Geolocation of wireless sensors with nonuniform GPS availability

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ABSTRACT

In order for the information provided by networks of unattended ground sensors (UGS) to be of use to the tactical planner, the location of each sensor must often be known. Sensor localization is typically achieved by careful hand emplacement, or facilitated by anchor nodes whose position is precisely known. Nova Engineering and Army Research Laboratory are currently designing a new sensor network architecture to meet the growing need for UGS networks that can self-localize using anchor nodes with imprecise prior location information. In this paper we present an overview of a prototype sensor network and an analysis of its capability. We also present new results on the effects of network deployment parameters on sensor localization error, such as the level of network connectivity and the number of GPS-enabled nodes on the network. We compare time of arrival (TOA) and time difference of arrival (TDOA) ranging algorithms for sensor localization, and we consider the benefits of including available direction of arrival (DOA) estimates. Selected scenarios of UGS deployments are provided for comparison.

Keywords: PODIS, UGS, Volcano, TDOA, TOA, DOA, ranging, sensor networks, self-localization, geolocation

1. INTRODUCTION

The reliance on GPS, anchor nodes, and hand emplacement for locating nodes is a shortcoming of the typical unattended ground sensor (UGS) CONOPS. This knowledge is unavailable at times due to the deployment mode or hostile operating environment. PODIS is aimed at satisfying the military's immediate need for a self-localizing sensor network with limited GPS access or without GPS at all. This paper represents the first implementation based on the self-localization research reported in [1-5]. The work is significant in that it addresses the critical and immediate need of forces on the ground to detect and localize threats such as sniper fire, armored vehicles and enemy combatants. Self-calibrating sensor networks also show promise in many commercial applications such as ocean search and rescue, disaster recovery, distributed sensing of large public areas for homeland security, and smart buildings.

The PODIS program applies a new body of theoretical development to a networked sensor radio system that is currently entering production. The purpose of the program is to demonstrate an acoustic sensor network with self-localizing capability when GPS is unavailable or limited to a few nodes on the network. In section two we describe the wireless sensor network and compare the concept of *aimpoints* to the more traditional *anchor nodes*. In section three we present deployment scenarios and an analysis of the effect of deployment parameters on localization accuracy. Section four describes the PODIS hardware.

2. PODIS Concept of Operations

The PODIS system is comprised of a network of acoustic UGS nodes, each containing a digital signal processor (DSP), networked radio, four microphones, and a loudspeaker. After the UGS network is deployed, the central information processor (CIP) that controls the network initiates a calibration sequence to determine the location of all nodes and the orientation of nodes with directional sensing capability. Each node that is equipped with a signal source (a loudspeaker in this case) broadcasts an acoustic pseudonoise (PN) signal while the other nodes receive the signal and compute a time of arrival (TOA) and possibly a direction of arrival (DOA) estimate from the received signal. The estimates are then sent back to the CIP, which performs the self-localization algorithm computations. The result of the calibration is an estimate of the absolute position and orientation of all nodes in the network.

2.1 PODIS Wireless Sensor Network

PODIS nodes use a power efficient, networked tactical UHF radio, typical of intelligent munition systems, for wireless networking. The networked radio also provides an accurate global time reference enabling coordination and comparison of local TOA measurements from sensor nodes. After the nodes have been deployed and the CIP completes its network discovery, the CIP commands each node sequentially to broadcast its calibration signal. Every node is equipped with a four element microphone array that is used to detect the presence of a calibration signal. Nodes estimate TOA and DOA of acoustic calibration signals, then transmit the measurements back to the CIP over the wireless network.

Erroneous TOA measurements impact the self-localization solution of the entire network, not just the node making the measurements, so identifying and discarding this bad data can improve the network's overall localization error. Erroneous measurements occur most often in low SNR environments, particularly as the received SNR approaches the threshold described in [6]. We add robustness to TOA and DOA errors by considering the known microphone array geometry. If the distance from the center microphone to a microphone on the edge of a star array configuration is known, then it imposes an upper bound on the difference between TOA estimates. If a differential TOA measurement exceeds this bound, we set an error flag for that channel. The number of error flags set for a particular node is returned to the CIP for analysis. As in the previous case, up to three transmissions may occur to eliminate any error flags; if, after three attempts, error flags are still present, a confidence metric is assigned to the node indicating the reliability of the data to be used in the localization estimate.

