to the damage or loss of individual nodes.**

I. Introduction

THERE is a need for cheap sensors that are robust, energy efficient, and easy to deploy as an ad-hoc network for monitoring large, remote, and often inaccessible areas. Such a network should be infinitely scalable and robust to failing sensors [1]. In a typical scenario, the sensor network could be tasked with notifying an outside observer of the presence and approximate location of a particular target. One such scenario is monitoring the security of national borders by detecting people and vehicles. Conventional distributed sensor network (DSN) nodes require abundant bandwidth to communicate to a global hub where information is integrated to make a detection decision. The bandwidth required for many nodes to communicate to a single central computer or cluster head can be prohibitive and have considerable power requirements [2]. Moreover, the expense of the hardware required to allow such communication protocols is not feasible for deployment over large, remote areas [1]. Here we propose a solution to such a remote monitoring problem with Biologically Inspired Distributed Sensors (BIDS). BIDS nodes are designed to be inexpensive enough to be distributed liberally across a wide area and able to be configured into a topology that is resilient to changes, such as nodes failing or new nodes entering. Because BIDS nodes use biologically motivated spike-based communication and simple analog components, they would consume significantly less power than a conventional DSN node that uses digital communication protocols. Thus, BIDS nodes could potentially be powered by scavenged resources, such as solar energy collected from cheap photovoltaic panels.

Individual BIDS sensors are expected to have a low signal-to-noise ratio (SNR) because of the need to make them small, cheap, and low power, which allows deployment over large, remote regions. However, the dynamics of the BIDS network can greatly improve the SNR through collective computation. To enable these dynamics, the individual BIDS node is modeled after a leaky-integrate-and-fire (LIF) neuron [3], [4]. Input to the sensor head increases the internal state potential of a node, which decays with a characteristic time constant. The inputs to the node are summed in parallel, which pushes the node toward a threshold. When the threshold is reached, the node fires an omnidirectional spike (mimicking an action potential in a neuron) represented by a radio-frequency (RF) pulse. The nodes within a given radius detect the spike, which increases their internal state potential. This form of communication is inspired by the concept of synaptic interactions between biological neurons. Whereas synaptic interactions between biological neurons can be either excitatory or inhibitory, depending on whether the resulting input drives the internal state closer or further away from threshold, interactions between BIDS nodes are purely excitatory and thus always act to produce an overall increase in excitation across the network. When one BIDS node fires a spike, it brings all the other BIDS nodes within its communication radius closer to their firing thresholds. If

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no target is present, and thus the individual sensor heads are responding solely to environmental noise, most nodes will be far from threshold and the net effect of any single spike will be negligible (i.e. unlikely to elicit any additional spikes). On the other hand, if a target is present, such that the individual sensor heads over some stimulated region are all receiving additional drive, then more of the nodes in the local network will be close to threshold and any single spike can elicit multiple additional spikes. Thus, the presence or absence of a target determines whether any single spike evokes a chain reaction, thereby causing a large general increase in firing activity across the stimulated portion of the network. In this way, even a relatively weak target signal can be amplified by collective interactions, producing a much more detectable signal with a much higher SNR. Here we will describe communication between BIDS nodes (RF pulses) as lateral interactions in order to distinguish them from the internal communication from the sensor head that is detecting the raw stimulus.

BIDS networks are scalable, robust and fault tolerant because each individual node performs local computations to determine if a detection has occurred. Because each BIDS node operates in a self-contained fashion, integrating its sensor input with generic input from surrounding nodes, the network can be extended or augmented simply by adding additional nodes. The individual nodes within a BIDS network do not need to communicate to a central computer, which greatly lowers bandwidth requirements and alleviates the need for complex communication protocols to deal with collisions and changing topologies due to damage, node loss, and other factors. The extremely simple and robust spike-based communication protocol also replaces the need for a MAC protocol [5]. These latter two points also give evidence that the BIDS nodes will have lower power requirements. Additionally, it has been well established that neuromorphic hardware requires substantially less power than digital hardware [6].

The focus of this work is to model a mechanism for a BIDS network to detect a signal reliably in spite of low signal-to-noise due to poor individual detectors and environment noise. This is accomplished through collective computation via interactions between the nodes. Although we will touch on proposed hardware and communication mechanisms, there are no fixed specifications for the individual nodes.

II. Related Work

Others have demonstrated a capability for high coverage, low power, inexpensive, and robust DSNs. To achieve high coverage, [7] presented mobile nodes that repel other nodes and obstacles to spread coverage with minimal nodes. This facilitates a large network coverage by distributing the sensor nodes as sparsely as possible. Although BIDS nodes are currently designed to obviate the need for mobile nodes, the algorithm and architecture can be used in mobile nodes to reduce the overall operating power.

