Using Gradient Descent to Optimize Paths for Sustaining Wireless Sensor Networks

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***Abstract*** — **A structural-health wireless sensor network (WSN) should last for decades, but traditional disposable batteries cannot sustain such a network. Energy is the major impediment to sustainability of WSNs. Most energy is consumed by (i) wireless transmissions of perceived data, and (ii) long-distance multi-hop transmissions from the source sensors to the sink. This paper explores how to exploit emerging wireless power transfer technology together with robot control of unmanned vehicles (UVs) to simultaneously select sensors to recharge, cut transmissions from long to short-distances, collect sensed information, and replenish WSN’s energy. Different from prior work focusing solely on energy replenishment, the proposed research will replenish sensors’ energy, significantly reduce WSN’s energy consumption, and efficiently deliver sensor data to the sink. This paper focuses on fundamental challenges associated with sustainable WSN development by jointly using wireless power transfer technology and controlling UVs. Energy costs due to power transmission are less than the UV’s transportation costs. This is true for WSNs spread over large geographic areas, terrain with obstacles, or where transportation costs are high, such as subsea or aerial UVs. This task focuses on algorithms that make such WSNs sustainable by focusing on path-planning, trajectory optimization, and responding to dynamic network conditions.**

### *Index Terms* — Ceramics, coaxial resonators, delay filters, delay-lines, power amplifiers.(need to write)

### I. Introduction

New wireless sensor technologies have enabled wireless sensor networks (WSNs) to proliferate in many different fields (e.g., battlefield surveillance, environmental sensing and biomedical observation) [[1]](#_References), [[16]](#_References), [[18]](#_References), [[31]](#_References). Although advances in processing and computing designs can endow sensors with a multitude of sensing modalities (temperature, pressure, light, magnetometer, infrared, etc.), the crawling development of battery technology imposes harsh energy constraints on battery-powered sensors and the sustainable working of WSNs. In WSNs, the majority of energy is consumed by (i) wireless transmission of perceived data [[17]](#_References), [[30]](#_References), [[31]](#_References), and (ii) long-distance multi-hop transmissions from source sensors to the sink. Research efforts to address WSN energy concerns have focused on energy conservation [[7]](#_References), environmental energy harvesting [[14]](#_References), [[28]](#_References) and incremental sensor deployment [[38]](#_References). However, energy conservation schemes only slow energy consumption, not compensate energy depletion. Harvesting environmental energy, such as solar, wind and vibration, is subject to their availability, and is often uncontrollable. Incremental sensor deployment makes WSNs neither sustainable nor environmentally friendly, since most disposable sensors’ batteries contain cadmium, lead, mercury, copper, zinc, manganese, lithium, or potassium [[12]](#_References). These heavy metals “can leach into soil and water, polluting lakes and streams, making them unfit for drinking, swimming, fishing, and supporting wildlife, and even posing hazards to human health” [[11]](#_References). It is more necessary now than ever before to design a sustainable WSN, one transparent to human and wildlife’s activities, friendly to the environment, and economically advantageous without repeated deployment.

Fortunately, recent breakthroughs in the area of wireless power transfer technologies (e.g. inductive coupling, magnetic resonant, and RF energy harvesting) [[23]](#_References) provide promising alternatives for deploying such WSNs. Magnetic resonant wireless power transfer [[23]](#_References) has the ability to wirelessly transfer electric power from the energy storage device to the receiving device efficiently within medium range (e.g., 40% within 2 meters). It is also insensitive to the neighboring environment and does not require a line of sight between the charging and receiving devices. Researchers proposed that a mobile unmanned vehicle (UV) carrying a wireless charging device could visit and recharge each sensor to sustain a WSN [[36].](#_References)

However, one UV may not be able to visit every sensor if the WSN is deployed in harsh environments/terrains (e.g. dense forest, mountains, underwater), or the WSN is large-scale, consisting of a great number of sensors. Although these seminal studies replenished sensor energy, most of the energy was still wasted by long-distance wireless transmissions of perceived data, especially by relaying sensors. Due to charging and travel time of the UV, some bottleneck sensors may drain their residual energy while waiting for the UV. Great unsolved challenges on control remain, including how to select the optimal path for the UV to travel within WSNs and how to efficiently dispatch multiple UVs to recharge WSNs.

