ANALYSIS, OPTIMIZATION, AND IMPLEMENTATION OF A UAV-BASED WIRELESS POWER TRANSFER SYSTEM

Andrew Mittleider
University of Nebraska-Lincoln, amittleider@gmail.com

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ANALYSIS, OPTIMIZATION, AND IMPLEMENTATION OF A UAV-BASED WIRELESS POWER TRANSFER SYSTEM

by

Andrew Mittleider

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ANALYSIS, OPTIMIZATION, AND IMPLEMENTATION OF A UAV-BASED WIRELESS POWER TRANSFER SYSTEM

Andrew Mittleider, M.S.
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Adviser: Carrick Detweiler and Sebastian Elbaum

Wireless power transfer is rapidly advancing in its ability to efficiently transfer power to a variety of devices. As the efficiency increases, more applications for these systems arise. Since magnetic resonant wireless power transfer can only transfer a small amount of power, most current applications only focus on powering low-powered devices. Wireless Sensor Networks are composed of many low-powered nodes which currently require human interaction to remain powered. We propose recharging a low-powered Wireless Sensor Network (WSN) with a magnetic resonant wireless power transfer system attached to a quadrotor Unmanned Aerial Vehicle (UAV).

This thesis addresses three main challenges with this method of powering a WSN. First, quadrotor UAVs are small and have limited payload capacities. Since a larger power transfer system generally results in better power transfer range and efficiency, we optimize the parameters of a wireless power transfer system for the small UAV. We show that, compared to our previous work, the power transfer coils' quality factor can be nearly doubled while retaining the same mass. Second, the UAV needs very precise control to transfer power to a small WSN node. We use a the sensed magnetic field from the Wireless Power Transfer system coupled with a simulated optical flow system to show that we can localize to within 21 cm to transfer 3.38 W to the sensor node. Last, the UAV has significant power limits of its own. We show that by optimizing the speed of travel and optimizing the mass of the UAV’s battery, we can
increase the range of the UAV from 3 $km$ in the worst case to 9.3 $km$ in the optimal case.
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Chapter 1

Introduction

Wireless sensor networks (WSNs) are used in a wide range of applications from large scale terrestrial habitat monitoring [1] to underground [2, 3] and underwater [4, 5] systems because of their ability to gather data from a multitude of sensors with high frequency over long periods of time. Their ability to monitor these locations over long periods of time is significantly advancing science. Powering these sensor networks, however, remains a challenge despite advances in energy efficient WSNs and battery technology. Current systems deployed for long periods either require additional infrastructure (e.g. power cables or solar panels) or periodic maintenance to replace batteries. One approach to this problem is to use a micro unmanned aerial vehicle (UAV) to recharge the network. This thesis shows that we are able to recharge a single WSN node using a UAV equipped with a wireless power transfer system.

Fig. 1.1 shows a motivating example for the proposed system where a number of WSN nodes are deployed along the bottom of a bridge. These nodes would be used to monitor the health of the bridges to avoid collapses, such as the recent collapses of the Minneapolis I-35 bridge in 2007 [6] and the California Bay Bridge in 2009 [7]. Installing the cabling and communication infrastructure required to support
this monitoring would be costly. Instead we propose using a UAV to wirelessly charge the nodes while also collecting data from the network. Wireless charging from a UAV is safer than contact-based charging since the UAV does not need to risk damaging the WSN node if the UAV control signals become noisy. In addition, the node could be embedded in the concrete or other materials during construction since resonant magnetic wireless power transfer works through many materials [8].

Recent work has demonstrated that the advances in wireless power transfer technology and low powered devices make such a proposed system feasible. Recently, medium range resonant wireless power transfer has received more attention due to the increase in popularity and availability of battery-powered, hand held electronics that need regular charging [9]. Researchers have also shown wireless power systems that can transfer significant power over medium distances. For instance, Kurs et al. transferred 60 Watts over 2 meters with 60% efficiency to power a light bulb [10]. More importantly, in prior work lead by Griffin et al. from the NIMBUS lab, they developed a resonant wireless power transfer system and proposed using a UAV to charge WSN nodes in hard to access locations [11, 12].

Furthermore, researchers have shown in simulation that automated recharging of the network has a significant impact on the lifetime of the network. Leng [13], from
the NIMBUS Lab, has shown that for small networks (tens of sensor nodes), a small quadrotor UAV can increase the lifetime of the network by up to 50% using just one flight out to the network. He also showed that if the UAV is able to make multiple flights out to the network, the UAV can keep the network powered indefinitely. This work is especially influential because the simulation is performed with real-world parameters for the UAV platform and power transfer system discussed in this thesis.

These advances have motivated our development of a UAV-based power transfer system that can charge remote sensors, but there are still a number of problems associated with charging sensors from a UAV. Existing wireless power transfer systems typically focus on creating lightweight receivers to embed in electronics but little focus has been placed on minimizing the weight of the transmitter. Many of these transmitters and receivers are much too large to attach onto a micro UAV. For example, Culberson and Jorgensen [14] built transmitters and receivers using 60 ft of 1/4 in copper tubing. At an estimated 4.5 kg, this system is much too big to attach to any commercial quadrotor currently available. Sensor networks can cover a large area, but micro-UAVs have quite limited flight times so it is critical to minimize payloads and optimize the flights to maximize range. In addition, GPS has relatively poor positional accuracy, but wireless power transfer requires precise control in order to efficiently transfer power. Since we cannot rely on GPS alone to maintain the closer distances, we must implement alternative localization methods.

## 1.1 Contributions

In this thesis we address the challenges associated with using a UAV-based wireless power transfer system to charge sensor nodes. Specifically, we:

- Develop and characterize a lightweight wireless power transmission and recep-
tion system that enables charging of a sensor node from a UAV (Chapter 4). We also optimize the parameters of the power transfer transmission coils to minimize payload but maximize power transfer (Chapter 3.2).

- Develop a relative localization algorithm that precisely aligns the UAV and the WSN node by measuring the magnetic field emitted by the wireless power transfer system and measuring the velocity of the UAV through optical flow (Chapter 6).

- Analyze and optimize the UAV’s flight speed and battery size to maximize the flight range in order to charge as many WSN nodes as possible (Chapter 7).

First, we mount a wireless power transfer system onto a UAV which can transfer up to 6.1 W of energy to a receiver node. The receiver node is a small, 8 cm diameter coil, which can be fitted onto many different types of small sensor network nodes. The power transfer system consists of a transmission circuit to drive the power transfer system, and a receiver circuit to receive the power that is being transmitted wirelessly.

Second, we examine the complex relationships between the variables in the wireless power transfer coils. Since larger, heavier coils can provide higher power transfer rates, we examine the power transfer capabilities and mass of the coils, keeping in mind the strict weight requirements of the small quadrotor UAV.

Third, we develop two localization strategies that allow the UAV to find the WSN node and get close enough to transfer power. These localization strategies are necessary because GPS lacks the accuracy needed to control the UAV to allow it to transfer significant power to the WSN node.

Last, we characterize the UAV flight dynamics and battery mass in order to maximize the amount of distance that the UAV can cover. This allows the UAV to charge
as many nodes in the sensor network as possible by minimizing the amount of energy necessary for flight.

This thesis begins by discussing the work related to wireless power transfer, UAV flight energy optimization, localization, and sensor network charging approaches. Chapter 3 gives background information regarding magnetic resonant power transfer and quadrotor dynamics. Chapter 4 discusses the components of the system in detail. This includes the UAV platform, the UAV power transfer system, and the wireless power receiver sensor node. We also introduce and characterize a magnetic resonant (MR) sensor, which is an essential component for the localization methods. In chapter 5 we examine the relationship between the power transfer coil mass and the coil’s ability to transfer power, which allows us to create efficient wireless power transfer coils despite the UAV’s strict weight requirements.

While the coils are optimized for a UAV, GPS is still not accurate enough to position the UAV within power transfer range. Chapter 6 addresses this issue and shows how the UAV can localize over a WSN node by estimating its velocity and measuring the magnetic field strength from the wireless power transfer system. We propose two localization schemes which allow for higher precision control than is available with GPS. In the first method (Chapter 6.3), we combine information from a single MR sensor with an estimation of the UAV’s velocity. In the second method (Chapter 6.4), we use four MR sensors, which measure the magnetic field emitted by the UAV, to estimate the position of the UAV.

Chapter 5 optimizes the power transfer system and Chapter 6 allows the UAV to get close to the WSN node, however, the UAV has a limited power supply of its own, and a wireless sensor network may cover a large area of land. Therefore, Chapter 7 addresses the limited power of the UAV. Vertical take off and landing UAVs such as helicopters or quadrotors generally have flight times between 10 and 20 minutes.
In order to charge an entire network of nodes, the UAV must be able to cover the distance efficiently. We examine the theoretical foundation of the UAV dynamics and evaluate our system empirically to achieve up to a 56% improvement in the UAVs capable range. With these modifications, the UAV spends much less energy on travel to allow it to transfer more energy to the WSN.
Chapter 2

Literature Review

Charging a wireless sensor network node with a UAV has a variety of challenges that must be addressed. This section discusses related work that attempt to overcome similar challenges. The literature review begins by discussing work in wireless power transfer technologies. Then, we discuss many different methods of localization and relate it to our own techniques. We also give background on work related to our analysis of the optimal flight speeds of quadrotors. Lastly, we discuss alternative methods for recharging a WSN and prolonging the lifetime of WSNs.

2.1 Wireless Power Transfer

Since UAVs have a very limited supply of energy, the vast majority of current research which focuses on interactions between UAVs and wireless power transfer attempts to maintain longer flight by transferring power from a ground station to the UAV. In 1964 wireless power was used to supply energy to a flying helicopter [15] and recently was used to enable a 12 hour, record-length flight [16]. The research presented in this thesis differs in that we aim to increase the lifetime of a WSN by supplying energy
to ground sensors from a UAV with a wireless power transfer system. The UAV acts as a mobile power station which can charge sensors and other electronic devices that are located away from conventional energy sources.