Another means to reduce the impact of measurement outliers on the self-localization solution employs an expectation-maximization (EM) technique. Results in [7] show that using the EM algorithm to identify erroneous measurements performs much better than using blind maximum likelihood methods alone.

2.2 Aimpoints vs. Anchor Nodes

Most sensor self-localization approaches assume that a subset of the nodes have known location (and possibly also known orientation). Such nodes are usually referred to as *anchor nodes* or *beacon nodes*. Anchor nodes are obtained by careful hand emplacement or by equipping a few special nodes with GPS systems. The anchor nodes are typically assumed to have *exactly* known locations. In practice, of course, it is rarely possible to provide exact locations; emplacement errors or GPS location errors are always present.

For the PODIS system, we take an alternate approach by assuming that the system has uncertain prior location information associated with a subset of the nodes. We refer to this prior information as the node *aimpoint.* The aimpoints can arise from a prior measurement of location, as provided by a person who hand-emplaces the node or by a GPS location estimate. Alternately, the prior location information could be an aimpoint from an air drop deployment or from a munition-based emplacement system such as Volcano. In any case, the prior information is characterized by a nominal location of the sensor and by a location uncertainty. We model the prior uncertainty as a bivariate Gaussian quantity.

The aimpoint approach generalizes the idea of anchor nodes in a way that provides great flexibility in applications. If anchor nodes with known locations are available, they can be considered special cases of the aimpoint approach, as nodes with very low uncertainty. For other cases in which the prior knowledge of node locations is uncertain, the uncertainty is quantified and can be addressed in the localization procedure in a statistically rigorous manner. Finally, the aimpoint approach handles correlated errors; for example, aimpoint errors due to wind might be correlated across sensors, and this correlation can be readily encoded in the prior statistical information as described in Section 3 below.

3. Network Multilateration

The goal of network multilateration is to estimate the locations and orientations of sensor nodes, and to quantify the location and orientation uncertainty of the resulting estimates. Information available to the system includes measurements of time and direction of arrival of calibration signals, as well as limited and possibly uncertain prior position information.

Our solution to the multilateration problem involves defining a statistical model that incorporates both prior information and calibration measurements, then estimating sensor locations and orientations using a maximum *a posteriori* probability (MAP) estimator. A detailed discussion of the algorithm and its statistical properties is described in [4–5]. We encode aimpoint information as a prior probability density function (pdf) of a subset of the node locations. The calibration measurements provide additional information on the node locations and orientations, which is modeled as a posterior pdf. Our estimate of the node locations and orientations are at the maximum on this posterior pdf.

3.1 Deployment Scenarios

In order to predict the level of localization accuracy expected from the PODIS network, we created a simulation tool capable of demonstrating deployment scenarios incorporating different geometries and varying levels of sensor capability. In this section we introduce several nominal scenarios in simulation describing the operation and accuracy of the PODIS acoustic localization application. In all cases, ranging measurements are taken from a Gaussian process with a 0.3 m standard deviation.

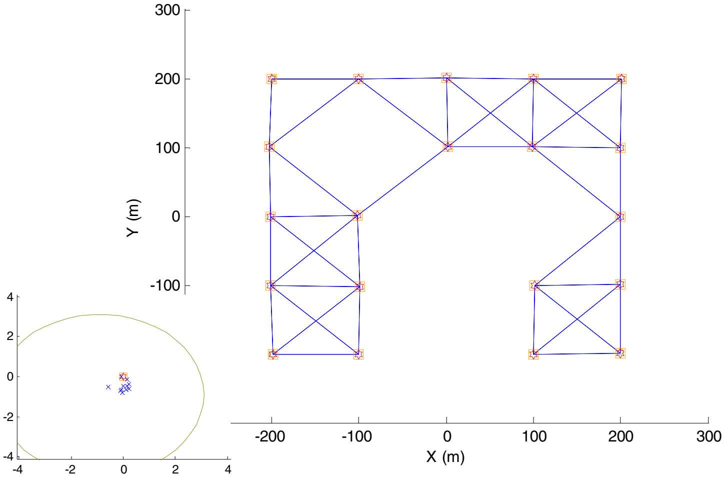

Figure 1: Rooftop network in a 400 m x 400 m area with 20 nodes sparsely deployed, each with sensor and source. The network has three GPS nodes at three of the four corners, and yields a localization error of 86 cm.