Power considerations were explored in [8], which argues that a dense network of nodes is detrimental to the network in several ways. The problem was alleviated by choosing a subset of the network's nodes to stay on for low power usage. We argue that multiple nodes with cheap hardware can achieve better detections as a dense network than as a sparse network. A dense network also reduces power consumption for each individual node because of low transmission range requirements.

Other work has explored the insight biology gives into dynamic networking, self-calibration, and peer to peer communications by modeling ants [9], cells [10], fireflies [11], and bees [12]. Specifically, [12] presented modeling biological behaviors such as "energy exchange, pheromone emission, replication, migration and death" to achieve autonomous, scalable, adaptable, self-healing, and simplistic networks. Similarly, we propose a DSN that models a network of neurons to achieve detections by exploiting a local, embedded algorithm.

Other research done by [1], [13] is closely related to what BIDS is trying to accomplish. [1] looks into local algorithms and a data-centric network. It is argued that each node does not need an identity to be useful to the network. This allows for a robust network that is resilient to topological changes. Directed diffusion [13], although local and robust, requires a query-driven data delivery model [14]. We are looking at a specific scenario of monitoring a large, inaccessible area where a simple detection scheme suffices. We believe that a sensor network with a simple communication protocol will lead to accurate detections for lower costs than [13] predicts.

III. Implementation

We used the open source neural simulation toolkit PetaVision [15] to model the sensor network. Our input was a simulated wave using the wave simulation toolkit k-Wave [16]. The simulation grid is imagined to be 60 m x 60 m with BIDS nodes spaced on average 0.94 m apart from each other. A synthetic 125 Hz sinusoidal wave was created with a wave speed of 350 m/s, which estimates the peak frequency of the sound originating from a moving vehicle [17]. The wave originates from a single point source moving across the environment at 8.9408 m/s (20 mph), which meant that it took 6.7 seconds for the vehicle to cross the environment. Wave attenuation was ignored, and the amplitude of the wave was arbitrarily scaled with respect to simulated 1/f noise to achieve a specific SNR for testing. Each node was set up to detect the simulated wave's frequency using a matched filter in a sensor head (see figure 2). Excitatory and inhibitory noise was also simulated in the sensor head to create a constantly varying state potential. This will be discussed in more detail below.

The final input for our experiment was a video with a dimension of 256 x 256 pixels, a scale of .234 meters per pixel, and a .12ms time step. There was a 20 px border placed around the outer edge (included in the 256 x 256 pixel size) where waves will not propagate to avoid edge conditions. The entire video was overlaid with temporally correlated pink (1/f) noise and the second half of the video had the moving stimulus, which traversed approximately from one end of the frame to the other horizontally. For computation reasons, we sampled every 100th frame from this video as an input to PetaVision, which amounted to 437 frames of noise followed by 437 frames of noise and stimulus. Each frame was presented to the network for 10 time steps (12 ms). The BIDS nodes were initially uniformly distributed onto the grid with a 25 percent density with respect to the pixel grid, as shown in the left panel of figure 1. The nodes were then randomly moved +/- 3 pixels along the horizontal and vertical axes to simulate imprecise placement that is likely to occur with massive deployment. The right panel of figure 1 shows an example of node placement in a BIDS network.

The individual BIDS nodes simulated a conductance model of a leaky-integrate-and-fire (LIF) neuron. Following the LIF neuron model, a node generates responses by thresholding its membrane potential. In our scenario, excitatory input originates from the sensor head and interactions between nodes where present. These two inputs arrive on separate sensor heads. The input from other nodes is spiking, while the input from the stimulus is a continuous-valued wave.

Each node is modeled as a single passive component that fires when its membrane potential exceeds a threshold potential. The node has excitatory and inhibitory conductance channels, $g_E(t)$ and $g_I(t)$. In the absence of input, the internal state potential of a node decays with a characteristic time constant, τ. The inputs to the node are summed in parallel into the excitatory conductance $g_E(t)$, which pushes the membrane potential, V_m, toward an excitatory synaptic reversal potential, V_E and thus toward a voltage threshold, V_{th}. When the threshold is reached, the BIDS node fires an omnidirectional spike (mimicking an action potential in a neuron) represented by a radio-frequency (RF) pulse. After the node emits a spike, the value for V_{th} jumps ΔV_{th} and then decays back to V_{th} according to a time constant τ_{th}. A refractory period is modeled after a neuron's transient potassium conductance, $g_B(t)$, in series with a potassium reversal battery, V_B.