Magnetic resonance is not the only method to transfer power wirelessly. Power can also be transferred wirelessly through microwaves, lasers, radio waves, and magnetic induction. Table 2.1 and Fig. 2.1 give a rough overview of the trade off between power and range of these different approaches. Magnetic resonance is the preferred method of wireless power transfer for charging a WSN from a UAV for many reasons. First, wireless transmission of microwaves and lasers are relatively efficient over great distances [17], but they are cumbersome due to their requirement to have a direct line-of-sight connection between source and receiver, and can damage objects that intersect the beam of energy. Traditional coupling based on Faraday’s law of magnetic induction, on the other hand, has good efficiency and power transfer over short distances (e.g., an electric toothbrush), but has extremely short range. Radio Frequency Power Harvesting has been demonstrated to wirelessly transmit power over 4 km [18], but provides roughly 6 orders of magnitude less power transfer than magnetic resonance [10].

Above all, the most valuable benefit of magnetic resonant power transfer is that it is nearly omni-directional and has little interference with any surrounding objects in its environment [9]. Unlike the other forms of wireless power transfer, this will allow the UAV to transfer power to sensors that are underground, underwater, or embedded in other materials. Researchers have tested the effect of magnetic resonance through materials such as softwood lumber, concrete brick, and drywall with insulation [8]. The primary effect of the materials is a minor shift in resonant frequency [10, 8]. If the electric field is contained within a capacitor instead of being exposed throughout the inductive wire, the external objects have nearly no influence on the wire because
<table>
<thead>
<tr>
<th>Wireless Power Type</th>
<th>Power</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Microwave</td>
<td>10s of kW</td>
<td>&gt; km</td>
</tr>
<tr>
<td>JPL Raytheon</td>
<td>30 kW</td>
<td>1.6 km</td>
</tr>
<tr>
<td>Laser</td>
<td>&gt; kW</td>
<td>&gt; km</td>
</tr>
<tr>
<td>LaserMotive</td>
<td>1 kW</td>
<td>1 km</td>
</tr>
<tr>
<td>Radio Frequency</td>
<td>10s of µW</td>
<td>&gt; km</td>
</tr>
<tr>
<td>Intel Research</td>
<td>60 µW</td>
<td>4 km</td>
</tr>
<tr>
<td>Magnetic Induction</td>
<td>100s of kW</td>
<td>&lt; 1 coil dis.</td>
</tr>
<tr>
<td>Energizer Charger</td>
<td>&lt; 5 W</td>
<td>contact</td>
</tr>
<tr>
<td>Resonant Coupling</td>
<td>10s of W</td>
<td>&gt; 1 coil dis.</td>
</tr>
<tr>
<td>MIT Researchers</td>
<td>60 W</td>
<td>2 m</td>
</tr>
</tbody>
</table>

Table 2.1: Comparison of power and range capabilities of different wireless power technologies with specific examples.

Majority of materials are non-magnetic and respond to magnetic fields the same as free space [9].

Magnetic resonance allows power transfer over medium ranges for up to a few meters. Researchers looking to improve the range and efficiency of Magnetic Resonant systems focus on increasing the Quality Factor, or Q, of the system. The Q is a dimensionless parameter that relates a resonators frequency, amplitude, and bandwidth. A higher Q can lead to greater coupling between coils with lower overall power losses [9, 19, 20]. Lee et al. [20] show that a higher Q factor always leads to a higher power transfer efficiency and range. Furthermore, they optimize the parameters of the resonant coils in order to maximize the Q value. We also optimize the Q-factor of our coils (See Chapter 3.2), however, our system has added weight and size constraints since it will be attached to a UAV. A derivation and more detailed discussion of quality factor is provided in Chapter 3.2.
2.2 Localization

Since GPS is not sufficiently accurate for our purposes, we must use another localization technique. There are a number of approaches to obtain more accurate position information for UAVs outdoors. Real Time Kinematic or Differential GPS systems can obtain decimeter-level accuracy [21], and with additional filters, researchers have achieved 1-2 cm accuracy with these systems [22]. Many researchers prefer to use these systems because they are very simple to use. However, they require infrastructure, expensive receivers, and the signals may still be blocked in certain locations where we may place WSN nodes, for example, under bridges.

Optical flow, often fused with inertial measurement unit (IMU) data, has been used on UAVs to provide good position estimates over the course of a UAV mission. In 2009, Farid et al. created an optical flow system by mounting a camera onto a quadrotor UAV and developing a three stage algorithm to compute the velocity of the UAV [23]. While the camera has low resolution, they are still able to estimate the velocity of the UAV with precision similar to GPS. They do this by using a
three stage nested Kalman filter. The first stage of the Kalman filter performs the optical flow computation, the second stage merges the optical flow data and the IMU data, and the third stage attempts to solve the Structure From Motion problem (a process of estimating three-dimensional objects with a two-dimensional image that is further complicated by features in the image moving) by detecting extra features in the camera images. While this work is influential, the accuracy of the method is still only as good as GPS, which is not accurate enough for our application.

Honegger et al. have also created an optical flow platform, PX4Flow, which contains a single camera and ultrasonic range finder [24, 25]. An onboard processor computes the optical flow at 100 Hz. The results show that the camera gives positional information to within 0.2 m error for a 28 m long flight. The work was so successful that they allow users to purchase their relatively inexpensive PX4Flow optical flow sensor. Unfortunately, this system is extremely sensitive to the viewing surface and lighting conditions, which prevents it from returning accurate velocity estimates in our lab (for more information on this, see Chapter 6.1).

Simultaneous Localization and Mapping (SLAM) is an alternative approach to optical flow. SLAM techniques allow a robot to build a map in an unknown environment as well as keep track of their current pose. SLAM algorithms and techniques are very influential because they allow for very precise pose estimation of the robot. This is especially true for quadrotors UAVs due to their need for a stable hover and precise movements. Weiss et al. used a monocular camera and IMU on a UAV to perform SLAM in a GPS-denied environment with only a few centimeters of error over one minute [26]. They do this by integrating the FAST SLAM algorithm, a Kalman filter, and a novel LQR controller. The FAST SLAM algorithm works by generating keyframes at occasional intervals, and then tracking the features found in the keyframes. This positioning data is fused with data from the IMU in a Kalman
filter. The LQR controller, which takes into account the non-linearities of quadrotors, then uses the resulting filtered data as control feedback. While this SLAM implementation works exceptionally well, it requires significant hardware. Mainly, it requires an onboard processor for the computations. The computations require at least a dual-core 1.6 GHz processor (mass of 90 g), but the recommended platform for their framework is an Intel i7 processor, with a mass of 341 g. The complexity of SLAM is unnecessary in our application, and the added weight significantly reduces the flight time of the UAV and therefore the amount of power that can be transferred to nodes.

In other SLAM work, Bachrach et al. used a laser scanner on a UAV to perform 2D SLAM inside large buildings [27]. Grzonka et al. perform SLAM in 3D on a UAV while navigating indoors [28]. While SLAM techniques on UAVs have sufficient accuracy for our system, they require significant processing systems that are heavy to carry and would greatly reduce flight time. Further, our approach only needs to know the approximate location of the sensor node that we are charging. Therefore, accurate installation is not required and we may still be able to find it and charge it even if the sensor node has moved.

Others have developed similar localization methods based on radio transmissions. For instance, Tokekar et al. used bearing and signal strength to locate radio tagged fish with a robotic boat [29]. They use many WSN nodes equipped with rotatable antenna to locate the fish. First, they map a relationship between the signal strength and the distance from a ground truth measurement. They fit a linear regression model of this data. When the radio strength is at its maximum value, the bearing and radio strength information is sent to a centralized computer. The position of the fish is then triangulated by creating an enclosed polygon with the bearing angles.

Triangulation is normally done using Least squares. Ismail et al. compare non-linear least squares with linear least squares, their lower bound errors, and many
variations of the two methods (such as different averaging methods and online methods) [30]. They find that non-linear least squares achieves the most accurate results, but demands more computation power than the linear counterpart. In this thesis we will look at localizing a quadrotor UAV on a WSN node using the nonlinear least squares approach.

While the above works correlate most closely with this thesis, there has been a plethora of influential research with respect to localization. Posch and Sukkarieh developed and simulated a particle filter to track radio tagged wildlife with a UAV [31]. Korner et al. extend the original work by Posch and Sukkarieh to the case where there are multiple radio tagged animals being tracked by a UAV in simulation [32]. Others have worked on using radio frequency identification (RFID) tags [33, 34] or WiFi systems [35] to localize mobile robots. Almaaita et al. localized individual RFID tags in 3D using a fixed array of readers and a single reader with adaptive power levels [36]. Gutmann et al. adapt SLAM techniques to learn the distribution of a continuous signal (potentially a radio signal), while also determining the signal source and the location of the robot [37]. Song et al. localize multiple radio sources with a mobile robot using a Monte Carlo method [38]. Much of the recent work in localizing based on radio signals focuses on dealing with reflections, attenuation, and other environmental impacts. Magnetic resonance is less susceptible to interference from the environment [8] [9], but has a relatively short range compared with radio.

These alternative localization techniques require substantial hardware or computing power. Since we already are transmitting a magnetic field, an efficient way to localize is to sense the existing magnetic field from the power transfer system. This will be discussed in Chapter 6.
2.3 Energy Optimal Flight

A UAV that is recharging a sensor network may have a lot of distance between nodes. Since the power of the UAVs is very limited, it is important to maximize the efficiency (range) of the UAV. There are a growing number of solutions to the problem of limited energy in quadrotor UAVs. Roberts and Zufferey investigate optimal battery weight as well as charted flight endurance estimations for various payloads [39]. Roberts found an optimal battery by gathering a set data regarding the mass and energy of real-world batteries. This thesis also explores an optimal battery weight, however while Roberts examine a discrete space by gathering real-world batteries, we examine the entire continuous space. Furthermore, we develop this model by collecting data from our particular model UAV and show how this information can be obtained for any multi-rotor vehicle.