Rooftop deployment: In the scenario shown in Figure 1, we expand the scene and reduce the sensor connectivity to test the effects of a more sparsely connected network. We assume that sensor connectivity is limited to 160 m, and that three nodes with tactical GPS capability occupy three of the four corners for an absolute calibration. In this case, despite multiple hops between most nodes and the GPS-enabled anchor nodes, the average absolute position error is 86 cm.

Roadside deployment: In this scenario, 24 sensors are deployed in a 60 m square area around a road intersection. At deployment time, the user emits a calibration signal at nine locations along the road. At several locations, the user logs a GPS measurement in order to calibrate the system in absolute lat-long coordinates. We assume the GPS readings are accurate to within 3 m. Figure 2 illustrates that PODIS calibrates the network to an average error of 31 cm. We also find that reducing the number of GPS measurements to three or two does not significantly affect the localization error in this scenario, as long as sufficient geometric diversity, discussed in the following section, is preserved.

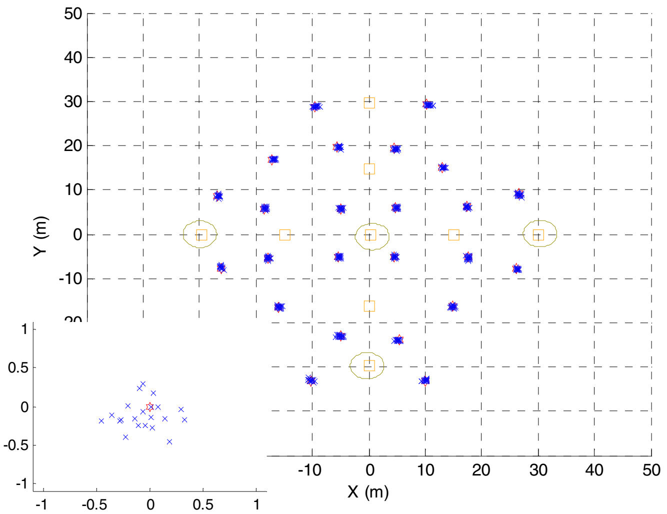

Figure 2: Roadside network in a 60 m x 60 m area with 24 nodes. Four nodes are equipped with GPS and used as aimpoints giving a localization accuracy of 31 cm.

3.2 Network Geometry Considerations

Results in [8–9] suggest a number of geometric considerations. First, distance and angle measurements exhibit similar trends in localization error with varying network density. The error when angle-only measurements are used is much higher than when distance measurements are used, for uncertainties typical of acoustic array processing. Network localization appears to be scalable since error propagation is very slow and since localization accuracy appears to be relatively insensitive to increases in the number of anchor nodes or aimpoints. Finally, when the aimpoint uncertainty is high, most location error is an overall translation and rotation error of the entire network, meaning that nodes may be accurately located relative to each other, if not to an absolute frame of reference.

