Task Scheduling in an energy harvesting WSN for Structural Health Monitoring

Project Progress Report

Background:
The process of monitoring structures for the purpose of damage identification is known as structural health monitoring (SHM). Structural health monitoring requires knowledge of the undamaged state of the structure as a means of comparison, as well as continual comparison of periodic measurements. This can be separated into two basic categories: rapid event assessment and periodic lifetime monitoring. While rapid event assessment or External Request addresses the need to obtain data from a structure immediately following a significant event (such as an earthquake); periodic lifetime monitoring or steady state operation seeks to identify damage that accumulates over long periods of time.

The SHM is an excellent sample application for an energy harvesting wireless sensor network (WSN). The adoption of wireless sensor networks in advanced Structural health monitoring (SHM) systems has proliferated in the last few decades due to their ability to operate reliably without human intervention in inaccessible areas. This has been made possible by the usage of wireless communication and environmental energy harvesters (EH). However, adopting an EH as the main energy supply limits the device's level of activity to the availability of energy in the environment. The most common energy source suited to outdoor SHM applications is solar energy, which is often inconsistent in its availability.

A significant challenge in this type of system is the management and conservation of energy while maintaining the minimum level of QoS required by the particular deployment. The embedded SHM system must consume only as much energy as the energy harvester can collect from the environment. Therefore, the task scheduler must ensure that task allocation is matched to the available energy.

Project Contribution:
In this project, we proposed a task scheduler for SHM applications designed to maximize both the number and the accuracy of SHM measurements on the energy harvested wireless embedded device. The proposed scheduler uses a Linear Regression based algorithm along with DVFS to adjust system workload and energy consumption to both available environment energy and desired SHM measurements QoS.

Approach:
For this project, we develop a linear regression based algorithm that relates the energy consumption, execution time and data accuracy to the number of tasks and their complexity. This model is then used to maximize the system performance with the constraint of energy availability. By using a linear regression based model, we utilize all the available energy to improve the task accuracy and number of measurements performed. We also incorporate a Dynamic Frequency and Voltage Scaling (DVFS) methodology to increase the efficiency of system energy utilization.

The embedded node used to perform SHM is called SHiMmer. SHiMmer is a wireless platform that combines active sensing and localized processing with energy harvesting to provide long-lived structural health monitoring. SHiMmer uses piezoelectric transducers (PZTs) to evaluate a portion of a structure to determine if damage exists. Unlike other sensor networks that periodically monitor a structure and route information to a base station, our device acquires data and processes it locally before communicating with an external device, such as a remote controlled helicopter.
Progress:
The work done so far has been primarily in SHM task graph development; and some part in task scheduler implementation. These have been described in the following sections:

SHM Task Graph:

SHiMmer is a standalone embedded system designed for active structural health monitoring. The implemented active SHM consist in analyzing a structure through the application of ultrasonic waves and the acquisition of the wave propagation response of the structure. Collecting information about wave propagation allows detecting and localizing structural damages.

SHiMmer platform comprises three boards: a digital board based on an ADI BlackFin DSP for data analysis and wireless networking, running a custom Linux-based OS; an analog board that manages 16 independent channels and generates high-voltage active SHM pulse for the lead-zirconate-titanate (PZT) sensors; and a power manager board that collects energy from a solar energy harvester, stores the energy into a Supercapacitor, generates the required power supply rails and manages a Li-Ion battery acting as back-up energy reservoir.

SHiMmer allows performing ultrasonic SHM analysis stimulating the structure with high-voltage pulses applied through 16 independent PZT sensors. The main advantage of active SHM measurement is the flexibility to adjust the stimulation process to the particular structure conditions.

SHiMmer implements the active SHM measurement following two procedures, Actuation and Sensing, which are performed recursively over all the possible pairs of PZT sensors. During the Actuation, the adopted SHM pulses are custom generated by the DSP, amplified by the analog board up to 30 V_{pp}, and transmitted to the structure selecting 1 of the 16 PZT sensors.

During the Sense, the structure response is selectively collected through each of the remaining 15 sensors, filtered through an anti-aliasing block, amplified by the analog board up to ±1V, and acquired by the digital board up to 25 MSPS. Due to the high-voltage amplification and high sampling-rate acquisition, Actuation and Sense procedures are high energy consuming activities, representing a significant and irreducible part of the overall SHiMmer power requirement.

SHM data analysis consists of three main steps: reducing the correlated and uncorrelated noises from the SHM signal, extracting the amplitude and frequency information of the measurements, and finally correlating the data provided by the selected set of PZT sensors to detect the presence of damage in the structure. Figure 1 shows the list of tasks involved in the SHM analysis and the accuracy provided by each set of tasks.

