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**Transferring Insights from Complex Biological Systems to the Exploitation of
Netted Sensors in Command and Control Enterprises**

DRAFT

C² Concepts and Organizations, C² Modeling and Simulation, and C² Experimentation

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Abstract

Exploiting data from a network of sensors (netted sensors) is an Enterprise System Engineering challenge. Successfully meeting this challenge will contribute significantly to improving the agility of today's Command and Control (C²) Enterprise by achieving its goal of decision superiority through better situational awareness. There is a pressing need to design fusion algorithms that combine data from heterogeneous sensors, with the goal of identifying well-defined Force Protection and Border Security threats. Data fusion for netted sensors requires sensor-to-sensor communication, as well as communication tipping points between the netted sensors and the C² Enterprise. Solutions are needed that fluidly respond to this multi-scale challenge. Quorum sensing or cell-to-cell “communication” in microbial populations has shown that bacteria can indeed act as a collective rather than only as individuals (Taga and Bassler, 2003). Analogously, an Enterprise has both individual and collective behavior. Decisions that are made at the collective scale (e.g. force) rely on information that is obtained at the individual scale (e.g. unit); this information must be communicated effectively. In this paper, insight gained from the mechanism used in a robust, adaptable biological system is applied to the technical challenge of data fusion for netted sensors.

Introduction

The integration and use of data from large networks of interoperable (netted) sensors can be characterized as a complex system engineering problem, which is defined here as a discrete or continuous system composed of many parts that interact in a nonlinear fashion. An Enterprise view of netted sensors is explored through a detailed study of one biologically inspired distributed control algorithm. Such algorithms are hypothesized to inform individual behavior to population response dynamics for important netted sensor applications. Distributed control algorithms that yield a desired global response without global control is vital for Force Protection and Border Security, using a variety of technologies including, acoustic, chemical, and biological sensors—on the ground, on soldiers, on equipment, etc. Similar issues also arise in Homeland Defense and Security, Distributed Operations, and Disease Transmission. In addition, this technology can be used for “always on sensors” that are carried on individuals to monitor local conditions.

Complex Biological Systems

In the area of complex biological systems, there are two approaches or themes that could benefit Command and Control Enterprises. The first theme (1) is using biological mechanisms for physical system or hardware design. Bogatyreva et al. (2005) has developed a ‘biological patents’ database called the TRIZ frame work, which is an attempt to catalog various biological mechanisms in a searchable database. The database catalogs and classifies the effects of a given action (mechanisms of function) from the molecular to ecosystem scale. The database primarily focuses on system design; for example, an individual jellyfish swims by partitioning its energy into three components: one generates pressure within a cavity, the second overcomes the inertia of the jellyfish’s movement, and the third deforms the tissue (database search—swimming). Theme 1, although productive, does not help in understanding the complexity of the C² Enterprise.

The second theme (2) accounts for the complexity of the C^2 Enterprise by using natural biological behavior to design Enterprise capability and functionality, such as data fusion. Natural systems evolve and often exhibit emergent behavior that has agility and robustness. This is exemplified well by the use of swarming behavior to design sophisticated algorithms; for example, swarming can be used for generating optimal search patterns for Unmanned Aerial Vehicles (UAVs). Reverse engineering of complex biological systems is hypothesized to provide novel approaches in netted sensor data fusion system design.

Strategies from the autonomic nervous system, namely, reflex reaction and health signs have been examined for use in Autonomic and Grid Computing (Sterritt, 2003; Bapty et al., 2003). Furthermore, Anthony (2004) used the pheromone-exchange communication system of ants to design communications protocols such as election algorithms. Traditionally, election algorithms are deterministic; however, the non-deterministic biologically inspired algorithm was shown to have robustness, stability, and scalability. Apoptosis or cell self-destruction has two control loops, one that promotes cell growth and self-destruction at the same time and one that provides an override for the self-destruction signal (Sterritt and Hinchey, 2005). Such biologically inspired algorithms are hypothesized to extend to other domains. Theme 2 addresses the complexity of the Enterprise by attempting to include the people, the processes, and the technology.

In summary, theme 1 applies to system design and theme 2 applies to Enterprise functionality. Our ongoing research program maps biological algorithms to netted sensor design challenges, using standard mathematical approaches to establish the properties and robustness of the emergent system behavior. One example, quorum sensing or cell-to-cell “communication” in bacteria is discussed in detail here. In the past 10 years, the biological sciences have become increasingly mathematical as engineers, mathematicians, and physicists have tackled biological problems. This synergy has led to an increasing number of research papers that mathematically describe biological mechanisms. In order to evaluate if biological mechanisms can provide insights for individual behavior to population responses in C^2 Enterprises, we must understand the biological dynamics as well as the netted sensor challenges. This will allow advantageous features to be adapted and disadvantageous features to be identified.