The previous thrusts assumed that energy costs due to power transmission greatly exceed the UV’s transportation costs. This assumption might not fit for WSNs spread over large geographic areas, or terrain with obstacles, of where transportation costs are high, such as subsea or aerial UVs. This thrust focuses on algorithms that make such WSN sustainable by focusing on path-planning, trajectory optimization, and responding to dynamic network conditions.

### II. Related Work

The path-planning problem for UVs has been investigated from several angles. To minimize path length, the authors in [[6]](#_References) survey the multiple-Traveling Salesman Problem, itself

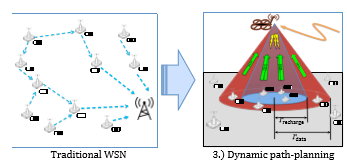


Fig. 1: Evolution from traditional wireless sensor networks (WSNs) to servicing WSN with UV(s). We present techniques that uses unmanned vehicles (UVs) to gather aggregated data and recharge sensors using one or more vehicles, and design energy-optimal control policies for the UVs.

a generalization of the vehicle routing problem [[13]](#_References). Servicing a WSN is closely related to coverage problems, recent work includes methods for optimizing speed along given routes [[32]](#_References), and techniques to continually improve existing routes [[33]](#_References). Using unmanned aerial vehicles to recharge other robots or sensor nodes has focused on physical design, which includes direct contact, such as swapping batteries [[34]](#_References), [[35]](#_References) or direct recharge [[27]](#_References), wireless resonant coupling [[15]](#_References), [[19]](#_References), [[20]](#_References), and electromagnetic radiation [[37]](#_References), and algorithmic improvements using graph theory [[26]](#_References), linear programming [[32],](#_References) and gradient descent optimization [[33]](#_References).

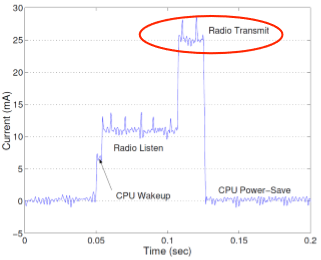


Fig. 2: Power usage in a wireless sensor node is dominated by transmission costs and listening costs. Figure modiﬁed from [26].

### III. Over View

The previous tasks use optimization/matching theory to assign one UV/multiple UVs to WSN nodes, and use a Hamiltonian cycle to visit each node. This is reasonable if recharging nodes is the largest component of a UV’s energy budget: If this assumption is violated, path-planning becomes the key concern. A simpliﬁed form of this decision could be written as.

Here represents the tipping point, the variable where the decision problem becomes fundamentally different. If is small, path-planning is inconsequential, and almost any solver is sufﬁcient. However, when is large, path-planning becomes the key consideration. This task’s goal is to explore tipping points in DARE-U. We will focus on three classes of tipping points: ravel vs. recharging (III-A), local density of WSN nodes (III-A), static vs. dynamic loading (III-C). The following subtasks delineate when each indicates a required change in algorithm, investigate a speciﬁc swarm robotics technique for each, and implement solutions. Together these techniques will increase sustainability of WSNs. Solutions for these subtasks will be veriﬁed using the quadcopter testbed described in III-C1.

*A. Travel vs. Recharging: mTSP for path-planning*

Given a list of cities to visit, the classic traveling salesman problem (TSP) attempts to ﬁnd an ordering of the cities that minimizes the total distance on a tour that visits all the cities once [[2]](#_References). The solution is the shortest Hamilton cycle. By labeling our nodes as cities, the solution to the traveling salesman problem gives the shortest length path. This problem is NP-hard, but many powerful heuristics are available, and software packages can provide answers for tens of thousands of nodes (e.g., the Concorde TSP Solver [[3]](#_References)). UVs have a limited energy budget. As the number of nodes grows, more UVs are needed. One solution is to require all UVs to return to the sink to recharge and return data. This formulation is called the multiple-Traveling Salesman Problem (mTSP) [[6]](#_References), but does not try to balance the workload between UVs. A good heuristic can increase TSP solver performance. In our preliminary numerical simulations, priming an open source genetic algorithm solver [[22]](#_References) by sorting the nodes by angle from the sink and dividing the sorted list equally between the UVs decreased path costs by 20%. Figure 3 shows results with 100 nodes and 5 UVs. We will take solutions from task 1, solve for the exact TSP solution, and compare energy costs as a function of. We will repeat this process using solutions for multiple UVs in task 2, using optimization techniques to ﬁnd approximate solutions for the mTSP problem, comparing as a function of. Results will quantify advantages of route planning, and enable more sustainable operation of DARE-U.