The connection strength is governed by the equation

$$W_{ij}(r) = S \log \frac{R_{max}^2 + 1}{R_{ij}^2 + 1}, \tag{1}$$

where W is the strength of the connection between two nodes; R_{ij} is the radius between BIDS nodes i and j; R_{max} is the maximum connection radius; and S is a strength parameter. In our simulation we used $R_{max} = \sqrt{2} * 65$ pixels and $S = 0.04$. In our simulation, R_{max} is the maximum connection radius, which is about 21.5m. This means that each BIDS node connects to 19 x 19 neighboring BIDS nodes where the weight of the connection is specified by equation 1. Note that it is possible for a node to be connected to another node with a strength of zero, which would computationally be equivalent to the nodes not being connected. Negative weights resulting from equation 1 were set to 0.

When $V_m^i < V_{th}$, the BIDS nodes are governed by the following equations:

$$\frac{dg_E^i}{dt} = -\frac{1}{\tau_E}\left[g_E^i - g_s^i - \sum_{R_{ij}<R_{max}} a_j W_{ij}(r)\right] + \eta^E \tag{2}$$

$$\frac{dg_I^i}{dt} = -\frac{1}{\tau_I} g_I^i + \eta^I \tag{3}$$

$$\frac{dg_B^i}{dt} = -\frac{1}{\tau_B} g_B^i \tag{4}$$

$$V_{\inf}^i = \frac{V_{rest} + V_E^i g_E^i + V_I^i g_I^i + V_B^i g_B^i}{1 + g_E^i + g_I^i + g_B^i} \tag{5}$$

$$\frac{dV_m^i}{dt} = -\frac{1}{\tau}(1 + g_E^i + g_I^i + g_B^i)(V_m - V_{\inf}) \tag{6}$$

$$\frac{dV_{th}^i}{dt} = -\frac{1}{\tau_{th}}(V_{th} - V_{th,rest}) \tag{7}$$

where g_s^i is the conductance change due to the sensor head at node i and is a function of the input signal strength. a_j is the activity of a neighboring node j at radius $R_{ij} < R_{max}$ from node i. At each time step, dt, noise is added to g_E with probability $dt * Freq_E$. The magnitude of the noise is a uniform random variable between 0 and Amp_E. Noise is added to g_I in a similar fashion. η^I and η^e are random noise variables based on the Amp and $Freq$ of the inhibitory and excitatory channels, respectively.

For any time step on which $V_m^i \geq V_{th}$, the node changes state as follows:

$$V_m^i \rightarrow V_{rest} \tag{8}$$

$$V_{th}^i \rightarrow V_{th}^i + \Delta V_{th}^i \tag{9}$$

$$g_B^i \rightarrow g_B^i + 1 \tag{10}$$

In our model, we use a time interval of $dt = 1.2$ms; resting potential of $V_{rest} = -70$mV; leak membrane time constant of $\tau = 10$ms; firing threshold of $V_{th,rest} = -43.38$mV for the scenario without lateral interactions and $V_{th,rest} = -42.97$mV for the lateral interaction scenario; refractory period time constant of $\tau_{V_{th}} = 10$ms; excitatory conductance decay time constant of $\tau_E = 1$ms; inhibitory conductance decay time constant of $\tau_I = 1$ms; potassium conductance decay time constant of $\tau_B = 10$ms; excitatory synaptic reversal potential $V_E = 0$mV; inhibitory synaptic reversal potential $V_I = -75$mV; potassium reversal potential $V_B = -90$mV;

