Bayesian Computational Sensor Networks: Small-Scale Structural Health Monitoring

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Abstract

The Bayesian Computational Sensor Network methodology is applied to small-scale structural health monitoring. A mobile robot, equipped with vision and ultrasound sensors, maps small-scale structures for damage (e.g., holes, cracks) by localizing itself and the damage in the map. The combination of vision and ultrasound reduces the uncertainty in damage localization. The data storage and analysis takes place exploiting cloud computing mechanisms, and there is also an off-line computational model calibration component which returns information to the robot concerning updated on-board models as well as proposed sampling points. The approach is validated in a set of physical experiments.

1. General Overview

The goal of structural health monitoring (SHM) is to determine the existence and extent of any flaws in a structure. SHM is applied to wide variety of structures, ranging from buildings, bridges,and roads to nuclear reactors to aircraft. Clearly the failure of such systems can lead to large-scale catastrophe resulting death and injury, and it is therefore important to correctly detect problems as early as possible. However, every structure has its own particular properties, and detection systems often use a standard set of parameters which may result in damaged areas being overlooked or cause the report of damage when none exists.

We have developed the Computational Sensor Network (CSN) approach [14, 15] which uses models of the object of study (e.g., the airplane wing material) as well as models of the sensor network in order to improve understanding of both and to reduce the uncertainty in the models. This requires relating the properties of interest in the sensor network (e.g., position, bias, etc.) to the sensed data concerning the physical phenomenon (e.g., sound waves, temperature, etc.).

CSN's are designed and developed using the model-based approach which provides a strong scientific computing foundation as well as the basis for robust software engineering practice. CSN is comprised of three main components: (1) models of physical phenomena, (2) models of sensor-actuator systems, and (3) sensor network computational models. Computational modeling requires the elucidation of principles to identify the state of the sensed phenomenon as well as the sensor network. The operational system development is then guided by these methods which are mapped onto the system architecture. Such a real-time computational mapping allows system parameters to be changed according to real-time performance measures.

The Verification and Validation (V & V) methodology [20] applied in high performance computing can be incorporated in the CNS framework; i.e., model impler-

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mentations may be verified for correctness and numerical properties like convergence and error. It is also possible to embed tests in the executable to check correctness during execution. CSN's offer a novel aspect in that they can sense and interact with the environment, and thus, can refute or confirm model parameters or structure by running validation experiments on the fly. As pointed out earlier the structure of the measurement system can be estimated using the phenomenon model. E.g., the partial differential equation describing heat flow can be combined with known temperatures at fixed (but unknown) locations in order to determine the positions of the sensors. We have, in fact, applied this method in an avalanche prediction system which modeled heat flow through snow [26]. Finally, real-time computational steering may be performed by (1) embedding verification and validation functions into the executable code, and (2) modeling component performance in terms of a statistically meaningful characterization of output features conceptually defined by the user.

The Dynamic Data Driven Application Systems (DDDAS) approach provides a way to develop custom models (e.g., material density, geometry, propagation properties, etc.) dynamically based on data acquired during inspection. Such improved models also allow the determination of more accurate state information about the sensor system (e.g., location, orientation, bias, etc.) usually with inverse solutions.

In the application presented here, a mobile robot moves along a metal plate and uses sound waves (ultrasound) to detect cracks and holes and report their locations and dimensions as accurately as possible. A Simultaneous Localization And Mapping (SLAM) algorithm is used to construct a map of the flaws, and at the same time, the holes and cracks are used as landmarks in the SLAM method to improve the pose estimation of the robot. In addition, off-line agents are used to dynamically calibrate the physics models and to propose optimal new sensing locations so as to reduce the overall uncertainty of the mapping process.

This application involved the development of a cloud-based computational and storage system where interactions between the mobile robot platform and the other computational agents are mediated by a highly customizable data sharing model optimized as sockets. This approach has been extended to perform geospatial intelligence analysis in the *BRECCIA* system [23, 24, 25]. *BRECCIA* receives information from humans (as logical sentences), simulations (e.g., weather or environmental predictions), and sensors (e.g., cameras, weather stations, microphones, etc.) where each piece of information has an associated uncertainty. This system has also been applied to Unmanned Aerial Systems flight planning in urban environments.