Individual Behavior to Population Response Dynamics - Biological Example

Modeling of the transmission of infectious disease is a good example of individual behavior to population response dynamics, which has also been modeled using various mathematical techniques. The various modeling approaches are reviewed here and their limitations are explored for use in the development of the quorum sensing algorithm.

Often, different disease transmission models give different results, as illustrated by the studies of Kaplan et al. (2002) and Halloran et al. (2002), in which assumptions on the homogeneity of the population led to opposite results for the effectiveness of mass vaccination for an outbreak of smallpox (Eubank et al., 2004). Figure 1 shows the studies reviewed included deterministic and stochastic models with various methods of assigning social and spatial structure.

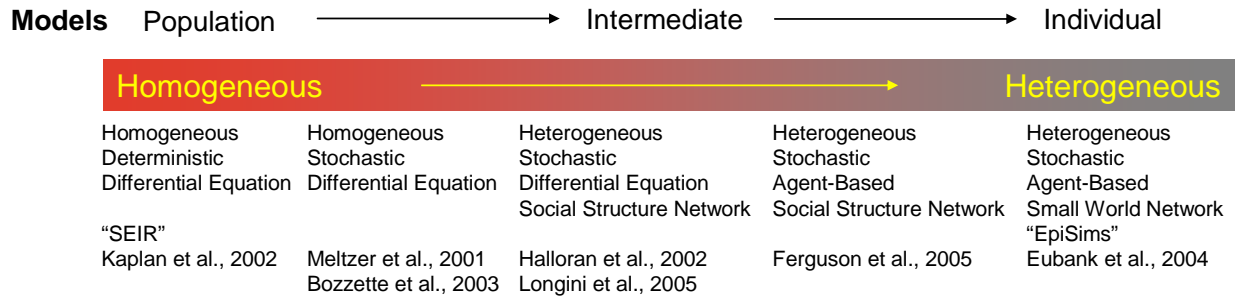


Figure 1: Recent modeling and simulation studies for disease transmission.

Population, intermediate, and individual (e.g. agent-based) scale dynamic models are used to model disease spread (Figure 1). In the dynamic population models, such as SEIR (susceptible-exposed-infectious-removed), differential equations provide a refined analysis of the path of the disease through a population. These standard tools also provide some robustness, provided dynamic parameters can be estimated. The standard SEIR model has homogeneous mixing—an individual has an equal chance of contacting any individual in the population (Ferguson et al., 2003). At the intermediate scale, models are often developed for populations stratified by age, socio-economic factors, geographical location, etc. In these models there is heterogeneous mixing—individuals have different probabilities of contacting specified population subgroups (Ferguson et al., 2003). There is a trend towards modeling techniques that predict non-linear population behavior from individual responses (e.g. homogeneous to heterogeneous models).

In the dynamic individual or agent-based models, disease is studied in a simulated society through interacting individuals or agents. The contact patterns and disease transmission on the scale of individuals has been used in the model EpiSim (Eubank et al., 2004), which provides an excellent tool to study emergent population-scale consequences. However, these models tend to be computationally and data intensive for adequate validation and parameter estimation (Ferguson et al., 2003). Theoretical viewpoints, such as small-world graph theory, continue to evolve in ways that have substantial impact on our understanding of disease consequence. Since individuals form stable networks, such as family, friends, and colleagues, this greatly determines transmission dynamics (Ferguson et al., 2003).

Lessons learned suggest that the degree of model detail should be as small as possible to capture the underlying dynamic of interest, yet must be balanced with the ability to validate the model. Historical data is often the most reliable data and is the only means of estimating certain parameters. Model detail, in this case, can include disease biology, human contact patterns or socio-spatial structure, cost-benefit analysis, risk assessment, disruption to civic society, level of vaccine use, overall resource requirements, and ability to implement policy (Ferguson et al., 2003). For example, if the disease spreads from person-to-person then it is necessary to include spatial structure in the model. Determining how infectious the disease is during its different phases can also have a large effect on model behavior.