Uragun has explored energy consumption with respect to on-board components, e.g. communication devices, processors, payloads, and controlling units [40]. Likewise, Špinka and Hanzálek explore energy usage by processing power in small fixed-wing and VTOL UAVs [41]. This previous work differs from this thesis in that we do not aim to optimize the power consumption of on-board components individually, but to optimally consume all of the energy of the system as a whole.

While we explore only the dynamics of quadrotor UAVs, others have been successful in optimizing flight paths of fixed-wing UAVs. Klesh and Kabamba find optimal flight paths with respect to energy consumption and solar power harvesting on fixed-wing UAVs [42], and Al-Sabban and Gonzalez find optimal flight paths with respect to wind vector estimation on fixed-wing UAVs [43].

Bohorquez and Pines examine rotor geometry for VTOL micro air vehicles and nano air vehicles to optimize thrust [44]. This work covers detailed descriptions of
the aerodynamics of their VTOL vehicles. Our work is different in that we do not explore all aerodynamic details such as momentum and blade flapping. While these details are important in some applications, we are concerned only with optimizing the performance on the macro scale.

### 2.4 Sensor Network Charging

The lifetime of a sensor network remains a performance bottleneck of many wireless sensor network applications. While this thesis focuses on recharging wireless sensor networks with a robot, many researchers take a different approach to eliminating this bottleneck. For example, Coleri et al. introduced the PEDAMACS control scheme, which shows that with an unlimited energy source for an Access Point coupled with transmission synchronization using Time Division Multiplexing, they are able to increase the lifetime of some networks by 1-2 years [45, 46]. Furthermore, Feeney et al. identified the complex relationships between energy consumption and transmission speed, transmission range, and node density [47]. This allows researchers to identify energy performance bottlenecks in a variety of wireless sensor networks. Roundy et al. reviewed many potential power sources for wireless sensor networks [48], allowing the lifetime of some networks to be prolonged.

Still, the lifetime of the network can only be lengthened so much using these methods. Recharging the network has the potential to power the network indefinitely. Bing et al. created an algorithm focused on replacing nodes in the network with a mobile robot or human [49]. The mobile system collects data about the network as it traverses the nodes, allowing it to perform centralized calculations, such as the average power level of the network. Also, the mobile system can relay to the sensor node when it will traverse the network again in the future. This lets the network collaborate in
a distributed manner to schedule their communication accordingly. They created many algorithms based on this concept, and evaluated them through simulations. Their algorithms aim to minimize the distance that the mobile robot or human must travel to replace all the nodes. They have shown that their algorithms are very close to optimal, and they greatly reduce the distance over using naive methods.

Researchers have discussed the scenario of periodically charging each sensor node with a mobile charging vehicle and created the concept of renewable cycle [50, 51]. The renewable cycle is the cycle through all nodes in the sensor network that minimizes the total distance traveled through ever WSN node, then retuning the robot to the base station to be recharged. This is the “renewable cycle”. They create many algorithms based on the renewable cycle and evaluate their algorithms through simulation. Their work shows that the most efficient cycle is the Hamiltonian Cycle, and they also develop approximation algorithms that are very close to the optimal solution. High level path planning algorithms are not explored in this thesis, however, these algorithms will be useful for the system that we describe.

These methods can be closely correlated with our work in order to make a robot recharging the network more efficient. However, many other methods have been proposed to extend a network’s lifetime. For example, Peng and Li [51] showed the concept that wireless power transfer can effectively prolong the lifetime of the sensor network. They used an energy station to monitor the status of the nodes and then guide the behavior of the mobile charger. They also showed that optimally deciding which sensor to recharge and how much energy to recharge is NP-Complete via a reduction from the Traveling Salesman Problem. Sheng et al. discussed how to use multiple mobile robots to collaboratively recharge the sensor network and proposed an optimal recharging algorithm for the scenario where nodes are distributed in one dimension [52]. Johnson et al. studied using a UAV as the mobile recharger. Their
work focused on the scenario of finding the best sink selection algorithm for improving network lifetime assuming a UAV can recharge only a sensor node each time [53]. Since this thesis only explores how to recharge a single WSN node, a high level path planning algorithm is not necessary. However, the algorithms developed by these researchers will be pivotal in our future work.
Chapter 3

Background

This chapter gives a brief overview of the UAV platform, background information on magnetic resonant wireless power transfer, and the basics of quadrotor dynamics. This information is important in the upcoming chapters.

3.1 UAV Platform

We use an Ascending Technologies Hummingbird quad-rotor UAV [54] to carry the transmitting coils and power system as seen in Fig. 4.3. The UAV has a mass of 368 g and has a recommended maximum payload of 375 g, although it is capable of hovering with a payload of nearly 575 g. The power transmitting coils are each 38 g and the Drive Board is 44 g. A 98 g plastic frame holds the power transfer components on the UAV. The UAV carries a 175 g, 2.1 Ah, 11.1 V LiPo battery (23.3 WHrs). Additionally, it carries a 40 g optical flow camera.\(^1\) The total mass of the UAV is 763 g. With an average power usage of 127 W, the UAV’s flight duration is 11 minutes if all the energy in the battery is utilized. Vertical take off and landing

\(^1\)However, to overcome its sensitivity to texture and lighting conditions, we simulate the optical flow system. This is explained more in Chapter 6.1
vehicles make such a proposed system feasible. The small body frame and relatively low energy usage make small quadrotors an obvious choice for an aerial recharging vehicle.

The UAV, power transfer system, and optical flow camera each controlled on their own independent 802.15.4 (Zigbee) radios operating at 2.4GHz. A laptop computer running Robot Operating System (ROS) [55] interfaces with these radios to control the overall system.

### 3.2 Wireless Magnetic Resonant Power Transfer Theory

In this section we present background information on wireless magnetic resonant power transfer. This information is needed to understand the design decisions faced when developing a UAV-based wireless power transfer system, as discussed in Chapter 5.

Inductive power transfer involves at least two coils in close proximity sharing alternating magnetic fields. An alternating current (AC) in the transmitting coil produces a magnetic field that generates an alternating voltage in the receiving coil that can be applied to power or charge a device. Standard inductive power transfer is only efficient over short distances, but this limitation can be overcome with the use of strongly coupled magnetic resonances.

Power transfer is much more efficient over medium ranged distances by including two coupled resonant coils between the driven and loaded inductive coils, as seen in Fig. 3.1. In this configuration, the primary inductive coil, or Drive coil, is driven by an AC power supply. Due to the close proximity between the Drive coil and the first
resonant coil, called the Tx resonant coil, oscillations occur and power is transferred to the Tx coil. The Tx coil causes the Rx coil to oscillate with a proportional degree of energy that is dependent on their coupling. The Tx and Rx coils do not have any direct load connected to them to interfere with the resonance. This allows them to couple and resonate over larger distances than is possible without resonant coils. The last coil, the Load coil, inductively receives power from the Rx coil in the same way that the Drive coil transfers energy to the Tx coil, and it applies the voltage that it gains across a load to receive the power.

The two primary factors that impact resonant wireless power transfer performance are the quality factor (Q) of the coils and ensuring that all coils naturally resonate at a similar frequency. The quality factor represents how well a resonant coil can hold energy without losses to heat. It is important that all coils naturally resonate at the same frequency since otherwise the coupling will be weaker and range and efficiency will decrease.

The quality factor, $Q$, of the resonant coils, is defined as [56]:

Figure 3.1: Schematic for resonant power transfer [12].
where \( R \) is the resistance of the coil (Ω),
\( L \) is the inductance of the coil (H),
and \( C \) is capacitance (F).

In order to calculate \( Q \), we must find the values for \( C, L, \) and \( R \). For this system, the capacitance \((C)\) is primarily determined by the size of the capacitor attached to the coils since the self-capacitance of the wires is minimal for our setup [11]. The inductance of the resonant coil is given by [57, 58]:

\[
L = \mu_0 r N^2 \left( \ln \frac{8r}{c} - 1.75 \right) \tag{3.2}
\]

where \( \mu_0 \), is a constant \((4\pi \times 10^{-7} \text{ Tm/A})\),
\( r, \) is the radius of the coil (m),
\( N, \) is the number of turns of coil,
and \( c \) is the wire bundle thickness (m).

The resistance of the resonant coils at the resonant frequency is given by [59]:

\[
R = \frac{2\pi r N}{2\pi r_w \sigma \delta} = \frac{r N}{r_w \sigma \delta} \tag{3.3}
\]

where \( r_w \) is the wire radius (m),
\( \sigma \) is the conductivity of the conductor (S/m),
and \( \delta \) is the skin depth effect (m) of conduction, defined as:

\[
\delta = \frac{1}{\sqrt{\pi f \mu \sigma}} \tag{3.4}
\]
where $\mu$ is the permeability of the conductor (Tm/A).

We must take into account the skin effect since the coils are subjected to high frequency alternating current, which causes charge to conduct along the surfaces. It is also possible to calculate the resonant frequency of the coil, $f_r$, in Hertz, given the capacitance and inductance with the following equation:

$$f_r = \frac{1}{2\pi\sqrt{LC}}$$ (3.5)

With these equations, we are able to calculate the quality factor from Eqn. 3.1. Intuitively, the quality factor can be thought of as how much energy a resonant system can hold compared to energy lost during a single cycle. While maximizing the quality factor is important when trying to minimize the losses within the coils, there are some drawbacks in having too high of a $Q$.