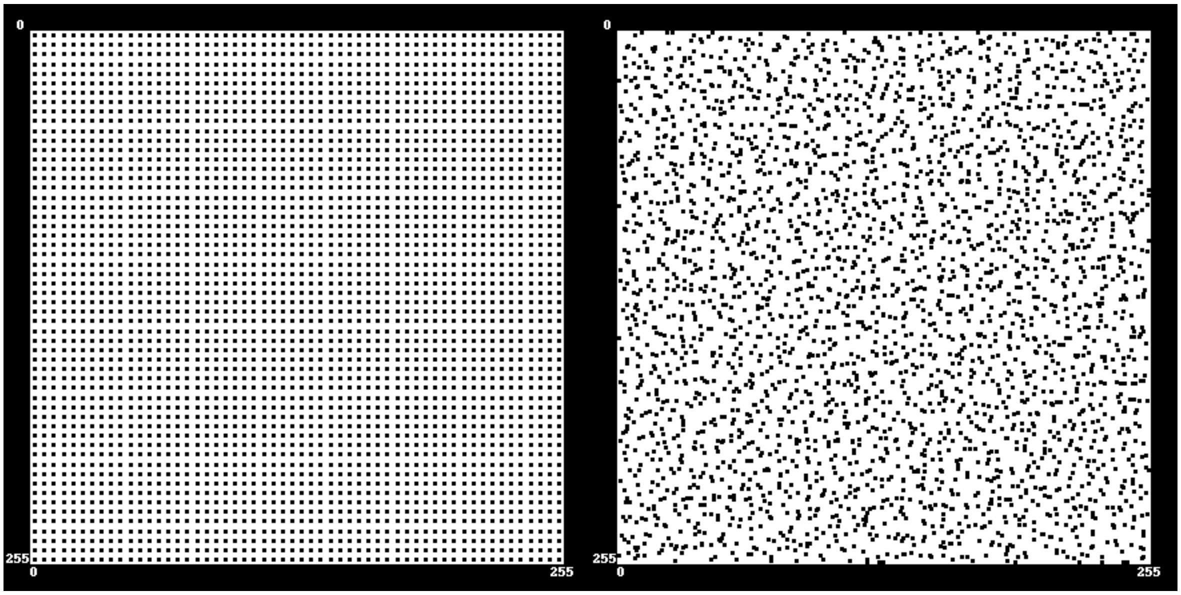

Fig. 1. The BIDS network utilizes random node placement in pixel space. A 256 x 256 pixel grid represents a 60 m by 60 m grid, with a scale of .234 m per pixel. Left: An example simulation environment before random movement of the BIDS nodes. The black dots represent node positions. Right: An example simulation environment after randomly displacing the BIDS nodes. Note that nodes may overlap in pixel space due to each node being enlarged for visibility.

threshold increase of $\Delta_{V_{th}} = 5\text{mV}$; excitatory and inhibitory noise amplitudes of $Amp_E = Amp_I = .5$; and noise frequencies of $Freq_E = Freq_I = 250\text{Hz}$. Our implementation currently only utilizes an inhibitory channel so that the BIDS node will receive both excitatory and inhibitory noise, which creates more randomness in firing [18]. The mean noise of the excitatory and inhibitory conductances were set to 5 percent of the leak conductance on average. A detailed explanation of the conductance LIF neuron, as well as a comparison with physiological data, can be found at [3].

In a physical system, spikes generated by surrounding BIDS nodes could be detected using an antenna coupled with a matched filter for receiving RF pulses. However, in our simulation, BIDS nodes are connected as described above, and therefore all spikes are perfectly detected where the amplitude of the incoming spike is modulated by equation 1. We model the increasing state potential by assuming that each received spike produced a brief change in an excitatory conductance (equation 3) that drives the internal state potential towards a positive rail voltage (equation 6). When no target was present, each spike produced on average less than one additional spike in the rest of the BIDS network regardless of lateral interactions. This is because the internal state potential of an average BIDS node is far enough away from threshold in the absence of a target that any extra activity tends to die off. When a target is present, however, the responsive BIDS nodes in the area receive additional excitatory drive from the sensor head. This extra drive pushes their state potentials closer to threshold so that any neighboring spikes will be more likely to induce additional spikes. Thus, in the absence of a target, isolated noise-induced detections would cause only small transient, local excitation, while detections in the presence of a target would be more likely to evoke additional spikes, thereby inducing a stronger, more prolonged excitation. The amplification would result in a higher spike count of each node per time interval over the stimulated portion of the BIDS network and thus indicate target detection.

In order to analyze the network's performance, we analyzed the performance of each individual BIDS node with and without lateral communication. In other words, the network performance is reported as the average performance of the individual nodes.

IV. Simulation Results

We ran 16 different scenarios to test the relationship between accuracy and input signal power of a BIDS network. The performance of the network was evaluated using a signal detection task. Eight different SNRs (2.5, 5, 10, 20, 40, 60, 80, and 90 percent) were used for the BIDS network, with and without lateral excitation between BIDS nodes. The SNR was computed by finding the root mean squared (RMS) value of the wave amplitude, simulated by pixel intensity, with respect to RMS intensity of the overlaid 1/f noise. Note that because the RMS value of SNR was used, amplitude peaks may be higher than the SNR. Detections were made by summing spikes over a fixed window at each BIDS node.

Figure 2 shows the detections with and without lateral interactions for a signal strength of 40 percent. A clear qualitative separation between the stimulus and no-stimulus spike rates is evident. The voltage threshold of the BIDS nodes was separately adjusted for each of the two lateral connection scenarios such that they both had a background firing rate of approximately 1 Hz when presented with 1/f noise.