2. State-of-the-Art, Challenges and Method

Structural health monitoring of aircraft poses a significant problem in their exploitation and maintence. To address this issue, the major specific objectives of our work are to:

1. Exploit Bayesian Computational Sensor Networks (BCSN) [14] to detect and identify structural damage. Here we demonstrate the combination of a Simultaneous Localization and Mapping (SLAM) method with the use of ultrasound to map damage in a small-scale structure.

2. Exploit an active feedback methodology using model-based sampling advice which informs the sample point selection during path planning for the monitoring task.

3. Provide a rigorous model-based systematic treatment of the uncertainty in the process, including stochastic uncertainties of system states, unknown model parameters, dynamic parameters of sensor nodes, and material damage assessments.

4. Achieve goals 1-3 exploiting cloud computing.

This work addresses 3 of the 4 DDDAS (Dynamic Data-Driven Analysis Systems) interdisciplinary research components: applications modeling, advances in mathematics and statistical algorithms, and application measurement systems and methods, and more specifically addresses several questions raised in the DDDAS-InfoSymbiotics 2010 Report [8] by Working Group 3 (WG3) Large and Heterogeneous Data from Distributed Measurement & Control Systems (Alok Chaturvedi, Adrian Sandhu): "DDDAS inherently involves large amounts of data that can result from heterogeneous and distributed sources which require analysis before automatically integrating them to the executing applications that need to use the data."

Figure 1 shows a conceptual layout of the problem addressed here. The mobile

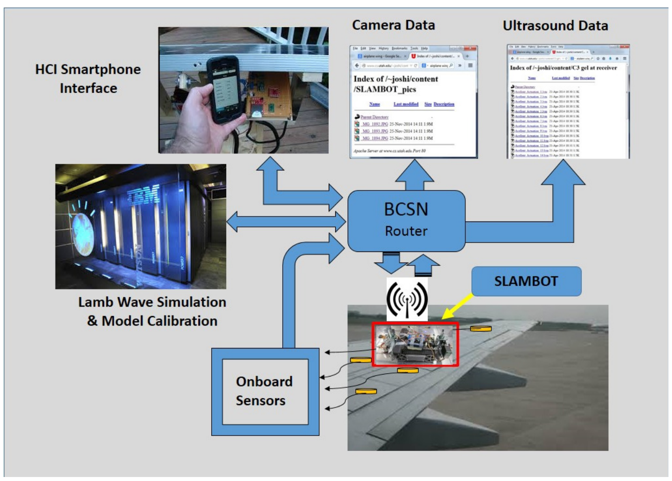

Figure 1: Small-scale Structural Health Monitoring in the Cloud.

robot (SLAMBOT) is placed on the structure to be monitored (here an aircraft wing), and performs its analysis by interacting with storage and computational agents in the cloud. In our work, the interaction is mediated by means of a highly customizable data sharing model which provides low latency between sensing and computational resources (using optimized socket applications), and dynamic routing. The various components include (1) the SLAMBOT, (2) storage capabilities for image and ultrasound data, (3) off-line simulation agents which can dynamically calibrate models and provide optimal sample point locations, and (4) some form of HCI agent (e.g., smartphone app or data analysis center). For another view, see [4].

In the remainder of the paper, we describe the following aspects of the small-scale structural health monitoring system:

1. **Robot Monitoring Agents**: a high-level monitoring agent is developed using the Contract Net approach; this agent is invoked by the human inspector.

It in turn contracts with the SLAMBOT to gather damage location information in terms of a map created during the ultrasound examination of the small-scale structure.

2. **Ultrasound Analysis Model**: An ultrasound range sensor is described which exploits a computational model of Lamb wave propagation through the structure to be monitored.

3. **Cloud Computing Architecture**: the cloud computing architecture allows various agents to efficiently exchange data and information.

4. **Validation Experiment**: a physical experiment using an aluminum plate, and a mobile robot is described which provides bounds on the uncertainty of the operation of the monitoring process.