In practice, the resonant frequency of all of the coils will be slightly different from each other due to manufacturing imperfections and component tolerances. High $Q$ factors causes a decrease in the bandwidth of the resonant coil, $\Delta f$ in Hz, which is defined as:

$$\Delta f = \frac{f_r}{A}$$ (3.6)

If the resonant frequency of one coil is not within the bandwidth range of the other coil, they will couple poorly as shown in Fig. 3.2. The figure represents two sets of resonant coils. The solid blue curves represent coils which have a resonant frequency $f_1$ and $f_2$, respectively, but have a high $Q$. The further the curves intersect on the $y$-axis implies a higher power transfer. So we notice that the high $Q$ means that the peak power transfer is higher, but because of the difference in the coils natural resonant
frequency, they are only able to transfer at about half of the optimal performance. The red, dashed curves show that even though they resonate at the same frequencies $f_1$ and $f_2$, respectively, the Q is lower, thus giving a larger bandwidth, which results in a higher power transfer.

There are also a number of other considerations when designing resonant wireless power transfer systems. For low frequency systems energy losses are dominated by ohmic losses and high frequency losses by radiative losses [9]. The primary loss in our relatively low frequency system is ohmic, which causes the coils to heat when high currents move through the slightly resistive winds of the wire in each coil. In addition, we have switching losses in our AC power system. By decreasing the resistance, we can increase the Q and decrease the former losses. Unfortunately this may cause an increase in the switching losses due to higher currents moving through MOSFETs. Further, while using a thicker gauge wire is an easy way to decrease resistance and increase Q, it also adds weight to the UAV. Similar trade-offs must be made when adjusting the capacitance and inductance in the system to attempt to maximize the quality factor. These design trade-offs for our system are discussed in Chapter 4.2.

![Figure 3.2: Quality Factor shown for two separate wireless power resonant system. The two pairs of coils each have one coil operating at $f_1$ and another coil operating at $f_2$. The blue coils have a higher Q, allowing for more coil efficiency at the peaks, however, the red coils with lower Q have a longer bandwidth, so are less susceptible to variations in natural resonant frequency. This allows the red coils to transmit more power even though the Q is lower.](image-url)
As seen in Eqn. 3.1, another way to increase the quality factor is to lower capacitance. Capacitance is easily decreased as this can be done by either pairing capacitors in series or by using new capacitors with a lower value. A significant effect of lower capacitance is a higher resonant frequency as shown in Eqn. 3.5, which limits higher currents due to voltages having less time to overcome magnetic momentum. This is shown by Eqns. 3.7 through 3.9. If a voltage is applied to a coil with a known inductance, it is possible to determine the current flowing through the coil given the amount of time the voltage is applied:

\[
V = L \frac{di}{dt}
\]

\[
di = V \frac{dt}{L}
\]

where \(di\) is the current through the inductive coil (A),

\(V\) is the voltage supplied across it (V),

\(dt\) is the time voltage is applied to it (s).

For any given frequency, \(T\) s is the period of time each cycle takes. When frequency represents the rate of alternating magnetic fields, there is both a positive and a negative voltage applied to the inductive coil for every period. Therefore the period of time that a single voltage is applied to the inductor, \(dt\), is equal to \(\frac{T}{2}\):

\[
f = \frac{1}{T}
\]

\[
dt = \frac{T}{2}
\]

Given the resonant frequency from Eqn. 3.5, the attributes of inductance from
Eqn. 3.7, and the relationship between frequency and $dt$ from Eqn. 3.8, we know that the current through the coils decreases with capacitance:

$$
\frac{1}{f_r} = T = 2\pi \sqrt{LC} \\
\frac{di}{dt} = V \frac{dt}{L} = V \frac{T}{2L} \\
\frac{di}{dt} = V \pi \sqrt{\frac{C}{L}}.
$$

(3.9)

Now that we have examined the theory behind wireless power transfer, we examine the parameters of our current coils with respect to the above equations. We then optimize the parameters of the wireless power transfer system for the UAV.

### 3.3 Quadrotor Dynamics

In this section, we provide background information on how quadrotor UAVs use energy in flight, but these results also extend to other multi-rotor UAVs. This information is necessary to understand Chapter 7. We are interested in observing a stable flight state and moving only in translation. Since the main forces acting on the UAV are thrust and drag, we simplify aerodynamic forces and do not consider effects such as such as blade momentum and flapping. Many other sources contain in depth details and derivations of these dynamics [22, 60, 61, 62].

The thrust, $T$, can be defined as:

$$
T = \frac{1}{2} \rho AC_T r^2 \omega^2
$$

(3.10)

where $\rho$ is the density of air,
Figure 3.3: The six degrees of freedom are produced by the four rotors. When thrust is produced equally by all four rotors, the UAV moves in the $z$ direction; when rotors 1 and 3 have different thrust values, a moment is produced around the $y$-axis; when rotors 2 and 4 have different thrust values, a moment is produce around the $x$-axis, and when the thrust of rotors 1 and 3 differ from the thrust of 2 and 4, a moment is produced around the $z$-axis.

$A$ is the blade area,

$C_T$ is a thrust coefficient,

$r^2$ is the radius of the blade,

and $\omega$ is the angular velocity of the propeller.

We consider most of these variables constant and set $K_T \approx \frac{1}{2} \rho A C_T r^2$, allowing us to simplify Eqn. 3.10 to:

$$T \approx K_T \omega^2. \quad (3.11)$$

Fig. 3.3 shows a UAV’s rotors and the various degrees of freedom. By inputting a thrust on a rotor, it produces a torque on the body of the vehicle. If the thrust and torques from all sides are equal, the vehicle will produce force in the $z$ axis. If they are not balanced this will cause rotational moments around $\psi$, $\theta$, or $\phi$ and will cause changes in the UAV attitude. Specifically, the inputs can be described as follows:

Vertical input:

$$u_1 = K_T \sum_{i=1}^{4} \omega_i^2 \quad (3.12)$$

Roll moment input:
\[ u_2 = K_T (\omega_1^2 - \omega_2^2) \]  \hspace{1cm} (3.13)

Pitch moment input:

\[ u_3 = K_T (\omega_1^2 - \omega_2^2) \]  \hspace{1cm} (3.14)

Yaw moment input:

\[ u_4 = K_D (\omega_2^2 + \omega_4^2 - \omega_3^2 - \omega_1^2) \]  \hspace{1cm} (3.15)

where the subscript 1 through 4 correspond with the rotors in the Fig. 3.3. To roll (\( \theta \)) rotor 2 is decreased and rotor 4 increased (Eqn. 3.13), to pitch (\( \phi \)) rotor 1 is decreased and rotor 3 increased (Eqn. 3.14), and to yaw (\( \psi \)) rotors 2 and 4 are increased and rotors 1 and 3 are decreased (Eqn. 3.15). To move in the z axis, the thrusts of the rotors are increased or decreased proportionally (Eqn. 3.12).
Chapter 4

System Components

Now that we have seen the background information on the power transfer system and UAV, we describe the specific hardware and software components of the system. Fig. 4.3 shows an overview of the wireless power transfer system on the UAV. The system consists of a UAV, the wireless power transmitter on the UAV, and the receiving wireless sensor node.

4.1 Software

Fig. 4.2 outlines the system’s sensors and communication at a high level. The UAV contains on board components such as GPS, an optical flow camera, an ultrasonic range finder, and wireless power transmission board. Note that the data from the optical flow camera is simulated for the experiments presented in this thesis. The WSN node contains a Magnetic Resonant (MR) sensor and any sensors specific to the node’s application. The MR sensor data and UAV sensor data is processed in a centralized computer. A PID controller is used to position the UAV at a target location based on the sensor values.
Figure 4.1: A representation of the communication nodes and edges in the ROS software system that runs the UAV power transfer code. The communication nodes highlighted in green are the Base Framework nodes, and the communication nodes highlighted in blue are the online production nodes which are specific to the wireless power transfer system presented in this thesis.
Figure 4.2: Architecture diagram for the system. ROS runs on a centralized computer which relays communications from the drone and the WSN node. It processes sensor data and sends control input signals to the UAV.

Figure 4.3: The wireless power transfer system. The three main components of the system are the power transmission (TX), the power receiver (RX), and the UAV. The TX and RX components each have resonant coils and hardware components which transmit and receive power, respectively.

The software system is built on the Robot Operating System (ROS) framework [55]. The Robot Operating System (ROS) is a publish and subscribe software system that allows for processing of the data from the many different sensors and components of the system. The software consists of many “ROS nodes”, or processes, each responsible for handling a system component. ROS nodes can publish or subscribe to other ROS nodes, creating the edges in a communication graph. Fig. 4.1 shows the graph of ROS nodes and edges that run the wireless power transfer system and UAV. Each edge represents a type of message sent to the subscriber.

There are 7 main ROS nodes: the wireless power transmission node, wireless
power receiver node, magnetic resonant sensor node, an optical flow communication node, UAV communication node, UAV control node, and a high level mission planning node. The remaining nodes in the software system either have low level purposes such as serial communication, polling the UAV for data, performing data conversions, or computing the control input from pose data. These nodes make up the basic framework of interaction with the UAV, and they are used by all the users in the lab.

The wireless power transmission node parses data that comes from the wireless power transmission board. This includes information regarding whether the system is currently transmitting power, the current resonant frequency of the system, the voltage, and the amps drawn. The node also has the ability to turn the transmission system on and off or change the resonant frequency of the system.

The wireless power receiver node is similar. We have the ability to activate or deactivate it, and it returns the amount of watts that are being transferred to the load.

The optical flow communication node sends optical flow data and ultrasonic data from the sensors on the optical flow camera into the UAV control node. And the magnetic resonant sensor node returns the voltage running through the receiver resonant coil. The information from the two nodes is then fused and sent through the UAV communication node to control the pitch, yaw, roll, and thrust of the UAV.

Similarly, the UAV has its own sensors that we must use for positioning. The IMU and GPS information from the UAV run through the UAV communication node to the UAV control node for processing (a motion capture system is used indoors instead of GPS). The output control signals are then sent back through the UAV communication node to control the pitch, yaw, roll, and thrust of the UAV.