*B. Using local density to optimize path speed*

Data aggregation and recharging shares similarities with persistent robotic tasks, such as cleaning, mowing, observing, and patrolling [[4]](#_References), [[8]–[10]](#_References), [[21]](#_References), [[25]](#_References), [[32]](#_References), [[33]](#_References). A key tipping point in these problems is if a UV can service multiple clients simultaneously. A UV has an associated recharging footprint and a data-transfer footprint, which can often be modeled as disks of radius and , as illustrated in Fig. 4. We represent the fraction of sensors that are clustered as .

In general, energy-efﬁcient recharging requires closer proximity than data transmission, so this implies there are two tipping points related to node density, , and . Correspondingly, the DARE problem has three regimes with differing solutions. Before the tipping points, nodes are sparse and not clustered. In this regime optimal paths are straight lines from node to node, and the optimal solution is a variant of the traveling salesman problem.

As sensors get closer together, the optimal path may be to take paths between one or more sensors. In Fig. 4, path B is designed to transfer data from all nodes, and

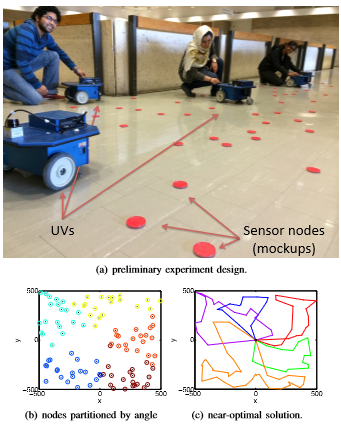


Fig. 3: Using our motion tracking system, we can abstract the problem of localizing our sensor nodes and focus on implementing path planning algorithms. (Right) screenshots from a mTSP solver aided by our heuristic.

the optimal solution is often to weave between clusters of nodes. The third regime is when many nodes are close enough for recharging.

Our eventual goal is to design full trajectories that optimize the path of each UV, by servicing multiple nodes simultaneously. However, even just the path-planning component is NPhard [[4]](#_References). To make progress, we will decouple the problem and optimize the speed of UVs along prescribed paths to service multiple clients when sensors are dense or clustered. This approach is reasonable for ground-based mobile UVs that are constrained to roads or trails, and aerial UVs constrained to air corridors. We will augment existing solvers [[32]](#_References) to account for battery levels of the nodes and UV. We will pose this as an LP, and share code on Matlab central. Solutions will be compared to results using matching algorithms in task 2.

*C. Static vs. dynamic loading: gradient descent on path planning*

The above algorithms assumed a static WSN, but often sensor data transmission is dependent on transient phenomena. For example, a swarm of subsea sensors may track a school of ﬁsh, the progress of an oil slick, or seasonal drift of ocean currents. These are time-varying phenomena, and so the UV servicing the sensors should be able to adapt. For this subtask we will design local

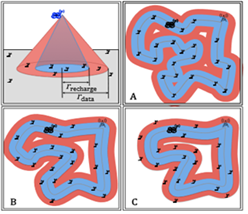


Fig. 4: A UV has an associated recharging footprint and a data transfer footprint, which can often be modeled as disks of radius and,. Path A visits each node, but path B is shorter because it is designed merely to recharge all nodes. Path C is the least tortuous because it is designed to transfer data from all nodes, and >. We will design speed controllers to service multiple clients when sensors are dense or clustered.

optimization techniques to iteratively adapt the paths of UVs. A schematic of our adaptive control law is shown in Fig. 5. Recent research has focused on local optimization techniques that gradually improve the paths followed by robots during persistent tasks [[33]](#_References). These techniques are amenable to DAREU. The base technique is a variant of Lloyd’s algorithm [[5]](#_References), [[24]](#_References). Each path is represented by a ﬁnite number of waypoints, and these waypoints are both attracted to the centroid of all sensor nodes within their Voronoi cell, and attracted to their neighboring waypoints. We will use both battery levels and the cost of transmitting data to weight the sensor nodes. We will also compare improvements using Newton’s method [[29]](#_References).