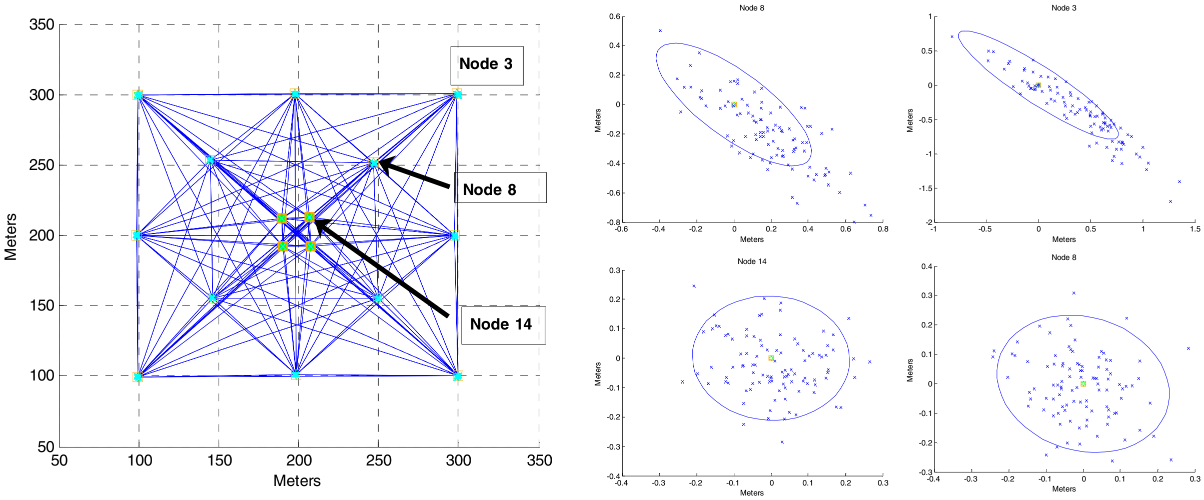

Figure 3: A 16 node network shows the effects of anchor node placement and dilution of precision. Each node is equipped with a signal source and sensor array. **(a)** In the first case, the four center nodes are anchor nodes, resulting in a high GDOP at nodes 8 and 3 (above). **(b)** In the second case, the anchor nodes are at the four corners of the network, resulting in relatively low GDOP at nodes 14 and 8 (below).

Geometric dilution of precision (GDOP) is effectively a multiplier on ranging error caused by the geometry of the network deployment, so minimizing GDOP results in the best position and orientation estimates for measurements with a given error variance. To illustrate the effect of GDOP, we simulated the 16 node network in Figure 3. In a best case GDOP scenario, we assigned the four corner nodes on the perimeter as anchor nodes with known location, resulting in an average 2-sigma uncertainty ellipse of 0.46 m with an average position error of 0.11 m. The 2-sigma uncertainty ellipse bounds 86% of the location estimates. In a worst case GDOP scenario, we assigned the four center nodes as anchor nodes, producing an average 2-sigma uncertainty ellipse of 0.83 m, with an average position error of 0.39 m. Although these scenarios represent the extreme cases, the network planner should be cognizant of anchor node placement during the deployment phase of an UGS network. Figure 3 illustrates the GDOP effects in these two scenarios: with poor geometric diversity, location accuracy is degraded in directions normal to the baseline between a cluster of anchor nodes and the sensor to be located. Simulated position estimates in this case agree with the error performance predicted by the 2-sigma uncertainty ellipses, though in networks with poor GDOP, the SNR must improve appreciably for the 2-sigma ellipse predicted by the Cramer-Rao bound to bound the estimates accurately.

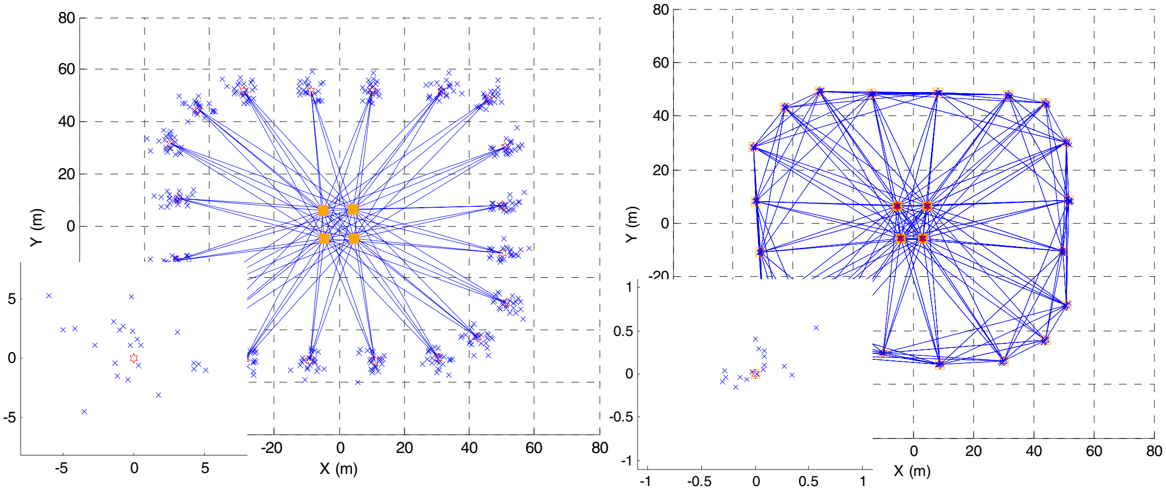

Figure 4: Perimeter network in a 100 m x 100 m area with 20 sensors and four internal anchor sources. **(Left)** With calibration sources solely on the network interior, dilution of precision limits the location accuracy to 3.3 m. **(Right)** When all sensors on the network interior and perimeter are colocated with sources or ranging actuators, the localization accuracy improves to 36 cm.