While the ROS nodes are used to control the UAV, the majority of the software required is used for creating or testing models offline. Table 4.1 outlines the code
distribution. We first write software to collect data from a particular sensor, and UAV is used to gather the experimental data. We do this by recording the messages that are passed between ROS nodes in the ROS graph. The data is then analyzed with Matlab or R. Once the necessary models or relationships are obtained and tested offline, we can move the model into ROS to run on the UAV.

<table>
<thead>
<tr>
<th>Type</th>
<th>Lines of Code</th>
</tr>
</thead>
<tbody>
<tr>
<td>Offline</td>
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</tr>
<tr>
<td>Online Experimental</td>
<td>2899</td>
</tr>
<tr>
<td>Online Production</td>
<td>1094</td>
</tr>
<tr>
<td>Base Framework</td>
<td>4995</td>
</tr>
</tbody>
</table>

Table 4.1: The line count (including blank lines and comments) outlining the code distribution of the system. Offline code is used for data analysis, model generation, and testing. Online experimental is code for online testing and data collection. Production is all the code that runs the high level mission planning and power transfer software. And the base framework is the size of the existing software that interfaces with the drone at a low level.

### 4.2 UAV Power Transfer System

Fig. 4.3 shows an overview of the wireless power transfer system. On the UAV, the Drive Board sends an alternating current through the Drive Coil causing an alternating magnetic field that drives the neighboring Tx Resonant Coil. The Tx Resonant Coil serves to focus the field for transmission to the Rx Resonant Coil, which is placed on the WSN node along with the Load Coil. A magnetic resonant (MR) sensor is connected to the Rx Resonant Coil to detect the Tx system and enable localization as discussed in Chapter 6. The Load Coil is connected to the receiving board, which draws energy from the Rx Resonant Coil. Finally, the energy from the Load Coil can be stored in the WSN node.

Many power transfer systems are large or heavy to produce high power transfer capabilities. Generally, larger power transfer coils have a higher Quality Factor, or Q.
The Q is a unitless measure of the frequency, amplitude, and bandwidth of a resonator (a higher Q corresponds with higher power transfer efficiency and range). However, we adapt our power transfer system to the drone by modifying the parameters to make a more lightweight system. The parameters of are a good trade-off between the coils’ Q, power transfer range, ohmic losses, and radiative losses. The parameters governing our power transfer system are given in Table 4.2. The lower Q provides the power transfer system with a relatively large bandwidth (refer to Fig. 3.2 in the next chapter). This is important because the lightweight coils are rather pliable. As the coils slightly change shape due to turbulences in flight and landing, the resonant frequency will shift slightly. In a system with higher Q, the resulting losses in power transfer range and efficiency would be greater than in a system with lower Q, due to the larger bandwidth of a lower Q system. Chapter 3.2 explains the relationships between these parameters of the power transfer system in detail and the parameters of these coils are further optimized in Chapter 5.

<table>
<thead>
<tr>
<th>Description</th>
<th>Variable</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coil Length</td>
<td>( l )</td>
<td>1.47655 m</td>
</tr>
<tr>
<td>Coil Radius</td>
<td>( r )</td>
<td>0.235 m</td>
</tr>
<tr>
<td>Resistance</td>
<td>( R )</td>
<td>0.0143 ( \Omega )</td>
</tr>
<tr>
<td>Number of Wraps</td>
<td>( N )</td>
<td>2</td>
</tr>
<tr>
<td>Inductance</td>
<td>( L )</td>
<td>( 5.20068 \times 10^{-6} \Omega )</td>
</tr>
<tr>
<td>Capacitance</td>
<td>( C )</td>
<td>( 1.5 \times 10^{-7} \ \text{F} )</td>
</tr>
<tr>
<td>Frequency</td>
<td>( f_r )</td>
<td>167 kHz</td>
</tr>
<tr>
<td>Bundle Thickness</td>
<td>( c )</td>
<td>0.004 m</td>
</tr>
<tr>
<td>Quality Factor</td>
<td>( Q )</td>
<td>411</td>
</tr>
</tbody>
</table>

Table 4.2: Parameters of the power transfer system mounted on the UAV and the WSN node.

The UAV carries the Drive Board (See Fig. 4.3). The main component of the drive board is an AD9833 programmable waveform generator that can generate up to a 12.5 MHz signal. This signal is input into an H-Bridge that generates a high-power alternating current that is driven through the Drive Coil. Typically we operate
with a 9-24 V input range with a current between 1-4 Amps, although the board is
designed to support up to 45 V and 8 A with a maximum power rating of up to
100 W. In addition, the Drive Board has a processor to control the frequency, enable
or disable power transfer, monitor voltage and current, and communicate with the
ground sensors and base station with a Zigbee radio.

Fig. 4.6 shows the amount of power that can be received by the device attached
to the load coil. This figure shows that there is a region with about 30 cm radius
which provides over 3 W of power transfer. As the distance from the transmitter to
receiver increases past this radius, the amount of power transferred drops significantly.
For our applications, 3 W in a 30 cm range suffices because most WSN nodes do not
require significant power. Plus, we will see in Chapter 6 that the UAV can consistently
localize to within 21 cm of the sensor. While we are less concerned with optimizing
the power transfer system, it is important to note that the overall power transfer
can be easily increased. Fig. 4.5 shows that we can double the power transfer by
doubling the input voltage. This can be accomplished with an additional battery
pack attached to the UAV or a larger UAV with higher operating voltage.
4.3 Wireless Power Receiver Sensor Node

A node in the WSN consists of the wireless power receiver board, coils, a magnetic resonant sensor, and any other sensors that are specific to the nodes application, such as vibration, temperature, soil moisture, or pressure sensors. In this paper we omit any application specific sensing system and instead focus on the power transfer system and localizing the UAV onto the WSN node. The receiver node can receive about 6.1 W at peak efficiency. With 6.1 W power transfer for 5 minutes we can nearly charge a typical NiCd rechargeable AAA battery, which can operate most types of low-power sensing systems for weeks. As with the transmitter, there is a Rx Resonant Coil in close proximity to the Load Coil. The receiver board draws energy from the Load Coil and may either use this energy directly or may charge batteries or super capacitors.
A Magnetic Resonant (MR) sensor (pictured in Fig. 4.8) is connected to the sensor node and can detect the presence of the UAV power transfer system. The MR sensor connects to the Rx Resonant Coil. When the Tx system approaches, the voltage in this resonant coil increases significantly and is measured by the MR sensor. The advantage of having the MR sensor is that it can detect the power transfer system from three times farther away than the Rx Load Board. This enables localization using the voltage signals gathered from the MR sensor.

It is important to note that embedding the MR sensor in materials has no effect on the magnetic resonance. Therefore, it has no effect on localization or power transfer. Fig. 4.9 compares the voltage through the resonant coil that is embedded in plastic, wood, and stone compared with a baseline measurement of air. The $x$-axis is the horizontal distance, which is circularly symmetric around the MR sensor. The voltage on the $y$-axis is used for localization and is also directly correlated with the power.
Figure 4.9: Voltage readings from an MR sensor which is embedded in different materials. We can see that the voltage is nearly equivalent regardless of the material, allowing the WSN node to be embedded in materials without hindering localization or power transfer.

We develop two different localization strategies using the MR sensors. First, we use 4 MR sensors in an array to estimate the pose of the UAV (Chapter 6.4), and second we use a single MR sensor and an optical flow camera to determine the relative pose of the WSN node (Chapter 6.3).

Fig. 4.7 visualizes the data returned from the MR sensors. The voltage readings are measured by a 10-bit analog to digital converter (ADC). As the transmitter approaches the MR sensor, the voltage values approach a maximum value of about 3.7 V. As the distance between the MR sensor and the transmitter increase, the voltage values approach a minimum of around 1 V. White values indicate that no data was collected at that position in space. The data show that the MR sensor can sense
the wireless power transmission system from up to 1 m away when the UAV flies at an altitude of 1.3 m above the MR sensor. We discuss the details of how this data is used for localization in Chapter 6.2.

In this thesis, the MR sensors are used for two separate localization methods. The first method uses one MR sensor attached to the WSN node and an optical flow camera which is attached to the UAV. The second method uses an array of four MR sensors placed around the WSN node (See Fig. 4.10). This eliminates the need for the optical flow camera, but adds hardware to the WSN node.

Figure 4.10: An alternative localization method uses four MR sensors to obtain a position estimation of the UAV.
Chapter 5

Coil Parameter Optimization

Since the UAV has limited payload capabilities, our goal is to optimize the parameters of the power transfer coils that the UAV carries. As mentioned in Chapter 3.2, the physical coil parameters determine the efficiency of the power transfer. During prior work in the NIMBUS lab, Griffin [11] designed the wireless power transfer coils. These coils have a radius of 0.235 m and 2 wraps, for a total wire length of 1.47655 m. Using 16 gauge wire with 2 wraps means the bundle thickness is 0.004 m and the coil’s resistance is 0.0143 Ω. A 15 µF capacitor is used on the coils to give a resulting inductance of 5.2 × 10^-6 Ω and quality factor of 411. More detail is given on the power transfer coils in the System Components chapter (Chapter 4) and they are summarized Table 4.2.

Power transfer coils range and efficiency is directly related to the coil’s Q. We use the equations from the previous section to maximize the coil’s Q while keeping the mass ($m$) of the system at a minimum. Specifically, we perform the following optimization:
Maximize \[ Q = \frac{1}{R} \sqrt{\frac{L}{C}} \] subject to \( f < 12.5 \text{ MHz}, \)
\[ C > 10^{-9} \text{ F} \]
\[ L > 0 \text{ H} \]
\[ r > 0 \text{ m} \]

over values of \( N = 1..10. \)

The relationships between these variables is not obvious. To maximize the \( Q, \) we must minimize the resistance \( (R) \) and capacitance \( (C) \), but increase the inductance \( (L) \). Both the resistance and capacitance depend on the radius \( (r) \) of the coil and the number of turns \( (N) \) in the coil. Furthermore, \( C \) can vary independently, but changes in \( C \) will either cause a shift in resonant frequency \( (f) \) or a change in \( L \).