Figure 3 shows a quantitative comparison of the detection capability for the two BIDS network scenarios (lateral interactions absent vs lateral interactions present) at 10, 20, and 40 percent signal strength. As the SNR increases, the distribution of the number of spikes fired by the individual BIDS nodes in response to the moving target becomes increasingly distinct from the distribution of spikes occurring during ongoing background activity. The increased separation of the two distribution histograms indicates improved detection performance of the corresponding nodes. Lateral communication improves the detection performance of the individual BIDS nodes at all SNRs tested, but the improvement becomes more pronounced as the SNR increases from 10 to 40 percent. A higher SNR drives BIDS nodes closer to their firing thresholds, and thus promotes stronger chain reactions as a result of lateral excitation. At an SNR of 60 percent, this effect saturates, at which point the BIDS nodes in the laterally connected network achieve essentially perfect detection, as indicated the non-overlapping spike distributions corresponding to target present (red) and target absent (blue), respectively. In contrast, spike distributions remain significantly overlapping without lateral communication between BIDS nodes. The origin of successive peaks in figure 3 for lateral interactions could be due to the unnaturally small region being modeled.

Figure 4 shows the ROC curves generated from the spike distribution histograms shown in figure 3. ROC curves are generated by sliding the target detection threshold, representing the number of spikes a BIDS node must fire in the 2.17 second summation interval in order to report a ”hit”, from left to right (i.e. from fewer to more spikes). The ROC curves plot the hit rate at each target detection threshold as a function of the false alarm rate. The 45 degree black line indicates chance performance. The area under the ROC curves, plotted in figure 5 as a function of SNR, measures the probability that the average BIDS node detects the target and does not responding to the background. It is clear that lateral interactions greatly improve the detection performance of the average BIDS node. Thus, even relatively poor sensors, whose detection performance is highly unreliable when acting in isolation, can become highly reliable detectors when acting in concert with a network of similar nodes mutually excited by generic, low-bandwidth, low-power, robust lateral interactions of the type described here.

V. Discussion

Our BIDS network simulation was set up using PetaVision [15]. The input to our simulation was a synthetic input video of a wave propagating through air to simulate a moving vehicle. The input consisted of 1/f noise for the first half of the video, followed by synthetic waves overlaid with 1/f noise for the rest. Eight different SNRs were used to test the network's ability to differentiate between the two halves of the video. The differentiation was quantified by calculating distributions of the difference in the number of spikes fired by the network nodes. We show that lateral interactions allow for each individual BIDS node to achieve much better detections than without lateral interactions.

One possible discrepancy that may occur between our model and reality is that although the sensor head model itself is noisy, destructive interference in wireless communication was not explicitly simulated. Destructive interference can decrease the number of successful transmissions from node to node. However, our simulation included ample noise in the sensor head as well as the environment, which should encompass small amounts of transmission interference. Additionally, the abundance of nodes and the nature of lateral interactions should make the system robust to lost transmissions. More specifically, because the many nodes are all communicating amongst each other with identical signal characteristics, communication errors from an individual node has benign effects on the network as a whole.

Another discrepancy is the fact that we chose to ignore wave attenuation and specific amplitudes of the input wave. Consequently, the scenario would not model a real-world situation correctly. In practice, nodes would not be able to detect a sound if the distance between the node and the source is too great, depending on the amplitude of the sound and properties of the location of the network. However, this paper shows that the accuracy of detections is improved when the network exploits collective computation when exposed to the same input.

In conclusion, our results show that collective computation improves detections of individual BIDS nodes in a high noise environment without increasing overall spike rates. This could allow for low-power, noisy individual detectors in a network spread over a large area.

VI. Future Work

It would be interesting to explore methods for determining the spiking histograms for a physical BIDS network. There are two proposed ways of doing this.

One idea is implementing delayed lateral inhibitory communication between nodes. In other words, when a node spikes, an excitatory lateral signal would be followed after a short delay by an inhibitory lateral signal. This second

