Performance Evaluation Modeling of Networked Sensors[1]

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Abstract—Substantial benefits are promised by operating many spatially separated sensors collectively. Such systems are envisioned to consist of sensor nodes that are connected by a communications network. A simulation tool is being developed to evaluate the performance of networked sensor systems, measured in such metrics as target detection probabilities, false alarms rates, and classification confusion probabilities. The tool will be used to determine configuration impacts associated with such aspects as spatial laydown (e.g., variance from geometric grid) and mixture of different types of sensors (acoustic, seismic, imaging, magnetic, RF, etc.). The QualNet discrete-event simulation environment serves as the underlying basis for model development and execution. This platform is recognized for its capabilities in efficiently simulating networking among mobile entities that communicate via multiaccess/broadcast media. We are developing innovative technology to characterize sensing aspects among cooperating elements, significantly extending QualNet's communications modeling constructs. For example, hierarchical layered sensing models will capture multi-target sensing (multiple access), sensor fusion (multicast), and multi-modal sensors (multiple quasi-orthogonal channels). Methods are also being developed for modeling the sensor signal sources (transmitters), signal propagation through the media, and sensors (receivers) that are consistent with the discrete-event paradigm needed for systemic performance determination of networked sensors. This work is supported under the Microsensors Technical Area of the Army Research Laboratory (ARL) Advanced Sensors Collaborative Technology Alliance.

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1. INTRODUCTION

An important emerging technology is networked sensors. In such a system, many sensor "nodes" are spatially distributed throughout an area of interest. Each node contains one or more sensors, a processor, a radio, and an energy supply. The nodes form a network and operate collectively to achieve greater functionality than the sum of their individual parts. However, it is inherently difficult to evaluate the performance of the complex adaptive system formed by the sensor collective using analysis. In this paper, we present a novel approach for deriving the sensing performance of a distributed sensor system using a simulation environment.

The key problem is to quantify the synergy derived from fusion of information collected from many spatially dispersed sensors. While fusion of collocated multi-modal sensors has been extensively studied, the benefits of combining spatially distributed sensors, even of the same modality, have only recently been pursued. Advancements in miniaturized devices (e.g., MEMS sensors) have enabled consideration of deploying arrays of sensor nodes and consequent interest in their performance evaluation. Potential applications of sensor networks have been described in earlier papers ([1]).

Considerable progress has been made in developing sensor network technology through such means as the DARPA Sensor Information Technology [2] and Power Aware Computing/Communication [3] research programs. Currently, we are participating in the Advanced Sensors Collaborative Technology Alliance (ASCTA), which consists of a powerful consortium of the Army Research Laboratory and a number of academic and industry organizations. Within the ASCTA is the Microsensors Technical Area. While there are varied applications of distributed sensor networks, including Space Science (see [4]), the focus of this paper is our ASCTA Microsensors progress, having Army applications.

A number of advancements have been achieved in

developing sensor nodes and in the communications among them. For example, novel information distribution methods, energy-efficient routing and scheduling of activities have resulted in substantial gains in the transmission of bits per meter per joule. Performance evaluation tools have been developed, such as SensorSim [5], which provide essential prediction of measures of throughput, latency and energy use. However, these tools generally do not provide measures associated with sensing itself, such as probability of detection, false alarm rates, target localization and track quality. We have developed a tool specifically to measure the sensing capabilities, particularly derived from fusion of spatially distributed sensors.

In the next section, we provide the context for the system for which performance is being derived, including the key entities of interest, and define the metrics. In Section III, we present the modeling approach used in developing the sensor network evaluation tool. The reasons for our choice of underlying simulation environment, Qualnet, are given next. Performance is derived for a number of illustrative examples in Section IV, followed by conclusions of the work.

2. System Context and Metrics

The context for our work is a military environment, in which there are numerous entities that are dispersed across a geographic region. There are mobile entities that may be vehicles or personnel; it is possible that animals may also be present. These entities are of different types, such as wheeled vehicles vs. tracked vehicles, or combatant (enemy or friendly) or noncombatant. They are also characterized by their location, and their track (historical and predicted). For simplicity, we will refer to any such entity as a "vehicle" or "target". The purpose of the sensor system is to provide the "situational awareness" of the targets and their attributes.