The first set of task that is performed is Actuation and Sensing, which consists of the iterative measurement with ultrasonic waveform through all the combinations provided by the 16 PZT sensors. The next stages of tasks are responsible for reducing the noise during measurement. These are averaging and filtering. The former reduces the uncorrelated noise by calculating the average over multiple sequences of samples in each path. The latter filters the signal in the frequency domain by means of a FFT computation of the acquired SHM response and subsequently eliminating the unwanted frequency components, which correspond to noise.

The amplitude and frequency are obtained from a SHM response by convolving the filtered set of data with a set of reference SHM responses, called baseline signals. This task is called feature extraction. To detect the presence of damage in the structure, all the SHM data is combined using a damage correlation function, thereby obtaining a map showing the current structure health.

The selection of the ADI BlackFin represents the optimum trade-off between high-performance and low-power characteristics. The former is due to a very efficient design of the core targeted to high speed complex data analysis; the latter is due to the native dynamic voltage
and frequency scaling (DVFS) algorithm, which allows reducing both the core voltage and frequency.

Based on the DVFS capability, the system has been designed to select one of three different working modes: Active High, \( f_1 \), where the core is running at 1.2V@300MHz, Active Low, \( f_2 \), where the core runs at 0.85V@150MHz, and a low-power idle mode where the core is set at 0.85V@75MHz, thereby reducing the system power consumption to 50mW. The reduction of BlackFin core voltage and frequency between the two active modes, allows savings of 30\% in the energy consumption.

Table I shows the comparison of energy consumption and computational time of the BlackFin core performing a basic operation of sum and multiplication under the two active modes. The adoption of DVFS and the two active modes, High – \( f_1 \) and Low – \( f_2 \), will be described in detail later on.

<table>
<thead>
<tr>
<th>DVFS mode</th>
<th>Sum (Integer value)</th>
<th>Multiply (Integer value)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( E_{EX} ) [nJ]</td>
<td>( T_{EX} ) [( \mu )s]</td>
</tr>
<tr>
<td>Active High</td>
<td>274</td>
<td>0.751</td>
</tr>
<tr>
<td>Active Low</td>
<td>192</td>
<td>0.932</td>
</tr>
</tbody>
</table>

Figure 1. The Structural Health Monitoring task graph shows the relation between the tasks and the accuracy of each path, \( n \), for all steps of analysis.
Task Scheduler Implementation:

The primary goal of the proposed task scheduler is to maximize the accuracy and number of SHM measurements with respect to the energy consumption and the execution time constraints. In particular, since each measurement has several tasks to be executed, maximizing accuracy and number of SHM measurements consists of performing the maximum number of tasks accordingly to system constraints.

The proposed scheduler maximizes the system performance adopting a set of linear regressions that relate the energy consumption, the execution time and the data accuracy. Indeed, SHiMmer prototype behavior has shown that SHM algorithms’ energy consumption, execution time and accuracy are linearly dependent on the amount of analyzed data provided by the set of executed tasks. For this reason, adopted linear regression allows the scheduler to adjust number of task and their complexity to the available energy. Furthermore, in order to improve the efficiency of the energy utilization the proposed task scheduling algorithms uses the DVFS policy provided by the DSP to optimize both the system computation capability and energy consumption.

The task scheduler algorithms manage the allocation of sequences of tasks according to the amount of available energy. At each time interval, the scheduler determines the energy available in the system buffer by tracking the energy collected by the EH as well as the energy consumed by system activities, as expressed by (1).

\[ E_{Buffer}|_t = E_{Buffer}|_{t-1} + E_{EH}|_t - E_{Consumed}|_t \]  

(1)

where \( E_{Consumed} \) is calculated at run time by the task scheduler, and \( E_{EH} \) refers to the amount of energy collected by the energy harvester during the time elapsed since last time interval. \( E_{EH} \) takes into account the efficiency of the photovoltaic panels and the leakage of the systems, as shown in (2).

\[ E_{EH}|_t = E_{PV\ panel}|_t \cdot \eta_{system} - E_{Leakage}|_t \]  

(2)

where \( E_{PV\ panel} \) is the energy provided by the photovoltaic panel, \( \eta_{system} \) is the efficiency of the power supply sub-system and \( E_{Leakage} \) is the sum of the energy leakage of the system, e.g. the supercapacitor self-discharge rate.

The proposed task scheduler algorithm exploits the linear regression model and the DVFS functionality in both the Steady State and the External Request operations.

Future Work:

Some portion of the task scheduler for the steady state mode is complete, but testing of results is underway. If the results are found to be satisfactory, the task scheduler will be extended to handle external request mode as well.

We hope to complete this remainder work by the end of this quarter.