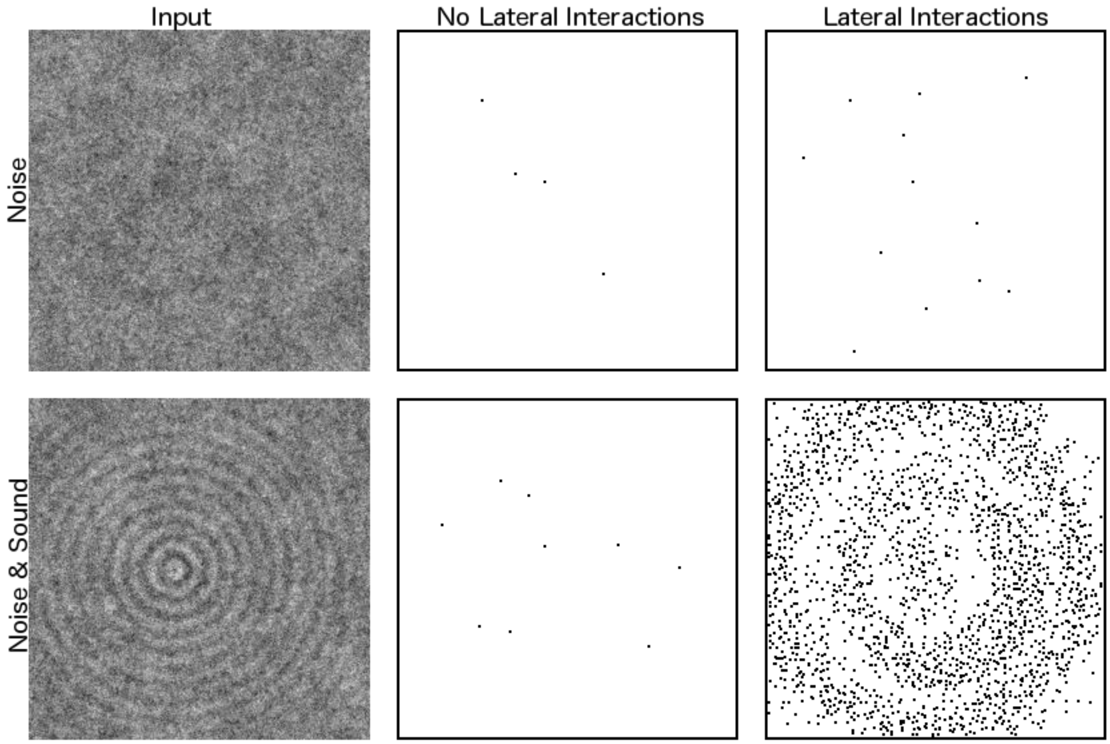

Fig. 2. Interactions between BIDS nodes results in improved detection. Images are of a single representative time step. *Left Column*: Visualization of input signal. *Top Left*: 1/f (pink) noise only. *Bottom Left*: 1/f (pink) noise with super-imposed stimulus. *Middle Column*: BIDS node output - no communication between nodes. *Right Column*: BIDS node output - nodes mutually excite each other via wireless communication (lateral RF pulses). The firing rate without the added stimulus (top row) for both scenarios was on average 1 Hz. The increase in activity produced by the stimulus is much greater with lateral interactions present (bottom right) than without (bottom middle). The stimulus consisted of a propagating radial wave, SNR of 40 percent. The black dots represent node spiking (the RF pulse).

signal decreases the firing potential of all nodes that receive it, with a strength proportional to the excitatory signal. Doing this will allow for the network's firing to oscillate synchronously when a detection is made [19]. This idea is modeled after the way information is transmitted from the retina to the cortex [20]. A single connected node on the outer edge of the network can look for this specific oscillation period in the network to notify the observer of a detection.

A second idea is that a BIDS node's functionality could be extended to have two output firing modes: a broadcast lateral interaction signal and a stimulus exfiltration signal. The exfiltration signal would similarly be a pulse to alleviate the nodes from having a MAC protocol. A node will broadcast an exfiltration signal when its integrated firing rate reaches a threshold. This signal can differ from lateral interaction communication in its power characteristics or frequency, for example. Nodes that receive this signal will forward the exfiltration signal with a refractory period. Connected nodes on the edge of the network will send the detection to the observer when the exfiltration signal is received. This strategy, similar to what [13] accomplished with direct diffusion, would allow for a detection by a local base station.

Further work must be done to model a real-world deployment of a BIDS network more accurately by taking sound attenuation and amplitude into account. Furthermore, although we have constructed prototype BIDS nodes, we have yet to define detailed hardware specifics and field test a BIDS network using prototypes. It would also be interesting to test a variety of BIDS network prototypes with various densities and signal types.

Further experimentation should be done to compare detection accuracy and power consumption between BIDS and other conventional sensor networks in our simulated environment. Specifically, it would be informative to implement [13] in our simulation to compare with the results of BIDS.

Other work can be done to BIDS to improve detections. Depending on the application, an additional sensor head can make BIDS more sensitive to a specific stimulus in exchange for more expensive and power dependent sensors.

Our current model of a BIDS node implements a static firing threshold, in which we hand tune to achieve certain firing rates. A dynamic threshold could be implemented to dynamically enforce a firing rate, as well as achieving more robustness to different types of environments with