3. Robot Monitoring Agents

The monitoring task is divided between a virtual agent which manages the monitoring process (the *manager*), and a set of inspection agents (the *contractors*) which are physical robots capable of mapping damage in the structure of interest. In addition, the *manager* may request bids on other aspects of the problem (e.g., computational simulations for model calibration, etc.). This approach has been chosen so as to make the solution more general and applicable to a wide variety of scenarios. For example, in aircraft inspection, we envision a set of SLAMBOT type robots which may be tracked ground vehicles, or quadrotors that are available to provide inspections, but which must be contracted to perform the work. The *Contract Net* protocol [27] is used which follows the following sequence:

- The *manager* agent issues a general broadcast task announcement with an eligibility specification, a task abstract, a bid specification and an expiration time.
- The *contractor* agents bid on tasks they can handle, and provide some information about their capabilities.
- The *manager* agent then awards bids (perhaps multiple).
- The *contractor* agents then proceed with the task and may exchange information with other agents as necessary to complete the task. They also store the acquired data in the cloud so that it is available to other agents involved in the process. Once the task is completed they announce that to the *manager* and submit a final report.

0.0.1 The SLAMBOT

In the current version of the system, we have developed the SLAMBOT [32] (see Figure 2). The SLAMBOT is equipped with a camera for SLAM, and two ultrasound sensors (front and back) for damage analysis in the structure. When taking ultrasound readings, the SLAMBOT lifts itself up on the ultrasound sensors so as to press them firmly against the material surface. The SLAMBOT is built on a *Systronix Trackbot* chassis and is a differential drive robot. The vision, motion, actuation and localization algorithms are implemented on-board by a minicomputer

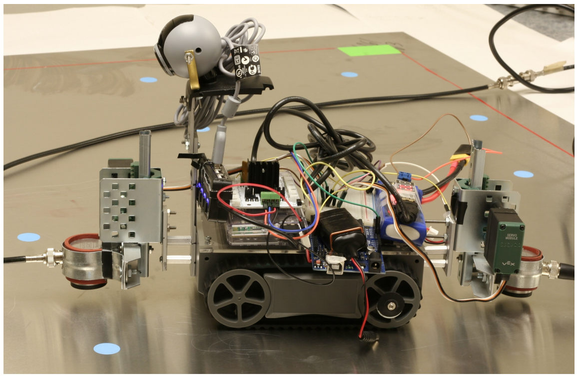

Figure 2: SLAMBOT for Structural Health Monitoring.

(*pcDuino*), which runs a version of the *Ubuntu* operating system and interfaces with the robot's hardware directly. Its wi-fi capability enables it to communicate with the cloud server and other agents as necessary. The SLAMBOT is equipped with a *Logitech C250* webcam for measurement (for locating landmarks and ensuring a collision-free motion on the surface being inspected). The ultrasound sensor carried by the robot is a *VS900-RIC Vallen Systeme* high sensitivity Acoustic Emission (AE) sensor.[2]

0.0.2 SLAM

We have implemented the SLAM algorithm from Thrun et al. [29] with the following modifications. For a landmark located at $[x_L, y_L]^T$, and robot pose $[x, y, \theta]^T$, the sensor returns the landmark's coordinates with respect to the robot frame. The return $z = [u, v]^T$ can be written as a function of $[x, y, \theta, x_L, y_L]^T$ as:

$$z = \begin{bmatrix} u \\ v \end{bmatrix} = h(x, y, \theta, x_L, y_L) = \begin{bmatrix} c\Delta x + s\Delta y \\ -s\Delta x + c\Delta y \end{bmatrix}$$

where $s = \sin\theta$, $c = \cos\theta$, $\Delta x = x_L - x$, and $\Delta y = y_L - y$.