Sensors may be deployed in the area of interest. Each target generally emits signals (unintentionally) that may be received by sufficiently proximate sensors. The propagation of the sensor signal will generally depend on the terrain, and environmental factors (e.g., day/night, wind, ground conditions, fog). Sensors having different modalities are beneficial in mitigating different environmental constraints, and can also provide complementary information ("features") that aid in resolving the target type. Typical sensors are acoustic, seismic, imagers (visual and IR), radar, magnetic and electric field.

The geographic area will typically contain characteristic locations of particular interest or require control. For example, a choke point may be monitored for activity. A one-dimensional problem arises with a border and concern for targets crossing it. This case might be covered using many sensors spread across the linear extent. A closed perimeter is similar, with the line closed on itself to encircle an area. Another one-dimensional case can arise from constraints in the terrain, such as constraining the vehicle to follow a road. More generally, a two-dimensional region will require monitoring, as can arise in "nonlinear" AirLand battlefield contexts. We are not (yet) concerned with three-dimensional characterization in our modeling efforts.

It is possible that a long-range stand-off sensor can provide coverage of a large geographic area. However, such assets tend to be limited by resolution, shadowing effects, single point failure risk, vulnerability (such as exposed aircraft), cost and availability (such as satellite-based sensing). Often, the only way to sense particular targets (e.g., armed personnel) is by "in situ" sensors. The microsensor network concept concerns the deployment of many sensors that are relatively close to the targets they are trying to sense. Generally, these are low-cost, small assets and can therefore be "organic" to lower echelon organizational units and deployed rapidly in immediate areas of operation.

The primary performance metrics for the microsensor network are probability of target detection, false alarm rate, quality in the ability to locate the position of the target, and quality of the target track (time-position curve). Generally, a variety of sensor modalities are deployed, and of key interest is the optimal "mix" of sensor types for expected scenarios. Furthermore, certain sensors and associated processing (e.g., beam-formers) consume considerable power, and therefore are best utilized when cued by other "tripwire" sensors that are able to operate with much less power but unable to provide adequate sensor performance alone.

3. Modeling Approach

Our sensor system model is based on the classic (one-way) communications model of Claude Shannon shown in Figure 1:

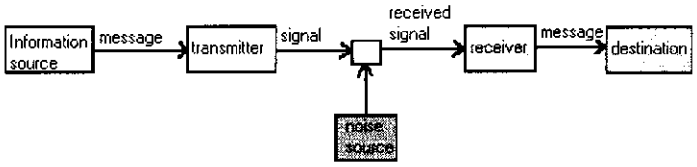

Figure 1: Shannon's Model of Communication

Recognizing the parallel between a communication system and a sensor system, we generalized and tailored Shannon's model for sensing as shown in Figure 2:

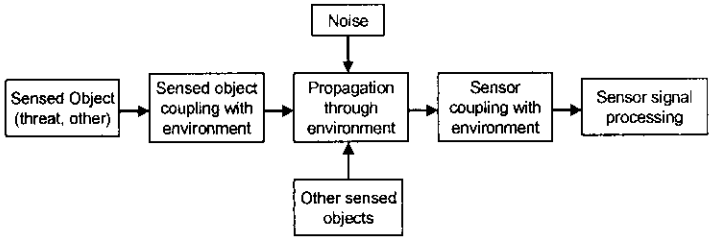

Figure 2: Model of Sensor System

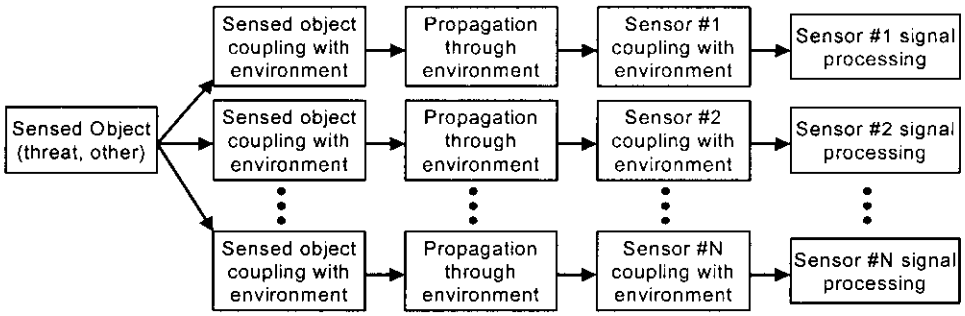

Figure 3: Multiple sensors detecting a single object

The key generalization is to replace "communications channel" by a general "sensor signal medium" shown as simply the "environment" for that sensor modality in the figure. For example, consider the propagation of a seismic signal through the ground medium. The emphasis is that, an object may be sensed by multiple sensor systems of different modalities (and hence involves multiple "channels") as illustrated by Figure 3. These may be similar sensors that are spatially dispersed, or sensors having different modalities. Furthermore, the multiple sensor systems can combine their results at different levels: direct combining of raw signals (possibly time-shifted and/or filtered), fusing of different intermediate features extracted by different systems (e.g., energy detected in specific spectral bands), or fusing of attributes decided by different systems (e.g., range and bearing). Modeling of these different methods of sensor system combination will be made explicit in future progressions of this effort. These models will necessarily include communications constraints that add latency and possibly errors in their operations.

It is also noted that sensor system management will dictate when/whether a particular sensor is active. For example, if a sensor is cycled on/off to conserve energy, then the latency before becoming active as well as any initialization delays (e.g., warm up/self calibration, initial signal acquisition) will need to be characterized. Similarly, performance will be affected when a particular sensor system is activated by means of being cued by another sensor system.

The five basic sensor system elements in Figure 2 are described further as follows:

1. **Sensed Object.** This component identifies the sensed object by name and incorporates all the inherent attributes associated with it. The objective of the sensor system output is to detect and identify this entity as accurately as possible. Several sensor systems may perceive different characteristics of the same object. In an accurate model, the sensed object possesses the union of all the attributes that the sensor systems may determine. Included in this set of attributes are the position characteristics, which include location, orientation, speed, and track. The near-term focus of ASCTA sensor network research is concentrated on sensing military vehicles and personnel (and objects that might be confused as such, e.g., animals). These are continuous point sources that are different from a biochemical gas cloud having spatial extent or an explosion event. Abstract attributes such as "having hostile intent" are currently outside the scope of this work. In our current simulation model architecture, it is assumed that the sensor system operations will not affect the behavior of the sensed objects. Thus, we do not consider a scenario where an object is detected, causing a fire mission, which causes the target to alter its direction of travel. In our current model, the sensed object's motion follows a fixed script.

2. **Sensed Object Coupling with the Environment.** The sensed object directly "modulates" its "signal" in some fashion, and the extent to which this occurs will depend on the characteristics of how it is coupled with its immediate environment. For example, a tracked vehicle can induce a periodic seismic signal due to "tread slap" (a function of speed and tread spacing). Also, the magnitude of seismic generation will depend on the immediate environmental conditions, such as whether the terrain is rough (potholes) or damp. As another example, acoustic signal generation by an exhaust pipe will have a preferential direction depending on the current orientation of the vehicle.

3. **Propagation through the Environment.** For each signal modality, a "channel" is modeled that captures the propagation of the signal through the environment. Essential aspects to model are: (1) the rate of signal loss with distance, and (2) propagation speed. These generally depend on the environment itself, e.g., seismic propagation differs for bedrock vs. sandy terrain, imaging systems will depend on atmospheric conditions (e.g., fog), and acoustic sensors will depend on day/night and wind. The simplest model for signal strength propagation is a "cookie cutter" model in which the object is sensed if and only if it is within a given fixed range of the sensor. Such a model may be defined with different ranges depending on the different attributes being sensed by the same

sensor. When a sensor senses multiple objects simultaneously, it is typically assumed that the signals are summed in a linearly additive manner. Non-linear combining of signals within the environment ("inter-modulation" effects, visual blockage, etc.) must be characterized with more sophisticated models.