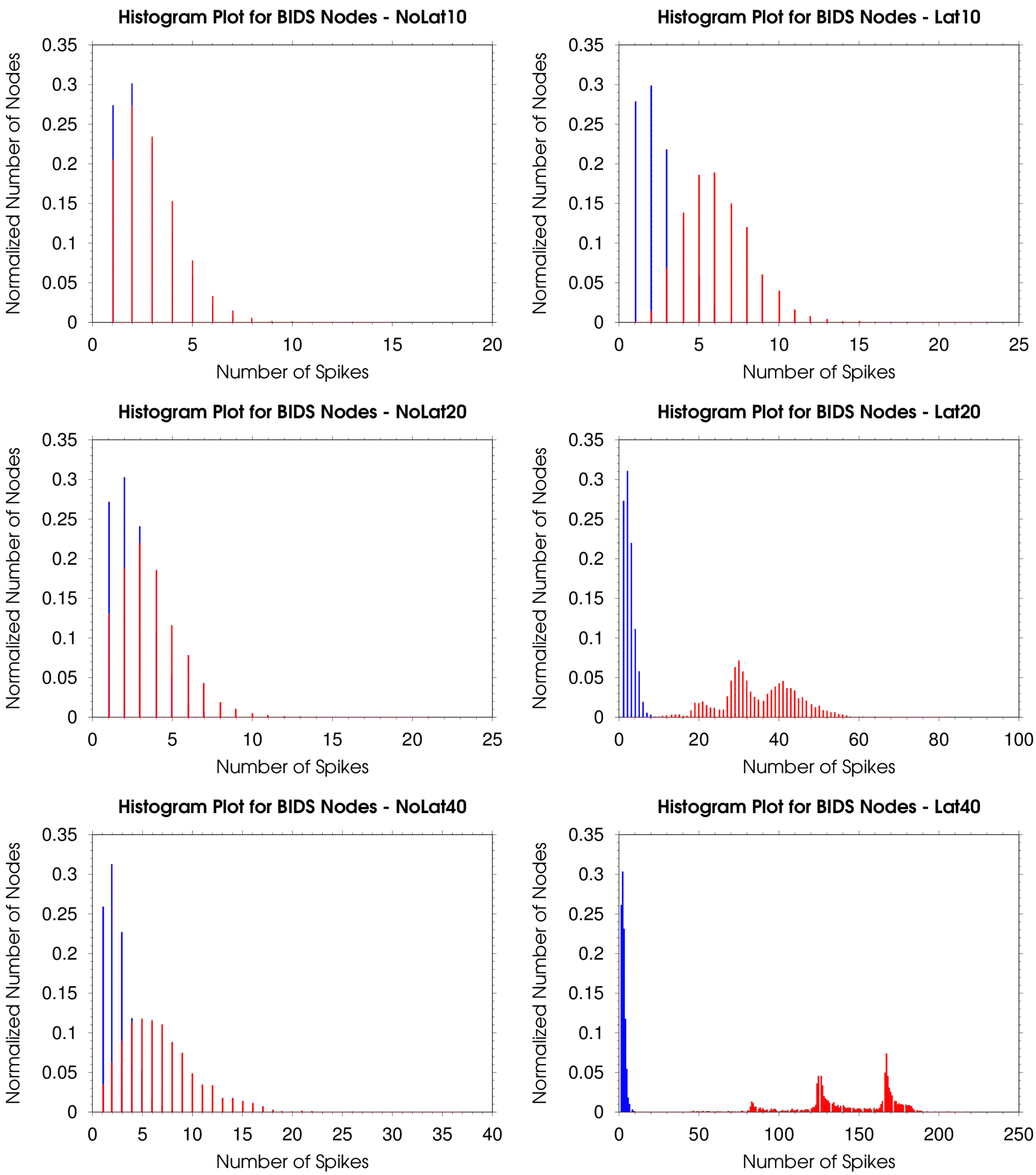

Fig. 3. The figure shows histograms of the distribution of the total number of spikes for each BIDS node in 2.17 s for SNRs of 10, 20, and 40 percent (top, middle, bottom rows, respectively). The bar height represents how many nodes spiked a given amount (indicated by the value on the horizontal axis). The blue bars designate the scenario when no stimulus is present and the red bars are when the stimulus is present. The left plot is for the system without lateral interactions and the right plot is for the system with lateral interactions. The amount of separation between the average values of the blue and red bars indicates the detection performance of the system. Zero overlap between the blue and red bars would indicate perfect detection performance.