An Initial Case Study – Netted Sensors

Netted sensors are a good candidate for individual behavior (e.g. sensor) to population response (e.g. situational awareness) dynamics. The initial case study of netted sensors for Force Protection and Border Security presents the following challenges: data processing, communication between nodes, network resource management, data fusion, and security. Biological systems are robustly adaptive and often rapidly converge to the most efficient energy state—a behavior desirable for data fusion algorithms. Bacteria can act as individuals or a population, as illustrated in Figure 2. In this example, an individual bacterium self-regulates its gene transcription to produce light or bioluminescence when a "quorum" of bacteria are present. The local population illustrates quorum sensing or cell-to-cell “communication” at a 20 μm spatial scale and the global population depicts a 250 km x 50 km area over the Indian Ocean that is bioluminescent (Miller et al., 2005). Though the three examples occur on different spatial and temporal scales, a common mechanism is shared—the diffusion of a quorum sensing molecule (QSM) that triggers gene transcription.

Similarly, Tier 1 consists of lower capability sensors (also referred to as motes) that are analogous to the bacterium. Tier 2 consists of higher capability sensor nodes that are shown spatially distributed in the southwest and northeast United States. Command and Control integrates information from Tier 2 nodes, in this diagram, with the overall goal of responding to a particular global situation by operating each sensor in a particular mode while minimizing inefficiencies. Therefore, we hypothesize that netted sensors can exhibit individual behavior to population response dynamics (Figure 2).

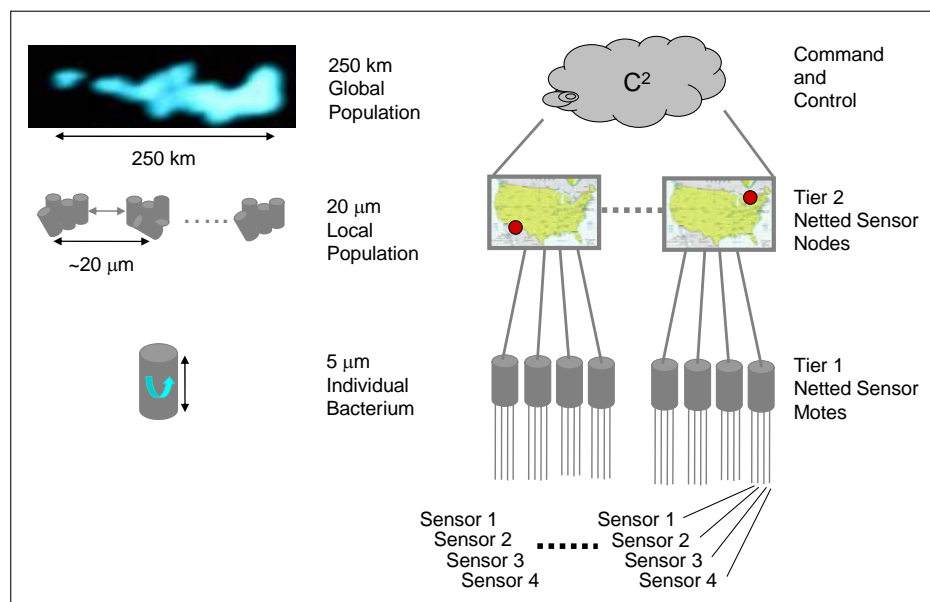


Figure 2: Similarities between bacterial quorum sensing or cell-to-cell “communication” (global bioluminescence image from Miller et al., 2005) and netted sensors.

We further hypothesize that biologically-inspired distributed control algorithms may provide novel solutions to address the data fusion challenge. Data fusion refers to collecting, processing, and combining information from different sensor and knowledge sources to increase the understanding of a situation. Analysis at both local and global data fusion scales is hypothesized to lead to decisions that results in an improved situational response. Sensor sources may include a variety of radars, passive and active electro-optic detection/imaging systems, as well as satellite imagery. In contrast, knowledge sources may include information streams supplied by experienced personnel on site or from remote locations. Additional fusion challenges arise because the statistics used to describe data supplied by sensor sources can vary dramatically from data supplied by knowledge sources (e.g. natural language descriptions).

Consider the two following data fusion challenges. First, a real-time operational data fusion system needs to assemble facts from both sensor and knowledge sources and generating hypotheses that best reflect the ground truth. Unfortunately, the amount of data produced by sensor sources often overwhelms human analysts; therefore, much effort in data fusion research has been focused on automating the processing of data from complete or incomplete data sets (Goodman, 1997). Second, a lack of standards in the data fusion field has been a major setback for automatic processing, integration, and re-use of available data fusion technologies. Several papers that suggest refinement to the widely used Joint Directors of Laboratories (JDL) Data Fusion model have been proposed (Linas, 2004).