4. **Sensor Coupling with the Environment.** The sensor itself will be associated with the environment by its position and orientation (if not omni-directional) as well as its immediate interface. For example, a seismic sensor will operate better if it is staked into the ground vs. laid on the surface. This model component will also incorporate inherent noise induced locally into the received sensor signal. Finally, the power consumption requirements of the sensor itself will be quantified.

5. **Sensor Signal Processing.** The raw sensor signal will be processed and result in actions. This may be detection of a simple threshold excursion that generates a communications act. The output may also generate a command that influences the sensor's coupling with the environment, such as mechanically slewing a gimbal to a new orientation to center the received signal within the field of view. The output of the signal processing will be associated with the different attributes of the sensed object that are detected and identified (including position/orientation and track aspects), and will stochastically depend on the quality of the signal (as determined by the preceding model components). Bandwidth and quantization/resolution levels of raw and processed signals need to be identified so that communications requirements for subsequent relay can be deduced. Such a representation may consist of a value (e.g., bearing rate) together with an estimate of its uncertainty. In addition to characterization of the possible actions made by received signals, the processing model will also identify the latencies and energy consumed by the signal processing (MIPS and assumed computational engine). Also, any mandatory commands that must be provided prior to processing should be identified, as well as default values used for initial sensor signal acquisition.

As indicated earlier, more sophisticated distributed signal processing architectures will be modeled as we continue in this effort. These will incorporate decisions regarding the amount of information propagated in the next step in the processing chain (e.g., a simple alert message for sensor cueing vs. forwarding the raw sensor stream for additional processing), as well as how combining of signals and decisions are made. Generally, a node may have multiple sensors, a radio and processing capability, and inputs to the node will come in the form of sensor signals as well as received radio messages. Performance will depend on communications resource consumption, latency, and need for covertness, as well as computational and energy resource demand.

4. Choice of QualNet Environment

There are a number of excellent highly capable simulation environments for communications networks. However, we selected QualNet because of its particularly advanced capabilities for modeling wireless nodes. Considerable care is taken to precisely model the reception of a common signal by multiple receivers, as well as the reception of overlapping signals generated from multiple transmitters.

Model Design using QualNet

Simulation provides insight and understanding of distributed sensor systems being modeled. Currently, there are very few sensor simulators. SensorSim [5] (an extension of ns-2) is developed by UCLA to model sensor networks. This tool focuses on the radio communication aspects among sensor nodes, battery models and throughput; this tool does not model sensing. SensorML [6] is a markup language that can be used to develop functional models of sensors by defining the geometric, dynamic and observational characteristic of sensors; it models the physical aspects of the sensors. However, it does not model sensor networks since the sensed data are archived for future post-processing; there is no interaction among the distributed sensors.

In [7], Fishwick described several models that can be used to model a complex system. A conceptual model may be used to give an overview of the hierarchy of abstractions and abstraction levels of the system. Each level of abstraction may be implemented using several different models. A declarative model is used for describing state transitions and events; this type of model is a finite state automata. Transitions in the declarative model can be defined according to probabilistic functions. Functional model is often used to describe a "black box" where certain mathematical computations are carried out; SensorML and MatLab are often used to develop functional models. Constraint models are used to describe systems with limited resources such as power, bandwidth or systems with invariance. Spatial models are useful when we need to associate different behavioral rules to different parts of the covered area.

From the simulation viewpoint, we did not choose SensorML or MatLab because those tools only support functional models. On the other hand, QualNet supports a hierarchical model design where hybrid models can be developed at different abstraction levels. For the declarative model, it is easy to create state-transition graphs using QualNet Designer to describe system behavior. To build a functional model, we can create a state and specify the associated function in C language. A constraint model can be built by stating the specific constraint as "guarded expressions" in the state-transition graphs. Depending on the specific spatial-dependent behavior, we can generate different spatial models for different regions. In modeling