*1) Hardware implementations*

Hardware implementations generate conﬁdence in solutions, often uncover assumptions in our theory, and are excellent for teaching. Our initial implementations will use an existing ﬂeet of eight industrial mobile robot bases (ERA), shown in Fig. 3(a). These robots are ideal for demonstrating

Figure-5

DARE because they are simple, have a long battery life, and are highly expandable. Each robot ﬁts within a 40cm cube, and can be accurately tracked with our OptiTrack motion capture system, allowing us to quickly focus on the algorithms. However, these dependable platforms are constrained to 2D movement, lack the outreach pizzazz inherent to quadcopters, and have limited range and speed. This proposal requests funding for a team of quadcopters. PI Becker has experience building a quadcopter lab at UIUC, and these vehicles will compliment his lab facilities, shown in Fig.6. Senior design teams have expressed an interest in programming teams of quadcopters, so this will engage undergraduate minority scholars in research and encourage them to pursue graduate education. In addition, quadcopter demonstrations of DARE will be an effective outreach tool for K-12 visits. Anyone who has witnessed the enthusiasm of K-5th graders at a circus plate-spinning demonstration (http://youtu.be/Zhoos1oY404), will appreciate the beneﬁt of a ‘keep-alive’ experiment where quadcopters sustain a network of sensors. We will have two modes so that students can manually challenge our algorithms, and witness the beauty and importance of STEM. Gamiﬁcation is effective for engaging underrepresented groups in STEM, so we will add a module on DARE to SwarmControl.net that replicates the ‘keep-alive’ demonstration.

### IV. A

Algorithm: IC (Interesting Closed) path controller for the waypoint in robot r’s path in a known environment.

Require: Ability to calculate Voronoi partition

Require: Knowledge of its two neighboring waypoints

And

1: loop

2: Compute the waypoint’s Voronoi partition

3: Compute according to (3)

4: Obtain neighbor waypoint locations and

5: Compute according to (6)

6: Update according to (5)

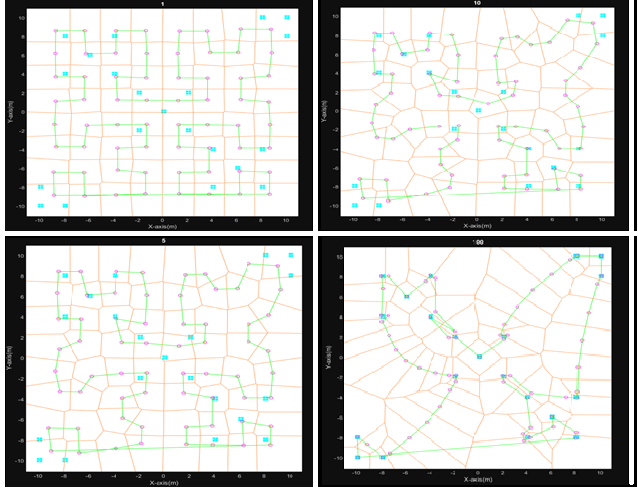
7: end loop [[33]](#_References)

It is important to have an initial path that fills the map so that the robots can identify all the sensory regions, which helps in forming an optimal path. A space filling algorithm needs to be implemented to fill the map. We adapt Hilbert Curve, which fills up the space and serves as an initial path for the first iteration. [[39]](#_References)

V. Simulation Results

*A. One UV*

A single UV system was simulated using MATLAB. The initial path was set to be a space filling Hilbert curve. This is done so that the robot has access to the whole map and identifies all the interesting points. As the simulation progresses the waypoints act according to the above proposed algorithm and adapt themselves to the given sensor information. As the number of iterations increases the path stabilizes and reaches an optimum value. This is observed in the graphs presented below.



*B. Multiple UVs*

A two UV system was simulated on MATLAB. As you can see they service different sets of nodes in the WSN. A multi UV system is apt in a practical sense since a single UV might not be able to handle a large network. A waypoint at 0,0 is stationary, it acts as a sink for the UVs. The UV understands its position on the map and attempts to service the sensor nodes with in its range. The initial path plays a major role in deciding the service strategy.

VI.Conclusion

An optimized path-planning algorithm was simulated to service a WSN. The path constructed is adaptive to the sensor node locations. In the future we would like to extend our simulation where sensor nodes are not stationary. We are in the process of implementing the algorithm on Mobile –robots. As we progress we would like to extend our implementations to a set of quadcopters and improving our algorithm.

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