Communication between motes can involve sending as little as a bit (2 levels such as active or passive) of data. Radio Data Standard (RDS) is a protocol currently used to communicate very small (~25 bits) packets of data (Nguyen et al., 2004; Ruffieux et al., 2004). TinyOS uses a protocol to communicate that has 29 bit data packets (Levis et al., 2004). Such a protocol together with a quorum sensing-based algorithm may promote the implementation of low power, low data rate, low bandwidth, short-range communications. Currently research on motes includes dynamically reconfiguring the mote fields. Data fusion for the lowest capacity operating systems or "mote fields" closely resembles a bacterial complex biological system. The quorum sensing mechanism in the bacterial population is very low level—it is not “intelligent” but genetically programmed in each bacteria. This contrasts with swarm intelligence where the agents or nodes are more sophisticated. We therefore explore quorum sensing and netted sensors in detail in the following section.

Applying Quorum Sensing Algorithm to Data Fusion

One candidate biological system, quorum sensing or cell-to-cell “communication,” is shown in Figure 3 (Ward et al., 2001). The quorum sensing molecule (QSM) and the quorum sensing protein (QSP) form a complex that binds to the chromosome. When the complex is bound to the chromosome, the production of the QSM is up-regulated (white) and when it is not, the gene-production rate is down-regulated (gray). Bioluminescence is produced when a threshold value of the QSM is reached.

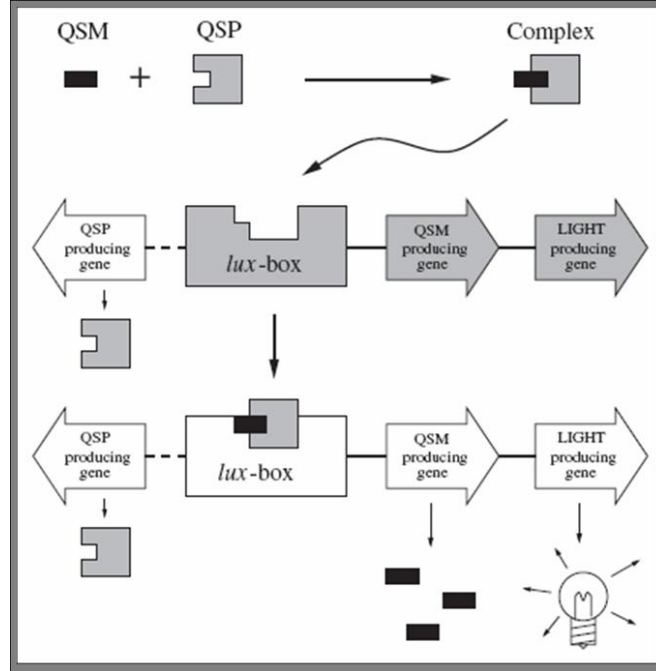


Figure 3: The mechanism for bacterial bioluminescence from Ward et al., 2001. The up-regulated state is shown in white and the down-regulated state is shown in gray.

The up-regulated state (N_u) is defined in Equation 1 and is a function of cell division (γ) where the doubling rate is $\ln(2)/r$, growth rate (F), complex formation ($G(A)$) where A is the QSM concentration. The α refers to formation rate of the up-regulated state while β refers to the breakdown rate—in other words, the dissociation of the QSM-QSP complex while it is bound to the chromosome.

$$\frac{dN_u}{dt} = r(\gamma - 1)N_u F(N_d + N_u) + \alpha G(A)N_d - \beta N_u \quad (1)$$

Similarly, the down-regulated state (N_d) is defined in Equation 2.

$$\frac{dN_d}{dt} = r(N_d + (2 - \gamma)N_u)F(N_d + N_u) - \alpha G(A)N_d + \beta N_u \quad (2)$$

The concentration of the extra-cellular QSM (A) is defined in Equation 3 and is a function of the production of QSM in both the up-regulated (rate K_u) and down-regulated (rate K_d) states, the use of QSM in complex formation ($G(A)$), where α is the formation rate of the up-regulated state and λ is the disappearance rate of the QSM (A).

$$\frac{dA}{dt} = K_u N_u + K_d N_d - \alpha G(A)N_d - \lambda A \quad (3)$$

The three equations above are deterministic population scale differential equations. The mathematical framework is assumed to be well-mixed, so there is no concentration gradient of the QSM. One extension of the existing research, includes introducing a spatial component that would represent a sensor network that is not homogeneously distributed—a spatially disbursed mote field. Reaction diffusion equations and wavefront propagation has been useful in describing biological systems that cannot be assumed to be well mixed (Doering et al., 2003). For example, mushrooms, the reproductive organ of fungus (e.g. ferry ring), can be described using two phases of wave front propagation (e.g. stochastic differential equations since partial differential equations requires that the $n \rightarrow \infty$). Therefore, fusion agent behavior that is advantageous is propagated through the sensor network. For example, nodes become active in a certain region and the threat is tracked through the network. This leverages understanding the local conditions, especially what happens on the edge of the detection zone, and exploiting the information.