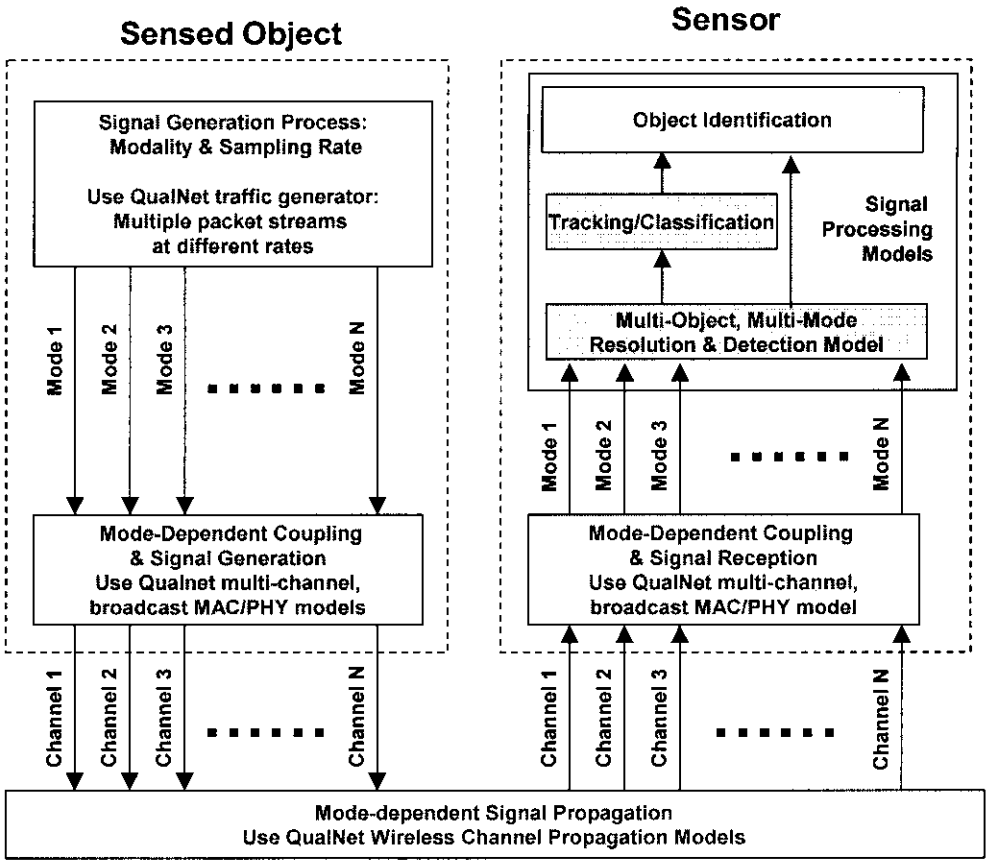

Figure 4: Sensor System Modeling in QualNet

sensing, we use an object-oriented approach. To model distributed sensors, we construct a model containing sensor objects where the objects are "connected" (interactions among objects) by message passing (communication). QualNet has high fidelity environmental modeling capabilities and built-in statistics gatherings for ease of execution analysis.

Model Implementations in QualNet

Figure 4 shows how the various components of a sensor system are modeled using QualNet. The "sensed object" and "sensor" are nodes/entities defined in the QualNet simulation environment. The "sensing" phenomenon – i.e. the emissions of signal from an object and the reception of the same signal with some distortion by a sensor – is modeled as communications between nodes. Although sensor signals are in reality broadcasted continuously, we simply model that as a continuing periodic sequence of emission at certain "sampling rate" for each source object and modality, using QualNet's traffic generator. While this method is computationally demanding, the QualNet tool is known for its efficiency and speed. This capability is very important to simplify modeling of large, complex scenarios and allow rapid executions in quantities sufficient for statistical performance characterization. Exceptionally large-scale simulation models may be executed using the parallel processing capability within PARSEC, although scalability is not a concern at this stage of our work.

The "sampling rate" at which periodic messages are broadcasted determines the time/spatial resolution of our simulation result and the speed of execution. Although object signal is, in reality, continuously broadcasted to all sensors, sufficient signal energy must be accumulated by the transducer circuitry to trigger the sensor's data recorder and subsequent signal processing. Therefore the reaction time elapsed from the first instance of signal presence till the completion of the appropriate signal processing algorithms on the recorded signal will vary depending on the nature of the object, the modality of the received signal, the required length of data sample, and data processor/algorithm performance. As long as this reaction time is comparable with sampling interval of the traffic generator, discrete event simulation can basically retain the same level of time resolution as the continuous time system. To maintain the spatial resolution in our simulation, higher sample rate is required for highly mobile objects.