Then the Jacobian of h at $[x, y, \theta, x_L, y_L]^T$ is:

$$\tilde{H}(x, y, \theta, x_L, y_L) = \begin{bmatrix} -c & -s & -s\Delta x + c\Delta y & c & s \\ s & -c & -c\Delta x - s\Delta y & -s & c \end{bmatrix}$$

According to the algorithm, the sensed data is considered to be from a new landmark if the likelihood is low that it is from an existing landmark. Let $\bar{\mu}$ be the mean of the current beliefs. The mean with new landmark locations is $\mu = [\bar{\mu}, x_L, y_L]^T$, where x_L and y_L are the unique values such that $h(\bar{\mu_x}, \bar{\mu_y}, \bar{\mu_\theta}, x_L, y_L) = z$. In our case,

$$\begin{bmatrix} x_L \\ y_L \end{bmatrix} = \begin{bmatrix} \bar{\mu}_x + \bar{c}u - \bar{s}v \\ \bar{\mu}_y + \bar{s}u + \bar{c}v \end{bmatrix}$$

where $\bar{c} = \cos\bar{\mu_\theta}$ and $\bar{s} = \sin\bar{\mu_\theta}$.

[2] From their website: "High sensitivity AE-sensor (wide band) with integral preamplifier (34 dB) and calibration bypass. Optimized for applications requiring sensitivity from 100-900 kHz. Able to drive long cables."

The update of the covariance matrix is more complicated. Since the new landmark was unobserved before, it is natural to extend the current covariance matrix to

$$\bar{\Sigma}_{ex} = \begin{bmatrix} \bar{\Sigma} & \mathbf{0} \\ \mathbf{0} & \gamma I_2 \end{bmatrix}.$$

for some large γ. γ is taken to be in $\Re$ to make computation possible. We use the limit result as $\gamma \to \infty$ later in this subsection.

The Bayesian inference using the Extended Kalman Filter is given as follows. Let Q be the covariance of the sensing noise, and let $F \in \Re^{5\times(3+2(N+1))}$, where N is the number of existing landmarks. All the entries of F are zeros except the upper 3 by 3 and lower 2 by 2 block matrices which are the identity. Let

$$H = \tilde{H}\begin{pmatrix} \bar{\mu}_x \\ \bar{\mu}_y \\ \bar{\mu}_\theta \\ x_L \\ y_L \end{pmatrix} F,$$

$$\Psi = H\bar{\Sigma}_{ex}H^T + Q,$$

$$K = \bar{\Sigma}_{ex}H^T\Psi^{-1}.$$

Then the new covariance is:

$$\Sigma = (I - KH)\bar{\Sigma}_{ex},$$

where in the limit case

$$\Sigma = lim_{\gamma\to\infty}\Sigma(\gamma) = \begin{bmatrix} \bar{\Sigma} & A \\ A^T & B \end{bmatrix}$$

with $A \in \Re^{(3+2N)\times 2}$, $A_{2,i} = \sigma_{i,1} - \Delta y\sigma_{i,3}$, and $A_{i,2} = \sigma_{i,2} + \Delta x\sigma_{i,3}$; $B \in \Re^{2\times 2}$, $B_{1,1} = c^2q_{1,1} - 2csq_{1,2} + s^2q_{2,2} + \sigma_{1,1} + \Delta y^2\sigma_{3,3} - 2\Delta y\sigma_{3,1}$, and $B_{2,2} = s^2q_{1,1} + 2csq_{1,2} + c^2q_{2,2} + \sigma_{2,2} + \Delta x^2\sigma_{3,3} + 2\Delta x\sigma_{3,2}$, and $B_{1,2} = B_{2,1} = c^2q_{1,2} + csq_{1,1} - csq_{2,2} - s^2q_{1,2} + \sigma_{1,2} + \Delta x\sigma_{1,3} - \Delta y\sigma_{2,3} - \Delta x\Delta y\sigma_{3,3}$ where $Q = (q_{i,j})$ and $\bar{\Sigma} = (\sigma_{i,j})$.

4. Ultrasound Range Sensor

Much work has been done on the theory and application of Lamb waves to structural health monitoring (see [1, 2, 3, 5, 6, 7, 9, 10, 11, 12, 13, 17, 18, 19, 21, 22, 30, 33]). We make use of these methods in our work. Given a received signal $f : \Re \to \Re$ and a time interval (t_0, t_1), the range finder estimates the trivial time of maximum energy delivery that is defined by the CWT (Continuous Wavelet Transform) based scaled-average wavelet power (SAP) (see [28], p. 166 for a description of this method) in (t_0, t_1). Define function $peek : C^2(\Re) \times \Re^2 \to \Re$ such that