To demonstrate the application of quorum sensing dynamics to netted sensors, we developed an individual node scale (e.g. agent-based) model with spatially distributed QSM densities. In this case, we formulate the model so that the spatially distributed population scale models have nonlinear dynamics similar to Equations (1-3) and adapted it to the detection problem at hand. For our illustration, 600 sensors are distributed randomly and independently, with uniform distribution, over a 1 km square region. Each sensor has a local neighborhood defined as all other sensors within a 100 m radius. Note that, since the sensor locations are random, the number of neighboring sensors is also a random variable. In our example, the mean and the variance of the number of neighbors are both approximately 18.5 (without edge effects, we would expect a Poisson distribution for this variable).

Figure 4 shows the placement and distribution of sensor nodes in the field. A detection target moves across the field from the lower left to the upper right in 1000 time steps. At each time step, each sensor independently has a probability of false alarm of 0.0005, leading to a Poisson distribution (mean: $300 = 600 * 0.0005 * 1000$) for the total number of false alarm events during the test. For each sensor located at x_s and target located at x_t , independently at each time step, we also have a probability of a sensor detection of

$$P_d = \frac{1}{2} \exp\left(-\frac{\|x_s - x_t\|^2}{2\sigma_t^2}\right) \quad (4)$$

Note that, for a sensor located directly at the moving target, that the probability of a detection is only $\frac{1}{2}$. Detection probabilities decline rapidly as the distances between sensor and target increase, with σ_t describing the spatial scale of detection. In the analysis that follows, we illustrate the challenges at different spatial scales. A sensor k registers a signal detection $h_k(t) = 1$ at each time step t if either a false alarm occurs or a target causes a detection, and $h_k(t) = 0$ at each time step if signal detection is not registered.

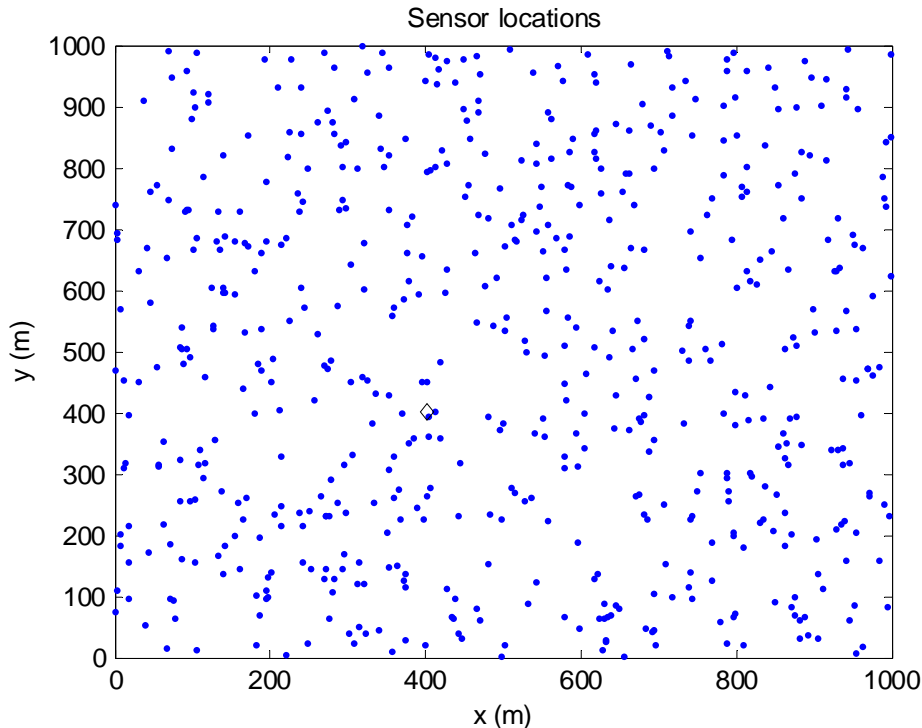


Figure 4: Sensor locations based on a Poisson distribution.