Currently, the only physical channel model provided by QualNet is a RF model. To model signal generation from generally mobile targets, and propagation of sensor signals

through different medium, we will augment the physical channel models substantially to include representations of various sensor phenomena. Propagation speeds and attenuation with distance are appropriately parameterized. For multi-modal signal reception, we use multi-channel and broadcast models at both physical and MAC layers.In addition, it is important to properly model the handling of overlapping sensor signals, which may carry substantially useful information, unlike "collisions" or even "capture" in the radio communications case. To accomplish this, we need to bypass the collision detection and capture features in QualNet's physical layer model. Information such as received signal strength for time-overlapping signals is passed to the signal processing modules, which will be developed in the future, that models the capability of a particular sensor system to resolve and detection one or more objects simultaneously. The existing Qualnet simulator structure provides a useful foundation to build our sensing and signal processing models.

The Qualnet tool also provides multiple "channels," nominally for modeling different radio subnets coexisting in the same spatial area. This is a critically important capability for our sensor networking use. A channel is associated with each sensor modality, with associated signal propagation laws defined parametrically. In addition, a receiver (sensor) of a particular modality is designed to operate correctly for aspects such as multiple overlapping emitters and directionality limitations. Every vehicle broadcasts periodic streams on every sensor "channel." This environment enables us to capture the essential fusion behavior of spatially distributed sensors.
Last but not least, QualNet provides the capability for modeling the interactive data communications between sensors during self-organization, distributed routing and messaging, and cooperative data fusion. Combined with the sensor system models, we have an integrated sensor/communications platform for performance evaluation.

5. EXAMPLE EVALUATIONS

In this section, we illustrate the use of the QualNet tool to evaluation a sensor network's ability to track a moving target within a 1000 x 1000 meter region. We assume the sensor nodes are "trip-wire" nodes, with detection range up to approximately 300 meters. A simple "track" can be constructed using the position coordinate of each sensor node and the time it first detected of the target. Suppose that n sensor reported detection of the target, then one can compile a sorted list of detection time $\{t_1, t_2, \ldots, t_n\}$ in ascending order and the coordinate of the sensor that reported the detection in the same order $\{p_1, p_2, \ldots, p_n\}$. We can then produce a "estimated track" as a continuous time function $P_{est}(t)$ given by:

$$P_{est}(t) = \begin{cases} p_i & \text{if } t = t_i \\ p_i + \dfrac{p_{i+1} - p_i}{t_{i+1} - t_i}(t - t_i) & \text{if } t_i < t < t_{i+1} \end{cases} \quad (1)$$

In between instances of detection, the location of the target is linearly interpolated from the two neighboring end points. In Figure 5, we show the setup in QualNet. The target has a predefined track starting from the upper-right corner of the simulation region; the sensors positions are uniformly distributed. We tested two cases, using 36 and 48 sensor nodes. Intuition tells us that using more sensors should give us better tracking accuracy.

Figure 6 compares the actual track with the estimated tracks derived from the target detections time and the sensor positions. The red(solid) line shows the actual track; the blue(dotted) and the green(dashed) lines represent the estimated track produced by using 49 and 36 uniformly distributed sensor nodes, respectively. For illustration, we marked the actual and estimated target position at t = 120 sec. Visual inspection shows the 36-node case (green dashed line) actually produce smoother track compare to the 49-node case. The "zig-zags" in the later case are the results of the target being detected by multiple nodes in relatively short time span.

To compare the tracking accuracies quantitatively, we compute the average tracking error as the average distance between the actual track and the estimated track. Let $P_{target}(t)$ be a two-dimensional vector representing the actual coordinate of the target at time t. $P_{est}(t)$ is the estimated target location at time t and T is the duration of the tracking operation. Then the tracking error is given by:

$$\varepsilon_{track} = \frac{1}{T}\int_0^T \left\| P_{target}(t) - P_{est}(t) \right\|_2 \cdot dt \quad (2)$$

Applying this metric, we see that the ε_{track} = 161.14 meters when using 49 nodes and ε_{track} = 188.02 meters using 36 nodes. Here we can clearly see that our intuition regarding the benefit of using more nodes is correct; however, it was not visually obvious. What we did not address in this demonstration experiment is the benefit of local data fusion.