Without constraints on the optimization, this function is unbounded. This is because we can continue to decrease the size of the \( C \) or increase the size of \( N \) to gain more \( Q \).

First, we constrain the capacitance, \( C \). In practical uses, a smaller capacitor cannot store enough energy and requires a higher voltage than a larger capacitor. Thus, it is infeasible to have a too small of a capacitor. Capacitors smaller than roughly \( 10^{-9} \text{ F} \) are more quite rare, we set this as the lower bound of \( C \).

Next, we constrain the resonant frequency, \( f \). Since the TX board hardware prevents the resonant frequency from exceeding \( 12.5 \text{ MHz} \), \( f \) is set to be no more than this value.

Lastly, we constrain the number of wraps, \( N \). Both \( L \) and \( R \) depend on the number of wraps of wire that make up the coil. Also, we notice that the function is unbounded as \( N \to \infty \). And since \( N \) must be an integer value, the optimization
problem becomes a mixed integer optimization problem, which are much more computationally expensive. To overcome these challenges, instead of attempting to find the optimal argument for $N$, we fix $N$ and perform the optimization problem multiple times (where $N = 1..10$). We will see in the optimization that by $N = 4$, the mass of the coil is over 80 $g$, which is already too heavy for the small UAV. Thus it is unnecessary to examine larger values of $N$.

Lastly, we impose the obvious constraints that the radius $r$, the capacitance $C$, and inductance $L$ must be positive.

Fig. 5.7 shows the resulting parameters that maximize $Q$. The $x$-axis in each graph represents the number of wraps, $N$, where $N = 1..10$.

First, we note that $Q$ appears logarithmic (Fig. 5.1) with respect to $N$, so there is the property of diminishing returns. However, $r$ (Fig. 5.2) increases linearly, and thus $m$ (Fig. 5.3) is exponential. These two facts mean that we should choose a coil with a lesser $N$ to decrease the weight on the UAV.

Next, we note that the capacitance has remained at its minimum value ($10^{-9}$ $F$, Fig. 5.4) which was imposed in the constraints. However, the frequency is unaffected by its constraint of 12.5 MHz (Fig. 5.6).

Lastly, we notice that the $Q$, even for $N = 1$, is higher than the $Q$ of the current power transfer system attached to the drone. The current system has $Q = 411$, but here $N = 1$ has $Q = 801$, or $N = 2$ has $Q = 953$.

From these graphs, we can conclude that we can probably not exceed $N = 3$ due to weight constraints. However $N = 1$ and $N = 2$ provide realistic parameters for the system. It should be noted that some researchers have been able to achieve even higher $Q$ factors with similarly sized systems. This is because they have altered the coil geometry, using concentric circles instead of a circular wrap, which changes the equation for $L$ [63]. Future implementations will use this coil geometry.
Figure 5.1: Quality (Q) vs. Number of Wraps
Figure 5.2: Radius (m) vs. Number of Wraps
Figure 5.3: Mass (g) vs. Number of Wraps
Figure 5.4: Capacitance (F) vs. Number of Wraps
Figure 5.5: Inductance (L) vs. Number of Wraps
Figure 5.6: Frequency (Hz) vs. Number of Wraps
Figure 5.7: Optimal coil parameters over $N = 1$ to $N = 10$. 
Chapter 6

Localization

In Chapter 3.2 we explored the details of the magnetic resonant power transfer system that is attached to the UAV and the WSN node. We showed that the system is able to transfer sufficient power to charge a low-powered WSN node. In this chapter we address the problem of getting the UAV close enough to the WSN node to transfer power. GPS can record the location of a WSN node when it is deployed, but GPS has up to 7.8 m error in a 95% confidence range [64]. Since the UAV must be within 30 cm to efficiently transfer power, in this chapter we develop two localization algorithms that use the sensed magnetic field information from the MR sensors to localize over the WSN node.

Fig. 4.3 shows a magnetic resonant (MR) sensors in the bottom left. The MR sensor measures the voltage through the resonant coil that surrounds the sensor. The measured voltage is used to estimate the distance between the UAV and the MR sensor, explained next in Chapter 6.2. The sensor measurements are then transmitted over a short-range radio to the UAV control computer that processes the data to provide an estimated position of the UAV relative to the MR sensor, which is placed on the WSN node.
Chapter 6.3 describes the first algorithm, which uses a single MR sensor and a simulated optical flow system. We show through experiments that we are able to locate the sensor with an accuracy of 21 cm after 36 seconds. The UAV can land on the WSN node to charge it at an average rate of 3.38 W.

Chapter 6.4 describes the second algorithm, which uses an array of four MR sensors to estimate the pose of the UAV. We can estimate the pose of the UAV with this method with 39.5 cm of accuracy. Using this method, the UAV can land on the WSN node to charge it at an average rate of 1.8 W.

Using either localization algorithm, we are able to land on the WSN node and charge significant power to the WSN node. However, they each have their own strengths and weaknesses. Using an array of MR sensors means that we must add hardware to the WSN node. In this particular setup, we arrange four MR sensors 0.5 m apart in a square formation. This means the WSN node is considerably larger and may not be suitable for all applications. However, this method does not require any additional hardware on the UAV, allowing it to travel a farther distance.

It is generally more advantageous to use the optical flow method of localization. Using an optical flow camera for position and control of the UAV means that we add hardware to the UAV, but the WSN node can be significantly smaller. Further, the power transfer receiver coil and the resonant coil is only 8 cm in diameter, so it can be applied to many different types of WSN nodes. Whereas using four MR sensors for localization requires the four small coils to be spaced out in order to triangulate a position estimation. Also, the position estimation of the UAV and therefore control accuracy is increased using the optical flow camera. This is because the position estimation from the array of MR sensors has 39.5 cm of error at any instant, producing an oscillating hover. But the optical flow camera measures the position of the UAV accurately enough to produce a stable hover.
6.1 Optical Flow Camera

The UAV carries a PX4Flow camera that computes optical flow. Merging this data with data from its ultrasonic range finder, it computes the velocity of the UAV [24]. While Honegger et al. have achieved $0.2 \text{ m}$ of accuracy over long missions, we have not been able to replicate their success, thus, in this thesis, the optical flow camera is simulated.

We gather data to attempt to find the range of accuracy that we may expect with an optimal viewing plane and optimal lighting conditions for the optical flow system. Five viewing surfaces are tested, seen in Fig. 6.6. The average positional error is recorded over a 10 second flight. Table 6.1 summarizes the positional error associated with each viewing surface. Wood texture I is roughly 4 times more accurate, with an average error of $0.05 \text{ cm}$ than the next closest surface, Wood texture II at $0.21 \text{ cm}$. Test flights show that stable hovering and control is possible with Wood texture I, but not with Wood texture II.
<table>
<thead>
<tr>
<th>Viewing Surface</th>
<th>Mean (m)</th>
<th>Std. Dev (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wood texture I</td>
<td>0.05</td>
<td>0.03</td>
</tr>
<tr>
<td>Wood texture II</td>
<td>0.20</td>
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</tr>
<tr>
<td>Tiles</td>
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<td>0.22</td>
</tr>
<tr>
<td>Wood texture III</td>
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<td>0.31</td>
</tr>
<tr>
<td>Carpet</td>
<td>0.70</td>
<td>0.45</td>
</tr>
</tbody>
</table>

Table 6.1: The average positional error mean and standard deviation associated with each viewing surface using optical flow.

Figure 6.1: Wood texture I  
Figure 6.2: Wood texture II  
Figure 6.3: Tiles

Figure 6.4: Wood texture III  
Figure 6.5: Carpet

Figure 6.6: The error of the PX4Flow optical flow camera is measured over various textures, ordered by average positional error. Wood texture I is the most accurate viewing surface, giving 0.05 m of error, and Carpet is the worst, giving 0.7 m of error.
6.2 Converting Measured Voltages to Distance Measurements

In order to estimate the position of the UAV, we must be able to map the voltage information received by the MR sensor to a distance between the UAV and the WSN node. This distance is then sent to the UAV from the MR board. Once the UAV gets within power transfer range, the MR sensor battery is quickly recharged.

We experimentally determined the relationship between the voltage and distance. We collected the data by recording the positions of the UAV and the MR sensor readings at 52 Hz (the rate the MR sensors transmit data). The UAV flew in the $x$ direction directly over the top of the MR sensor while holding $y$ and $z$ constant. We do this because the magnetic field is radially symmetric, there is no need to vary $y$. Furthermore, we assume that $z$ remains relatively constant, however a model including the $z$ axis may be possible and is part of our future work. Fig. 6.7 shows curves that represent distances from the sensor for $z$ values between 70 cm and 180 cm. These curves are circularly symmetric on any radial axis. The figure shows that for $z$ values which are too close to the MR sensor, there are significant lobes in the magnetic field. This may be caused by poor coupling or overcoupling that can cause destructive interference within the resonant coil [19]. The lobes make it difficult to estimate the range of the UAV because one reading may correspond to two possible ranges. However, when the UAV is sufficiently far from the sensor (in the vertical direction), the magnetic field is still strong but there are no lobes. This shows that it is best to fly with a $z$ distance of roughly 1.3 to 1.6 meters from the sensor, which can be accomplished by using the height estimates from the acoustic range finder on the optical flow system.

Fig. 6.8 shows the data (black) and model (red) from 10 passes of the UAV over
6.3 Localization using Optical Flow and a Magnetic Resonant Sensor

Now that we have an estimate of the distance to the MR sensor based on the measured voltage, we can develop a localization algorithm for the UAV using range readings...
from the MR sensor. Since the MR sensor only gives a range and not direction, we need additional information to aid in localization. We cannot use GPS since the error is too high and the update rate is low. Instead, we use an optical flow camera, since it can provide accurate motion estimates over short periods of time [23, 26] with higher accuracy than GPS. In our system, the UAV is equipped with an optical flow camera, but as discussed in Chapter 6.1, due to the sensitivity of the viewing surface of the camera, we simulate optical flow using a motion capture system.