Next, we investigate the dynamics. For sensor k , let state $u_k(t)=1$ indicate target present and 0 indicate no target present. $A_k(t)$ will then represent the QSM concentration or shared information for node k . We implement a split step procedure for updating the node. First, we find $A_k(t)$ and $u_k(t)^-$ based on the current network state. We then check for new sensor signal detections $h_k(t)=1$ and update $u_k(t)$. We have

$$\begin{aligned}
 A_k(t) &= \frac{1}{2}A_k(t-1) + \frac{1}{2N_k} \sum_{m \in \text{neighborhood } k} u_m(t-1) \\
 P(u_k(t)^- = 1 | u_k(t-1) = 1, A_k(t)) &= 1 - \beta \\
 P(u_k(t)^- = 0 | u_k(t-1) = 1, A_k(t)) &= \beta \\
 P(u_k(t)^- = 1 | u_k(t-1) = 0, A_k(t)) &= \alpha A_k(t) \\
 P(u_k(t)^- = 0 | u_k(t-1) = 0, A_k(t)) &= 1 - \alpha A_k(t)
 \end{aligned} \tag{5}$$

$$u_k(t) = \max(u_k(t)^-, h_k(t)).$$

Here N_k is the number of neighbors of node k , β describes the decay or forgetting rate of the detected signal, and α the quorum sensing effect. In our illustration below, we use $\alpha = 0.15$ and

$\beta = 0.25$ to balance the nonlinear increase against the decay. Figure 5 shows a typical time snapshot of the sensor field tracking the target. The maximum neighborhood here is the neighborhood of the node k at time t with maximum QSM concentration $A_k(t)$.

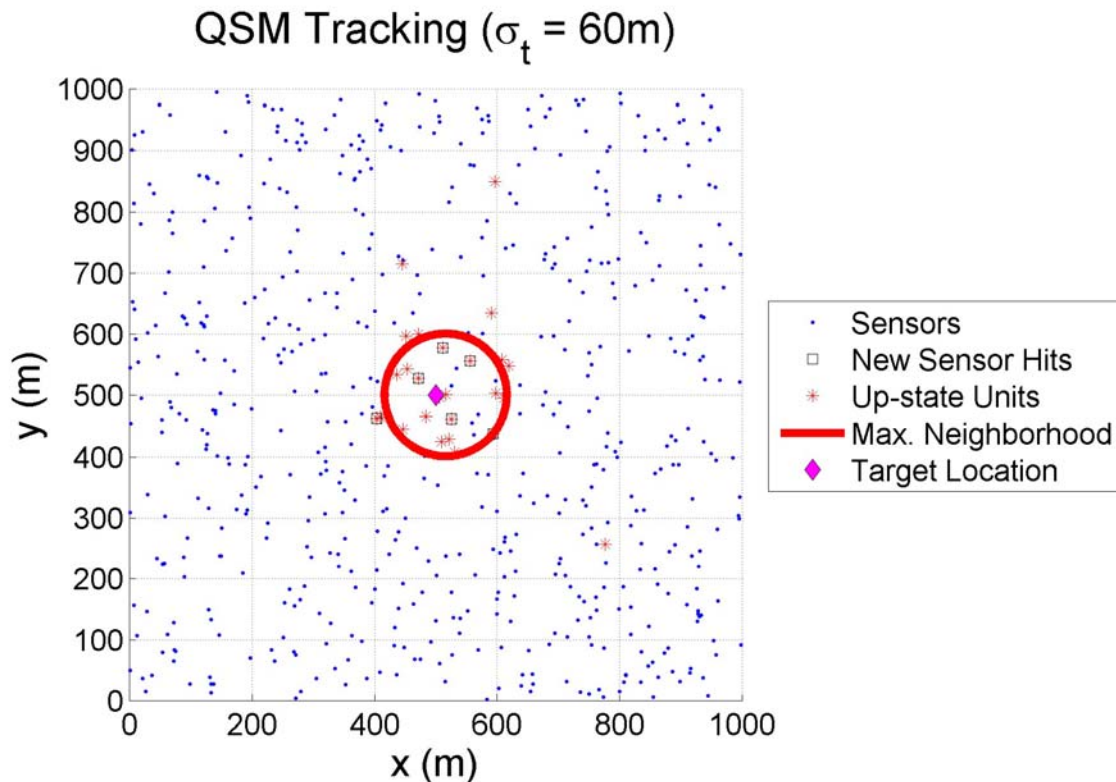


Figure 5: A tracking example for detection scale $\sigma_t = 60$ m.

Success in tracking is closely dependent on the scale of the node neighborhood and the scale of the target detection scale σ_t . If σ_t is too small, then too few sensor signal detections occur to establish a track. If σ_t is too large, then the detections form a large group, and the target, although inside the group, may sometimes not be in the neighborhood of the node k at time t with maximum QSM concentration $A_k(t)$. Figure 6 illustrates this behavior. For very small σ_t , the target is in the maximum neighborhood less than half the time. Misses in this case tend to be large, with the track dropped. Tracking for well-matched σ_t is excellent, with misses occurring primarily for targets at the edge of the sensor field. When σ_t is too large, the target is sometimes quite near, but still outside the maximum neighborhood.