GDOP can also be improved by increasing the level of network connectivity. We show in Figure 4 a perimeter sensing network with 20 sensors and four interior sources with known position (anchor nodes). In the first example, all sensors calibrate based on measurements from the four sources on the interior only. The narrow range of angles of arrival of the calibration signals at each node results in a high GDOP in the localization estimates, with an average error of 3.3 m. Supposing that each sensor in the same network were equipped not only with sensing capability, but also with the ability to transmit its own calibration signal, we arrive at the second network shown in Figure 4. Here we assume that the sensor range is limited to 70 m, so the network is not fully connected, but each sensor sees more signal sources from a wider distribution of angles. Though the number and location of nodes with prior location information remains unchanged, the improved GDOP yields an order of magnitude improvement in the average localization error.

3.3 Network Connectivity

Of primary importance is a sensor deployment density that is high enough so that a sufficient number of sensors can detect transmitted signals and accurately estimate the TOA and DOA of these signals. Each sensor must receive at least two signals from neighbors in order for the two-dimensional calibration to succeed. Moreover, recent studies on network density effects [8-9] have shown that localization accuracy improves substantially as the network density increases to approximately six neighbors per node; beyond six neighbors, accuracy increases only modestly. The maximum distance between connected nodes depends on transmit power, receiver sensitivity, environment noise, and propagation considerations [10]. Results in [8] consider only distance information; we seek results for sensor networks capable of measuring both distance and angle.

We simulated an ensemble of random networks with 20 nodes, three of which are assumed to have known location. We assume that TOA and DOA measurements are Gaussian with a standard deviation of 1 ms and 3 degrees, respectively. When the source emission times are not known, as might be the case when sensors and sources are not colocated (e.g. Figure 4a), then the system effectively computes a TDOA solution where the emission times are estimated as nuisance parameters. We varied the number of neighbors that each node can hear until we reached a fully connected network. For each sample network we calculated the average equivalent 2-sigma uncertainty radius, then averaged over an ensemble of 100 networks. Figure 5 shows the effect of increasing neighbor nodes for both TDOA and TOA cases, in each case with and without available DOA information. Figure 5 verifies results for distance information given in [8], that localization accuracy increases only modestly beyond six neighbors. Our results also show that including DOA information reduces the RMS localization error appreciably for networks that are sparsely connected, but has little effect on well connected networks. In fact, beyond eight connected neighbors, knowledge of the source transmission time plays a larger role in improving the average localization error than the availability of DOA measurements.

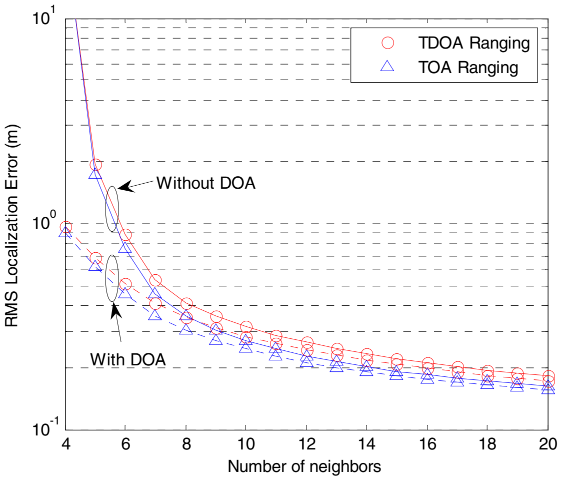

Figure 5: Localization error decreases as the level of connectivity increases, and when TOA measurements are available. Including DOA estimates drastically improves localization error for sparsely connected networks.