The MR sensor is placed directly on the receiving resonant coil of the WSN node. We then use a least squares approach to find the location of the WSN node. We do this by attempting to find a location ($\hat{x}_s, \hat{y}_s$) which minimizes the difference between the position of the UAV and the range measurements from the MR sensor. Specifically, we minimize the function:

$$\arg\min_{\hat{x}_s, \hat{y}_s} \sum_{i=1}^{n} ((\hat{x}_{uav_i} - \hat{x}_s)^2 + (\hat{y}_{uav_i} - \hat{y}_s)^2 - \hat{d}_i)^2$$

(6.1)

where ($\hat{x}_{uav_i}, \hat{y}_{uav_i}$) is the estimated position of the UAV given by the simulated optical flow.
flow, and $d_i$ is the distance measurement from the MR sensor that corresponds with that UAV position. Fig. 6.9 shows an example of how this minimization function works.

We then find the estimated position of the MR sensor, $(\hat{x}_s, \hat{y}_s)$, that minimizes this function over the $n$ readings. The data used for input to the minimization function is in the structure of a circular queue that holds up to 10 seconds of data. Allowing this temporal property prevents the minimization function from becoming overweighted with areas with dense sampling, producing erroneous position estimates from too few samples, and problems from longer-term optical flow position estimation drift.

Minimizing Eqn. 6.1 produces accurate position estimates as long as there are sufficient samples within 1 m of the MR sensor (as per Fig. 6.7). Alg. 1 shows the algorithm we use to ensure good sampling of the area. The localization algorithm works by first approaching the position of the sensor that was recorded during deployment using GPS alone. The UAV will be near the sensor when it arrives at its coarse position, but not close enough to be able to transfer power to the sensor. The control
Algorithm 1 Localization Algorithm

1: procedure LOCALIZE($x_{sc}, y_{sc}$)  \(\triangleright\) Main localization method given the coarse position of the sensor
2: \hspace{1em} GPsiTo($x_{sc}, y_{sc}$) \(\triangleright\) Fly to the coarse position
3: \hspace{1em} \hspace{1em} \triangleright\) Now switch to Optical Flow + MR sensor control
4: \hspace{1em} OptFlowFlySquare(Size = 2 m)
5: \hspace{1em} OptFlowFlyTo($\hat{x}_{s}, \hat{y}_{s}$)
6: \hspace{1em} while True do \(\triangleright\) Continually refine estimate
7: \hspace{2em} OptFlowFlySquare(Size = $d$)
8: \hspace{2em} OptFlowFlyTo($\hat{x}_{s}, \hat{y}_{s}$)
9: \hspace{1em} end while
10: end procedure

11: procedure ON new MR reading(Volts)
12: \hspace{1em} $d \leftarrow$ Volts_to_range(Volts)
13: \hspace{2em} $X_{uav} \leftarrow$ Append($X_{uav}, \hat{x}_{uav}$)
14: \hspace{2em} $Y_{uav} \leftarrow$ Append($Y_{uav}, \hat{y}_{uav}$)
15: \hspace{2em} $D \leftarrow$ Append($D, d$)
16: \hspace{2em} $\hat{x}_{s}, \hat{y}_{s} \leftarrow$ ArgMin($\sum((X_{uav} - \hat{x}_{s})^2 + (Y_{uav} - \hat{y}_{s})^2 - D)^2$) \(\triangleright\) Eqn. 6.1
17: return $\hat{x}_{s}, \hat{y}_{s}$ \(\triangleright\) The estimated position of the sensor.
18: end procedure

then switches to using the optical flow camera and MR sensor data. The UAV starts by going to points in a square surrounding the estimated position (line 4). Once the square is complete, the UAV flies to the estimated position of the WSN node (line 5), which is computed in a separate thread continuously (lines 11 through 17). This procedure is performed in a loop to continually refine the estimate (lines 6 through 8) until some other action is taken (for example, land, fly home, fly to another WSN node).

6.3.1 Evaluation

To evaluate the localization algorithm, we perform a series of trials where both the MR sensor and the UAV are placed in random starting positions in the test room (size $3 \times 3 \text{ m}$). In line 2 of Alg. 1 shows that the UAV must go to the GPS location that was recorded when the sensor was deployed. We simulate this by sending the UAV first to the center of the test room. The simulated optical flow system introduces
error into the position estimation of the UAV. Honegger et al. have shown that their optical flow system is able to provide accurate position estimates to within 0.2 m [24]. We induce this level of error as random Gaussian noise.

The results from one experiment are shown in Fig. 6.10 and Fig. 6.11. Fig. 6.10 shows the range readings compared to ground truth (obtained with a potion capture system) and the power transfer rate, and Fig. 6.11 shows the flight path. During time $t = 0$ to $t = 5$, no valid range estimate had been found, thus there is no estimated distance. The UAV continued the scripted flight until $t = 15$, when it then flies to the current estimate of the sensor’s position. In this particular experiment, the position was found within 6 cm of the true location after 24 seconds. At this distance, the WSN node receives 5.49 W and the MR sensor is at 100% of its maximum value.

We performed 20 experiments and all successfully found the location of the MR sensor. On average, it took the UAV 36 seconds to localize the sensor with an average positional error of 21 cm (48 cm maximum, 13 cm standard deviation), where the WSN node receives an average of 3.38 W (0.2 W minimum, 1.7 W standard deviation). At 21 cm, the MR sensor value is at 98.6% of the maximum. Since the MR sensor reaches its maximum value before the UAV is localized precisely over the sensor, an MR sensor with a higher maximum value may improve the final localized position. These experiments show that we can quickly localize the MR sensor and get close enough for good power transfer using only an optical flow camera and range information from the MR sensor.

### 6.3.2 Variations

Here we use a slight variation of the previous method by modifying the algorithm and the minimization function. Instead of weighting all samples equally, here the
Figure 6.10: The distance from the WSN node in meters. In this case the position of the UAV is estimated by a simulated optical flow system and the position of the WSN node is unknown. At $t = 20s$, the UAV has found the position of the MR sensor at $t = 19s$, and the UAV continually updates its position to hover over the location by time $t = 23s$.

Figure 6.11: The flight path of the UAV as it searches for the MR sensor.

...minimization function weights samples based on the distance between the transmitter and receiver. Closer samples (samples with higher voltage) are weighted more heavily than samples further away. Also, the algorithm is modified to use circular trajectories instead of approximating using a square.
This experiment is set up exactly the same as the original version. The WSN node and UAV are placed in random starting positions throughout the test room. The UAV first goes to the center of the test room, which can be thought of as the gps position that is recorded when the WSN node is deployed.

Specifically, the minimization function is slightly modified to:

\[
\text{arg min}_{\hat{x}_s, \hat{y}_s} \sum_{i=1}^{n} \left( (\hat{x}_{uav_i} - \hat{x}_s)^2 + (\hat{y}_{uav_i} - \hat{y}_s)^2 - \hat{d}_i \right) \cdot V_i^3
\]  

(6.2)

where \( V_i \) corresponds with the voltage of the \( i \)th sensor reading. This takes into account not only the range estimation from the MR sensor, but the original voltage reading. The equation is virtually identical, except the function is multiplied by the cube of the voltage in the MR sensor. This means that high voltages, which correspond with small range estimations, will penalize the function value much more for incorrect arguments.

Furthermore, the algorithm is slightly modified (See Algorithm 2). Instead of using a square trajectory, we use circular trajectories immediately after a non-zero reading from the MR sensor is encountered. This difference is seen in Line 4 and the new Procedure starting on Line 7.

Circular trajectories cause the position estimation to converge more quickly. This is because if we use a straight line trajectory, the range estimates from the sensor could correspond to two locations. However, a circular trajectory eliminates this. Fig. 6.12 shows the UAV path localizing the sensor with this method.

Over 10 trials, the UAV localized with an average error of 15 cm, with a 6 cm standard deviation. This is 6 cm more accurate than the previous minimization function. The localization time is 46 s on average, 10 s longer than the previous method. However, this is within one standard deviation of both methods (14 s and
The localization time for this method is slightly longer than the previous method. However, if we look at only the time that it took to compute the estimated position, but not the time that it took to actually arrive at that location, using the combination of the circular trajectories and the weighted minimization function, the UAV was able to estimate the position of the WSN node within 20 cm in just 13.8 s, whereas it took the previous method 24.8 s. The most likely reason for this is that the circular trajectories simply take a longer amount of time to fly than the square trajectories. This is only due our implementation of the PID controller on the UAV, and the circular trajectories can be flown much more quickly with an improvement to the controller. Improving this controller is part of our future work.