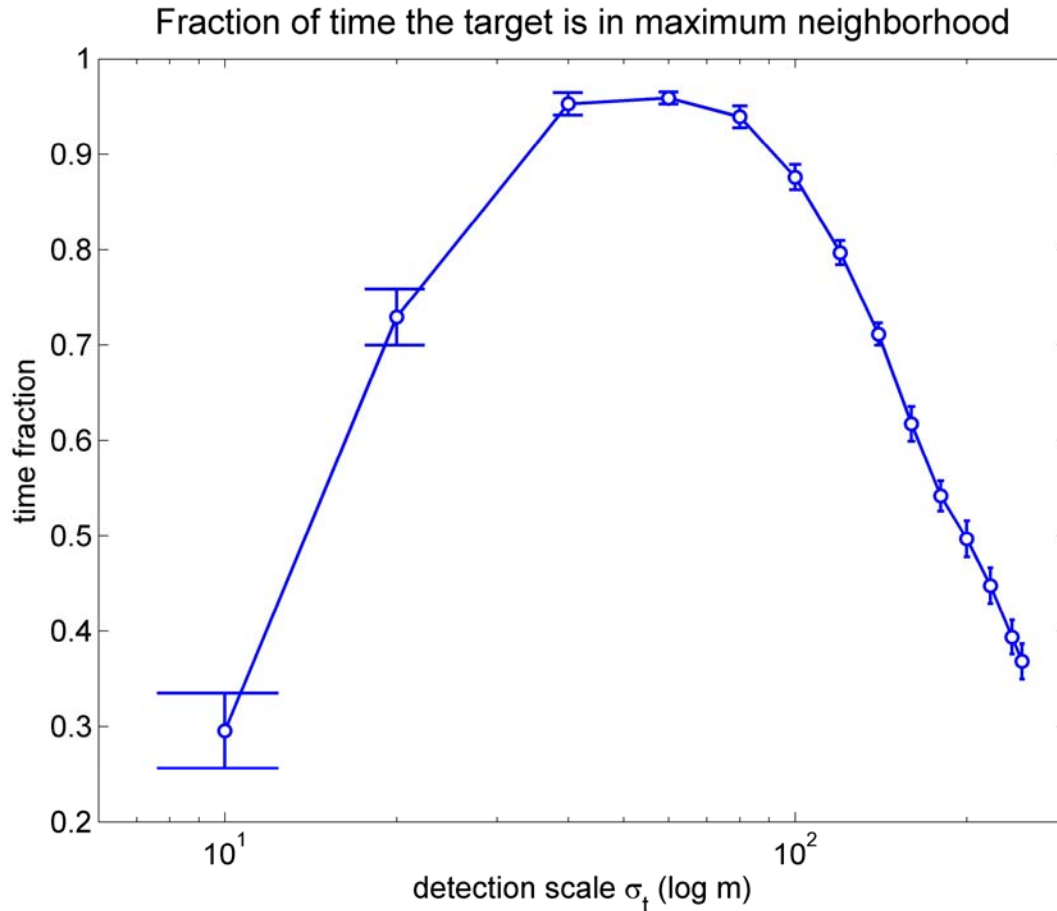


Figure 6: Fraction of time the target is in the maximum neighborhood based on 10 simulated runs at each detection scale (log scale). Error bars are 95% confidence intervals.

Agent-Based Approaches to Complex System Engineering Problems - Data Fusion

How can modeling and simulation assist in complex system management when by definition complex systems are unique and impossible to predict? Developing models with a high degree of accuracy or fidelity will not benefit complex System Engineering, where changing the pace or direction of the complex system is the prime objective. However, if models could be developed cheaply (e.g. medium fidelity) to explore alternatives—they may be of use. Running multiple scenarios would make it possible to provide decision makers with the probability of how certain interventions may affect the complex system or Enterprise. For example, using a simulation model to test how changing the current operating parameters will affect the threat being handled. Such a modeling effort would not provide exact predictions, but would indicate the probability of certain outcomes—or consequence analysis. Complex biological systems and Enterprises function at multiple scales; thus, a technical approach is needed that can model multiple scales and respond to complexity. The approach needs to accommodate emergence (self-organization) as well as allow top down (hierarchical) directives.