$$peek(f, t_0, t_1) = \underset{t\in(t_0,t_1)}{\arg\max}\, sap(f)(t).$$

The $peek$ function returns a t such that the SAP of signal f is maximized in (t_0, t_1). Then the range finder is defined by

$$\underset{d\in\Re^+}{\arg\max}\, |peek(f, t_0, t_1) - peak(sig(d), -\infty, \infty)|,$$

where $sig(d)$ is the signal that should be received at distance d away from the actuator in the homogeneous plate. In our simulation, we model the wave propagation by the 2D Helmholtz Equation

$$\Delta u + k^2 u = g,$$

where g is the actuation signal and u is the wave function, and Sommerfeld radiation condition

$$\lim_{|x|\to\infty} \sqrt{|\ x\ |}(n \cdot \nabla u - iku) = 0,$$

uniformly for all $|\ n\ |= 1$. If the actuator is located at x_s and emits a signal g, the solution of u is that

$$u(x_r, t) = \frac{1}{2\pi}\int_{-\infty}^{\infty} d\omega \hat{g}(\omega) G(x_s, x_r, \omega) e^{-i\omega t},$$

$$G(x, y, \omega) = \frac{i}{4} H_0^{(1)}(k|x - y|),$$

where H is the Haenkel function, and k is the wave number that is a function of ω in dispersive materials. For a thin plate, k can be approximated by the Lamb Wave approximation (see [31]). Our sig function is defined as

$$sig(d)(t) = u(x_r, t)$$

for all $|\ x_r - x_s\ |= d$.

Figure 3 shows the ultrasound range sensor principle. An ultrasound signal is transmitted by the emitter, and the receiver gets the directly propagated signal from emitter to receiver, followed by any signals reflected from features in the material (e.g., damage locations, edges, etc.). Thus, the time of arrival of the reflected signal

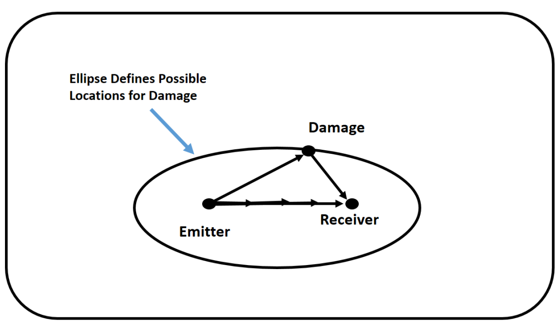

Figure 3: Damage Detection with Ultrasound Network.

allows the calculation of the distance traveled by that signal, and this means that the feature causing the reflection is located somewhere on an ellipse around the emitter-receiver pair.

The following discussion follows our exposition in [16]. Several measurements are needed to get the best location estimate for a feature; these range values are collected by having the robot place the actuator and receiver at different locations, and the location is constrained by the corresponding ellipse. Thus, by using an accumulator array and adding a 'vote' to each location on the ellipse, these six sensed range values allow the determination of the most likely location of the reflecting point (damage in this case). This 'voting' is done with a Gaussian spread which leads to a smooth accumulator surface.

Observed and simulated reflected A0 mode signals with known minimized possible reflection range are shown in Figure 4. There is significant overlap between the directly propagated and simulated reflected signals. This necessitates a method to separate reflected versus directly propagated waves in the observed data. In addition, we would like to isolate the main component of the reflected signal in the data. To achieve this, signals outside a certain reflection range are eliminated. Figure 5

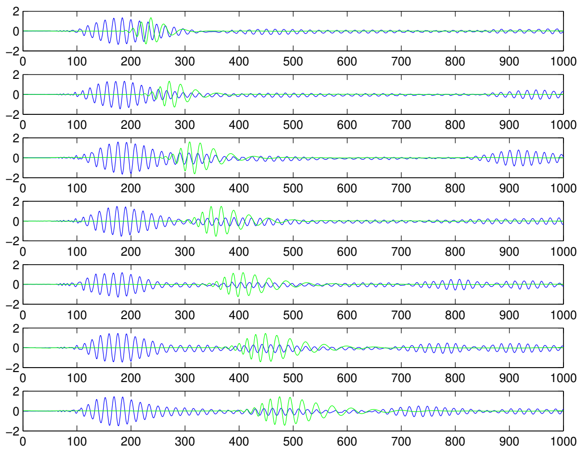

Figure 4: First Step in DSR Sensor comparing Actual Data with Simulated Signal.