When the number of sensors in a network is large, it is frequently the case that two or more sensors can observe the same target at the same time. We believe that one can further improve the tracking accuracy by combining information locally. For example, one can perform simple election algorithm to determine which sensor is the closest to the target at a given time instance and only report that sensor's location to generate a more accurate track; or triangulation can be performed to narrow down the region of uncertainty regarding the targets true location. To properly model advanced distributed network-centric sensing in the future we will leverage the extensive communications models already build into QualNet to study complex

scenarios involving cooperative data fusion performed by multiple sensors.

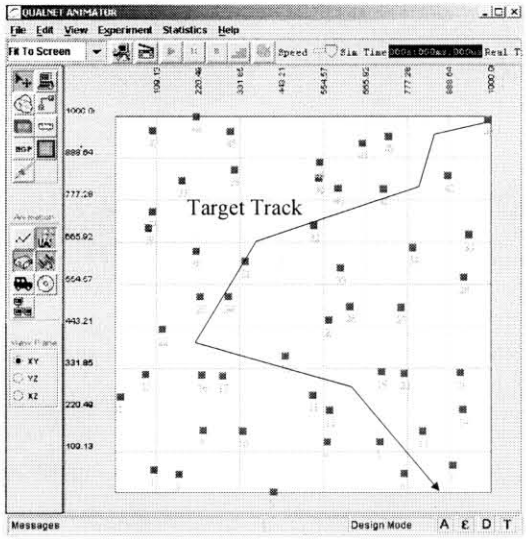

Figure 5: QualNet Tracking Experiment

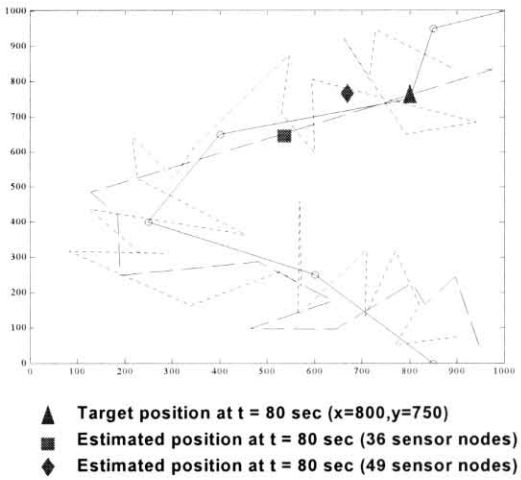

Figure 6: Tracking Results

6. Conclusions

In this paper, we presented a novel approach to simulate multimodal sensing by extending Shannon's communications model, using the QualNet simulation tool. We have demonstrated using our sensor model in QualNet to evaluate the ability of a field of tripwire nodes to track a moving target. This tool can be used to evaluate performance of complex distributed sensor systems where the system is highly dynamic. Specifically, we will be able to measure detection probabilities, false alarms, determine the number and type of sensors for coverage and for hierarchical layered sensing, and sensor data fusion. We use an object-oriented approach for developing sensing models. By augmenting the communication models in QualNet to model physical sensors in detail, we will be able to provide a simulation tool for sensing that will substantially benefit distributed sensing applications.

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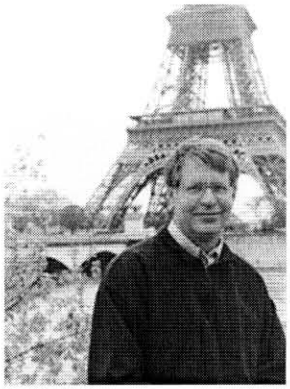

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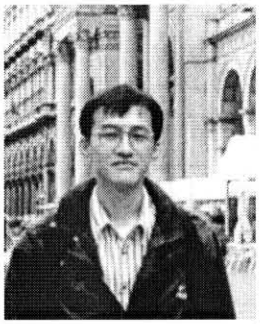

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