In computer science, management, and the social sciences, complex systems composed of disparate elements have been analyzed using distributed or agent-based approaches. Agent-based modeling has been successfully used to explore stock market dynamics (Nasdaq), design department/grocery stores (Macy's and Sainsbury's), explore hiring strategies (Hewlett-Packard), explore operational risk (Societe Generale), and design stadiums, shopping malls, and amusement parks (Bonabeau, 2002), as well as in disease modeling (Eubank et al., 2004). Information exchange between parts of the Enterprise can be (1) tight coupled in which groups strongly influence each other, (2) loose coupled in which groups do not strongly influenced each other, or (3) decoupled in which groups do not interact with each other. Loosely coupled systems tend to have greater flexibility promoting robust and adaptive behavior (e.g. Internet). In loosely coupled systems, control is separated from the system through the specific control interfaces (points of coupling). A distributed or agent-based approach, as illustrated using quorum sensing algorithm, can leverage this attribute.

In netted sensors, the distributed sensor node or agent must be able to automatically start up, determine its resources, receive communications (from higher Tiers, Command and Control, and/or neighbors), and fuse information as shown in Figure 7. Based on information fusion, decisions to sample or transmit information are made. The proposed quorum sensing algorithm is for information fusion or integration; for example, a decision to turn on (up-regulation in Figure 2) or turn off (down-regulation) the sensor. Similarly, the decision could be used for deciding whether or not to communicate with neighbors.

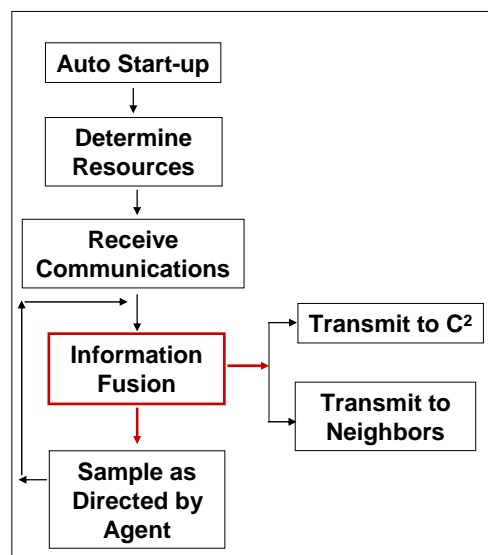


Figure 7: Functions of the distributed sensor node or agent.

Modeling agents captures the heterogeneity of the system. Emergent phenomena are often distinct from the behavior of the agents. As outline by Bonabeau (2002), top down techniques use global equations and frameworks and emergent behavior is bottom up, starting with local interactions of independent “agents” that lead to group behavior. Furthermore, Bonabeau (2002) states that regression analyses and system dynamics (differential equations) “are currently impotent in analyzing and predicting them [emergent phenomena]” and “agent-based modeling

helped connect the local behavior of country managers to the global performance of the organization (Bonabeau, 2002).” It appears that a hybrid technique, both bottom up and top down, may be necessary and this has recently been endorsed in tackling problems in the US healthcare system, including Enterprise management tools supply-chain management, game theory, system dynamics, and productivity measuring and monitoring (Reid et al., 2005).

Concluding Remarks and Future Work

This interdisciplinary effort reflects an Enterprise view of netted sensors through the exploration of biologically inspired distributed control algorithms. Such algorithms are hypothesized to inform individual behavior to population response dynamics for important netted sensor applications such as data fusion for Force Protection and Border Security, as well as extending to other domains. Quorum sensing or cell-to-cell “communication” has been shown to have promise for tracking a target in a sensor field. Through distributed control or agent-based approaches, mote fields can be designed to allow for emergent behavior and learning.

Biologically inspired distributed control algorithms that yield a desired global response without global control is desirable for each mote. Once candidate algorithms are developed, the sensor network performance, both for hierarchical (e.g. resource manager) and flat (e.g. distributed) architectures, can be determined. Quantitative figures of merits such as receiver operating characteristic curves and efficiency of detection can then be generated. A quantitative method to identify the global situation (e.g. Command and Control) from the state of the entire population can also be established. Lastly, the fundamental differences and similarities between the biological and netted sensor systems can be determined.

Parallel research in parley and consensus data fusion in the engineering literature also has valuable information for algorithm development (Xiao et al., 2005; Boyd et al., 2005; Ren and Beard, 2005), and will be investigated. Particle filtering (Djuric et al., 2003) has some similarities to the quorum sensing mechanism. A dynamic parameter is estimated similar to the population density in the bacterial system. Both the particles and the bacteria are discrete, which may lead to insight for the robustness and adaptability of the system. Providing rigor to agent-based modeling is necessary. Much work exists in the artificial intelligence community. Process algebra or preference based decision making from theoretical computer science can be used to promote favorable emergence.

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