shows the windowed signals versus the simulated signals as described above. In this form, the peak amplitude is not clearly identifiable. We therefore compute the CWTbased scaled-average wavelet power (SAP) (see [28] page 166, for a description of this method). The computed SAPs are shown in Figure 6; as can be seen in this figure, the peaks are more clearly discernible.

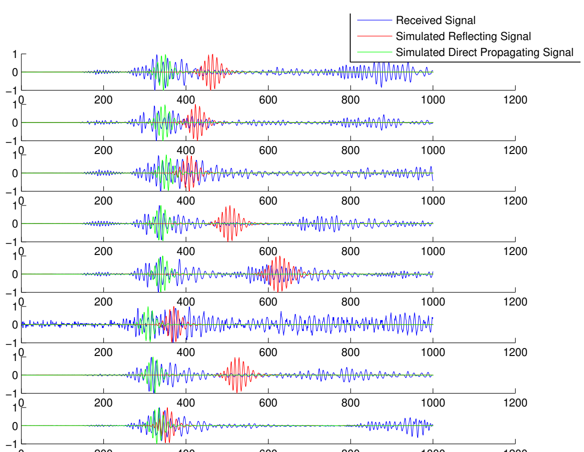

Figure 5: Windowed SAP Signal versus Simulated Signal.

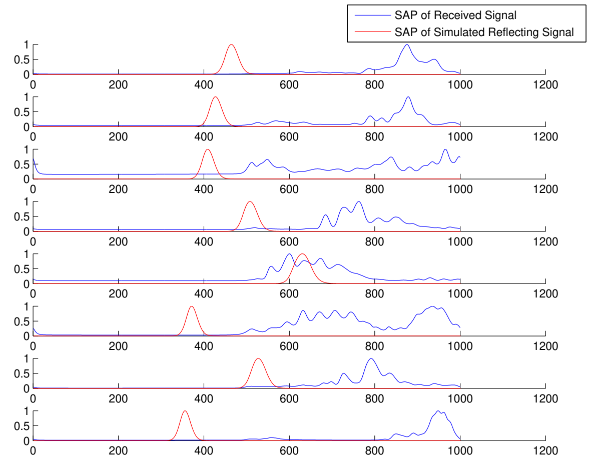

Figure 6: Computer Scaled-Average Wavelet Power (SAPs).

5. Data Routing Model for Distributed Cloud Computing

This is a highly customizable data sharing model between sensing and computing resources. The model enables multiple sensing nodes to open connections with computing resources and retrieve results. The presence of multiple processor and broker nodes nodes reduces the chance of failure. RabbitMQ message broker provides reliable, flexible, highly available and multi-protocol communication system. It also provides the ability to handle multiple protocols and supports message tracing. Figure 7 shows the current implementation layout. As can be seen above, the

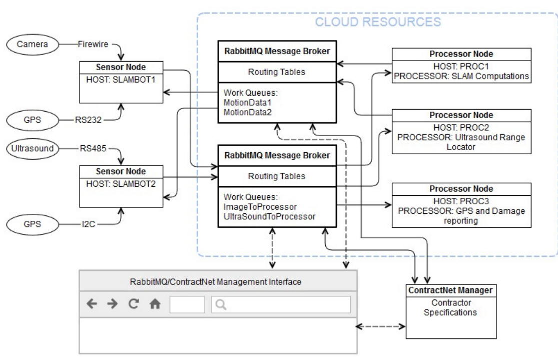

Figure 7: Cloud Component Architecture for Small-scale Health Structure Monitoring.

system gains its advantages from the five main components: (1) sensor nodes, (2) router, and (3) processor nodes. A model as customizable as this enables failsafe and quick communication between resources while providing isolation between sensing and computing resources. The dynamic queuing eases development and scalability.