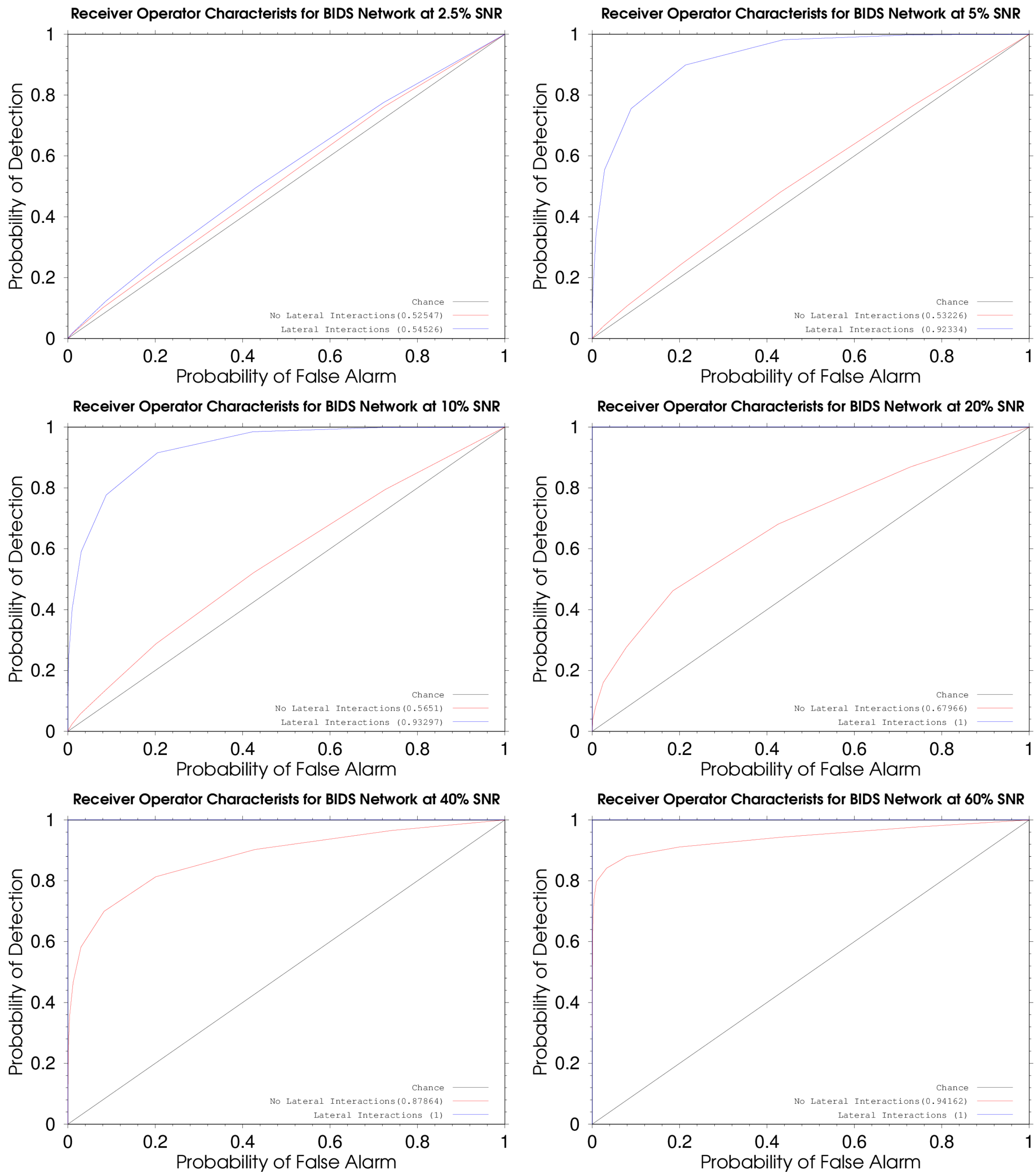

Fig. 4. ROC curves compare model performance with and without lateral interactions at 2.5, 5, 10, 20, 40, and 60 percent SNR for each BIDS node. The curves show that wireless communication between BIDS nodes leads to greatly increased detection accuracy.

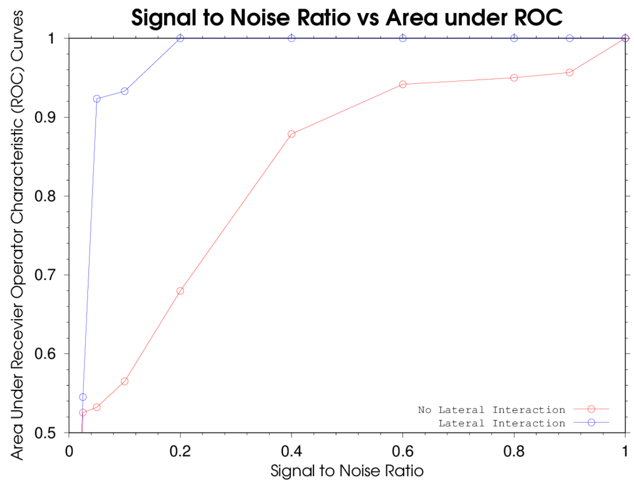

Fig. 5. Relationship between the SNR and the area under the ROC curve. SNRs of 2.5, 5, 10, 20, 40, 60, 80, and 90 percent were used. SNR is given by the ratio of the RMS amplitude of the wave input, measured as pixel intensity, over the RMS amplitude of the 1/f background noise. Lateral communication resulted in dramatic improvement of detection performance over no lateral communication.

different noise levels. The enforcement of a firing rate allows for more control of power consumption, as well as an direct comparison of lateral interactions versus no lateral interactions by taking out the difference of firing rates.

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