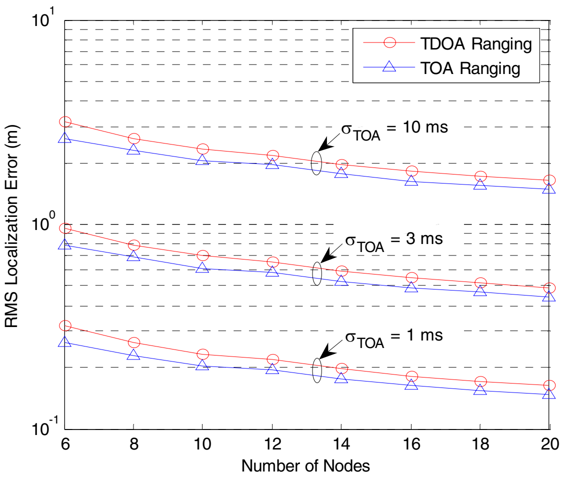

Figure 6: For both TOA and TDOA cases, localization error decreases as the size of a fully connected network increases. Also shown is a linear dependence on TOA measurement quality.

3.4 Network Size

We investigated the localization accuracy as the number of nodes on a network increases. We created an arbitrary network with six nodes, three of which had known locations, then calculated the average equivalent 2-sigma uncertainty radius. We then added nodes to the network one at a time, each time computing the average uncertainty radius. Figure 6 shows the resulting localization accuracy. We also see the effect of degraded TOA measurement accuracy on localization. Figure 6 shows that the RMS error tends to decrease as expected as the number of nodes increases on a fully connected network. We also note that the RMS localization error scales linearly with the RMS range error.

4. PODIS Hardware

The prototype PODIS sensor package measures 3.5×6×8 inches, as shown in Figure 7. Each node has four A/D inputs and two D/A outputs with a variable sampling rate from 8 kHz to 96 kHz. We use all four analog inputs with an 8 kHz sampling rate to obtain our TOA and DOA estimates. We use both analog outputs in a bridged mono configuration to generate the calibration signal. The DSP core is an Analog Devices SHARC DSP with a clock speed of 200 MHz. A USB port allows a single host laptop to connect to the CIP or master node and visualize the network during localization. Communication on the sensor network is achieved through a low power, networked radio that is IMS compliant. This radio enables multi-hop routing and secure communications.

5. CONCLUSIONS

PODIS is a sensor network enabling a tactical user to deploy a network of self-localizing sensors with limited GPS availability. The PODIS network uses an aimpoint approach to generalize the traditional idea of anchors nodes, providing greater deployment flexibility with and without the use of GPS. Dilution of precision effects can be appreciable in some cases; network planners should consider its effects during network deployment to minimize position and orientation error. When available, DOA information can reduce localization error for sparsely connected networks.

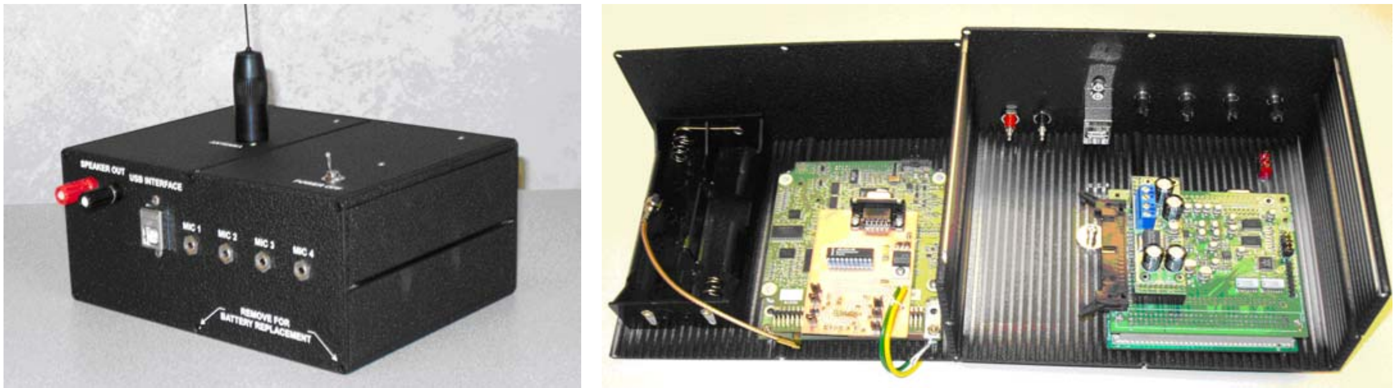

Figure 7: (Left) PODIS sensor node packaging. **(Right)** PODIS node package includes battery, radio and sensor processing.

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