Sensor Nodes The sensors on the individual devices communicate with network connected sensor nodes which in this case are physical SLAMbots. This communication can be over the preferred sensor protocol. For example, GPS sensors can exchange data over I2C or RS-232(serial) interconnects with the nodes. The sensor nodes are applications running on host devices that have the capability of posting messages onto the rabbitMQ message broker queues. The sensor nodes gather sensor data, serialize it and put them onto the relevant work queues. Thus, they are unaware of the computing resources on the cloud. Any processor capable of handling the work posted on the relevant work queue can pick it up. Also, the node only needs to subscribe to the work queue that is relevant to it.

RabbitMQ Message Brokers This is a highly reliable message broker that has several built in features. This has allowed us to create a fault tolerant, persistent messaging system between processes running on disparate devices. Work queues can be spawned by remote applications dynamically. This allows creation of a highly configurable easy to use messaging system. It contains routing tables contain routing information regarding the available processing and sensing nodes.

ContractNet Manager This agent arbitrates allocation of work awards to sensor node agents that bid on a task. It accepts tasks provided by the user and sets up contracts. It has knowledge of contractor capabilities that it uses in making this decision.

RabbitMQ/ContractNet Management Interface A web interface to a service running on the message broker and contract manager allow us to monitor the messaging activity. This helps in not only debugging the system but also in managing a large environment. This interface allows manually declaring queues, sending and receiving messages and monitor connections.

Processor Nodes This application runs on a remote machine that has a good computing capability. This application generally handles singular responsibilities but can also be used to consolidate data from multiple sensors and take a decision based upon the multiple data points.

6. Validation Experiments

Figure 9 shows the experimental layout for our testing scenario. The aluminum panel is 121.92cm^2, and 1.6 mm thick, the sensors were *VS900-RIC* Vallen transducers, and the excitation signal was a 200 KHz 5 cycle, Hann-windowed waveform. Figure 8 shows a trace of a sample SLAM run; as can be seen, the localization results are good for the robot and for nearby landmarks. However, more distant landmarks are poorly localized due to the failure of the underlying assumptions. We are planning on performing a multi-robot SLAM with another tracked robot on the surface and a quadrotor hovering above the plate. Figure 11 shows the range ellipses derived from ultrasound signals reflected from a large hole. As can be seen, the intersection of the signals localizes the damage in the structure (in this case a hole in an aluminum plate). Figure 10 shows ellipses produced by reflections from the boundary.

7. Conclusions and Future Work

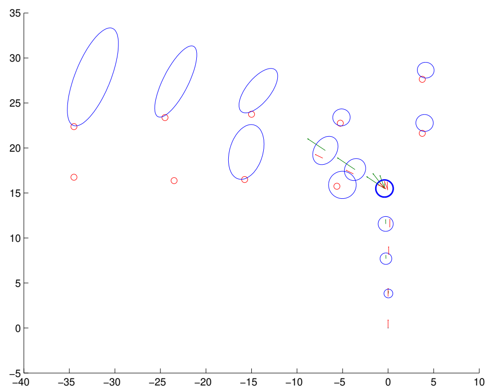

Figure 8: Results from a SLAM Run.

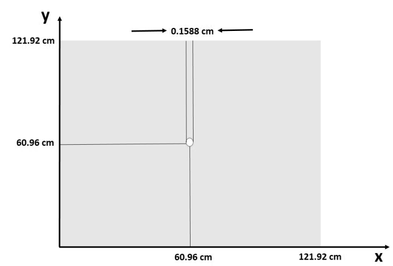

Figure 9: Experimental Layout for Damage Localization using the Lamb Wave Range Sensor in an Aluminum Plate.

We have developed a cloud-based architecture which supports multiple agents working together to provide a structural health monitoring capability on a small-scale structure. This includes not only agents who contract for monitoring service and those that deliver it, but also agents that analyze the data delivered by the monitoring robot (e.g., here this includes both camera and ultrasound data; the Lamb wave based range finder function is performed by an off-line agent in Matlab and that information can be exploited by the mobile robot running Python). The combination of Lamb wave damage analysis with a robot SLAM methodology allows for more autonomous mapping of damage in structures.

We are currently investigating the following aspects of the system:

- More precise mathematical characterization of the uncertainty in the results. While the covariance matrix of the EKF SLAM method gives some insight into the uncertainty, we believe that this can be further constrained by using multiple robots, and a better understanding of the Lamb wave uncertainties.

- The system is being extended to include multiple robots in order to reduce the uncertainty in the the localization results. Moreover, we are looking to use other bases for the SLAM technique itself; e.g., Lamb wave reflection patterns at individual locations (e.g., similar to visual SLAM based on the appearance of the surface), as well as other robots to locate the ultrasound sensors on the surface.

- We also are looking at extending the system to inspecting composite materials.

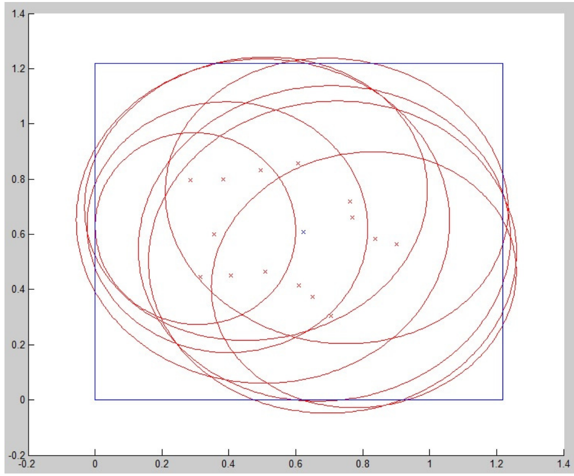

Figure 10: Range Data from the Boundary.

This will be especially important for aircraft monitoring.

8. Summary

The methods presented here are applicable to a wide variety of disciplines and applications. The Computational Sensor Network framework provides not only a means for scientists and engineers to develop systems which self-calibrate their models, but also supports the deployment of autonomous systems which can verify and validate their own computational components and physics models.

Three main DDDAS concepts have been used in this work:

- *advances in mathematics and statistical algorithms:* methods have been developed to exploit Lamb waves in the detection and localization of structural defects, and an uncertainty characterization is provided for the results of the analysis,
- *applications modeling:* an overall cloud computing and storage architecture is provided which enables heterogeneous computational agents to contribute to solving the specific application problem in a coherent way, and
- *application measurement systems and methods:* validation experiments conducted using aluminum plates are presented which involve the detection of defects by a custom mobile robot using onboard ultrasound sensors.

These results demonstrate the feasibility of using Computational Sensor Networks in a wide variety of applications, including structural health monitoring, large-scale outdoor surveying (e.g., open mines), nuclear facility inspection, etc. Moreover, the cloud-based computational framework has been extended and demonstrated in a geospatial analysis system, *BRECCIA*, to support rational decision making based on the fusion of multi-source information (from humans, simulations, sensors, etc.). The goal in this case is to support (1) the use of both discrete logical processes and continuous models, (2) the ability to simulate courses of action that

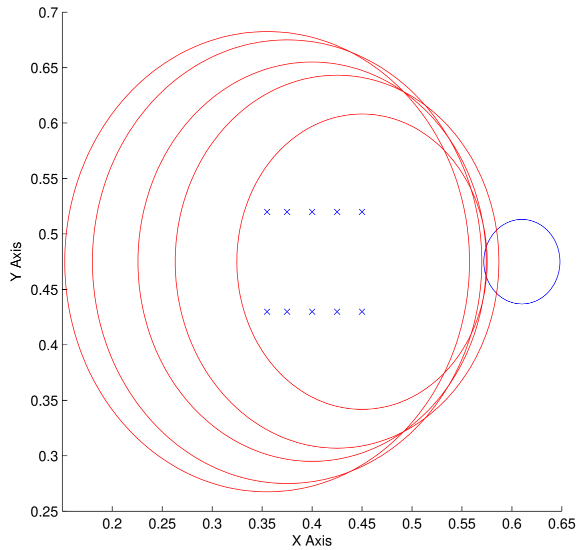

Figure 11: Range Finder Ellipses to Damage (from 5 locations).

take into account real-time data, and (3) the ability to automatically and continuously plan new optimal data acquisition strategies.

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