6.3.3 Summary of localization using optical flow

We have shown a localization method that enables recharging a WSN node autonomously using one Magnetic Resonant sensor. The UAV is able to localize to
Algorithm 2 Localization Algorithm

1: procedure LOCALIZE($x_{sc}, y_{sc}$) \Comment*[h]{Main localization method given the coarse position of the sensor}

2: \hspace{1em} GPSFlyTo($x_{sc}, y_{sc}$) \Comment*[h]{Fly to the coarse position}

3: \hspace{1em} \Comment*[h]{Now switch to Optical Flow + MR sensor control}

4: \hspace{1em} OptFlowFlyCircle(Radius = 2)

5: \hspace{1em} OptFlowFlyTo($\hat{x}_s, \hat{y}_s$)

6: end procedure

7: procedure ON NON-ZERO MR READING(Volts)

8: \hspace{1em} while True do \Comment*[h]{Continually refine estimate}

9: \hspace{2em} $d \leftarrow$ Volts to range(Volts)

10: \hspace{2em} OptFlowFlyInCircle(Radius = $d$)

11: \hspace{2em} OptFlowFlyTo($\hat{x}_s, \hat{y}_s$)

12: \hspace{1em} end while

13: end procedure

14: procedure ON NEW MR READING(Volts)

15: \hspace{1em} $d \leftarrow$ Volts to range(Volts)

16: \hspace{2em} $X_{uav} \leftarrow$ Append($X_{uav}, \hat{x}_{uav}$)

17: \hspace{2em} $Y_{uav} \leftarrow$ Append($Y_{uav}, \hat{y}_{uav}$)

18: \hspace{2em} $D \leftarrow$ Append($D, d$)

19: \hspace{2em} $\hat{x}_s, \hat{y}_s \leftarrow$ ArgMin($\sum((X_{uav} - \hat{x}_s)^2 + (Y_{uav} - \hat{y}_s)^2 - D)^2 \cdot V_i^3$) \Comment*[h]{Eqn. 6.2}

20: \hspace{2em} return $\hat{x}_s, \hat{y}_s$ \Comment*[h]{The estimated position of the sensor.}

21: end procedure

an average of 21 cm to land on the WSN node and recharge it for an average of 3.38 W. In some situations, it may not be possible for the UAV to land on the node, for example, if the node is underneath a bridge or under water. In this scenario, the UAV may hover over the sensor to charge it at an average of 0.44 W (the difference between the UAV and WSN node in the $z$-axis is 7 cm). Though 0.44 W is relatively low, our power transfer system is inefficient compared to related works. Others have achieved over an order of magnitude more power transfer at the same distance.

The benefit of using just one MR sensor and an optical flow sensor for localization is that it minimizes the hardware necessary to add the WSN node. Chapter 6.4 shows that we can use multiple MR sensors instead of an optical flow sensor for localization. However this adds hardware to the WSN node. The coils attached to the MR sensors
are just 8 cm in diameter and 2 cm tall, so they may fit on many different types of sensor nodes (the actual sensor board is just 1 cm by 1 cm).

6.4 Localization with an array of Magnetic Resonant Sensors

![Image of MR sensors setup](image)

Figure 6.13: Here we use four MR sensors to obtain a position estimate of the UAV.

While cameras or optical flow systems have been used for accurate control of quadrotors, they add extra weight to the UAV. By using four MR sensors, we can accomplish the task of localizing the sensor for power transfer. The drawback to this method is that it requires additional hardware on the WSN node, which limits the applications.

This localization method gives fine-grain control of the UAV to localize the sensor. We show that by using four MR sensors, the UAV is able to transfer sufficient power to a small device autonomously.

The MR sensors work by measuring the strength of the magnetic field that sur-
rounds the UAV when the wireless power transfer system is activated. By intelligently positioning the MR sensors around the receiving device, the MR sensors can provide an estimation of the position of the UAV to within the required error tolerance. The results show that the average error in estimated $(x, y)$ position of the UAV is $39.5 \text{ cm}$ on average. This error is small enough to allow the UAV to land on the receiving device. Results show that the average power transferred from the UAV to the receiver coil after it has landed on the sensor is $1.8 \text{ W}$.

The localization algorithm operates under the assumption that the $z$-axis is relatively stable. The $z$-axis can be controlled easily using ultrasonic sensors or laser range finders [65]. The MR sensor array is used to estimate the $(x, y)$ position of the UAV.

The first step in estimating the position of the UAV over the receiver is to convert the voltage measurements from the MR sensors into a distance measurement. The relationship between voltage and distance is experimentally determined. We do this by developing a regression model that maps the voltage readings from the MR sensors into a distance measurement. The regression model is different from that used in Section 6.3. Here, we use a linear regression model instead of the lookup table. This linear model is an older model that we were using, and is less accurate than the lookup table.

We can estimate the position of the UAV by minimizing the sum of squares between distance measurements. Specifically,

$$\arg \min_{\hat{x}, \hat{y}} \sum_{i=1}^{4} ((\hat{x} - x_{s_i})^2 + (\hat{y} - y_{s_i})^2 - \hat{d}_{s_i})^2$$  \hspace{1cm} (6.3)

where $(\hat{x}, \hat{y})$ is the estimated position of the UAV, $(x_{s_i}, y_{s_i})$ is the location of sensor $i$ relative to the receiving coil, and $\hat{d}_{s_i}$ is the estimated range calculated from the
Figure 6.16: Position estimation accuracy (y-axis) of the non-linear least squares method. The red line shows where a perfect position estimation would lie. The estimated position is most accurate when the UAV is within ±0.5m of the receiver.

The variables $x_{s_i}$ and $y_{s_i}$ are obtained by manual measurement when the MR sensors are deployed. For example, the four MR sensors in this setup are in $1 \times 1$ m square, so $(x_{s_0}, y_{s_0})$ is $(-0.5, -0.5)$, $(x_{s_1}, y_{s_1})$ is $(-0.5, 0.5)$, $(x_{s_2}, y_{s_2})$ is $(0.5, -0.5)$, and $(x_{s_3}, y_{s_3})$ is $(0.5, 0.5)$.

Fig. 6.14 and Fig. 6.15 show the accuracy of the position estimation. The blue line of $y = x$ shows where a perfect position estimation would lie. The graph shows that the error in position estimation is higher when the UAV is very close or very far away from the center. The estimated position is most accurate when the UAV is between $-0.5m$ and $+0.5m$ of the receiving coil. The range estimation model in this experiment is different from that used in Section 6.3. Here, we use a linearized model of the range estimation. Therefore, the errors at the extremities of the figures are due to the linearization of the range estimation on an individual MR sensor (See Fig. 6.17). We believe the error beyond ±1m may be eliminated by using a non-linear model for the range estimation, as used in Chapter 6.3.
Figure 6.17: The range estimation regression based on the ADC values from the MR sensor. A blue, linear model is used here, but a more accurate lookup table is used in Chapter 6.3.

The figures also show that there are certain areas around the MR sensors that cause extreme under coupling or over coupling, resulting in outliers. These areas cause a high variance in the estimated position. To account for these anomalies in the data, the estimated position of the UAV is Kalman filtered before any control is executed. This estimated position is then passed to a PID controller to move towards the target location.

6.4.1 Evaluation

We characterized the performance of three different methods of recharging a device. The first experiment shows that the UAV can hover over the WSN node while transferring power. The second experiment shows that the UAV is able to land on the
WSN node using the positioning algorithm. This allows the UAV to transfer power more efficiently than transferring while hovering.

The experiments are performed in a $3 \times 3$ m area. The receiver is placed in a random location throughout the room. The UAV must take off and search for the receiver in the room. While the UAV is searching for the receiver, its position is given by the motion capture system. This mimics an outdoor scenario where the UAV would use GPS to first search for the receiver. When the UAV determines that it is within range of the WSN node, the UAV switches to the localization algorithm explained above, and does not rely on any external localization information. Then when the UAV is centered over the receiver, it can either land to start transferring power or it can continue transferring power while hovering.

### 6.4.2 Hovering over the Receiver

The first experiment tests the ability of the UAV to hover above the receiving coil and transfer power to the WSN node using location information derived from the MR sensors. The amount of power transferred and the error in estimated position is recorded. Fig. 6.18 shows the error in position estimation. The MR sensors detect the presence of the UAV at $t = 0$. During the majority of the flight ($t = 20$ to $t = 50$) the position estimate is within $\pm 0.2$ m of the actual position.

Fig. 6.19 shows the distance from the UAV to the receiver and the amount of Watts transferred to the receiver for the same flight. For the duration of the flight ($t = 20$ to $t = 60$) the average distance from the receiver is 0.45 m. The figure shows that in order to obtain reasonable power transfer, the UAV must be within 0.3 m of the receiver, which happens rarely during the flight. This is not only due to error on the $x$- and $y$-axes, but the distance from the receiver is further increased by the $z$-
axis because the UAV is required to hover at a safe distance from the receiver. These tests are performed over 10 trials. In the average case, 0.44 W are transferred, the mean distance from the receiver is 52 cm, and the mean error in position estimation is 39.5 cm (in the x, y axes).

6.4.3 Landing on the WSN Node

Since hovering does not achieve high levels of power transfer, in this experiment, the UAV instead lands on the receiver to increase power transfer. The UAV is set to hover over the WSN node and transfer power using the localization algorithm. When the power transferred to the WSN node reaches a threshold (2 W), the UAV lands, which will increase the power transfer due to the closer proximity. This threshold was experimentally determined to be a good trade-off between flight time and total power transferred. The power transferred is recorded after the UAV has landed. The results of one experiment are shown in Fig. 6.21. The figure shows that the UAV converges on the node between $t = 0$ and $t = 20$. There are oscillations around the receiver
between $t = 20$ and $t = 35$. Finally at $t = 40$, the amount of power transferred to the receiver reaches the required threshold and lands on the node, transferring roughly 2 W to the receiver. We performed the experiment is performed 10 times. The landing positions of each test are shown in Fig. 6.22. The mean power transfer to the WSN node after the UAV has landed is 1.8 W with a standard deviation of 1.5 W, min of 0.0 W and max of 4.3 W.

### 6.4.4 Summary of localization using MR sensor array

In conclusion, we have shown a localization method that enables recharging a WSN autonomously by a UAV using a small array of Magnetic Resonant sensors. These sensors can sense the magnetic field of the transmitter and allow the UAV to localize over the receiver for power transfer. We have demonstrated that it is possible for a UAV to transfer sufficient power to devices autonomously using our localization algorithm. The results show that the average power transfer while the UAV is hovering over the receiver is 0.44 W, and the UAV can reliably land on the receiver to transfer
an average of 1.8 W.

While this method of localization does not require additional components on the UAV (such as an optical flow camera), it does require extra hardware on the WSN receiver node. Since the size of the WSN node is critical in most applications, the localization method described in Section 6.3 is a better option.

6.5 Summary

In this chapter we have shown two separate methods for localizing on the WSN node. Localizing with the optical flow camera and one MR sensor is able to localize more accurately and transfer 2.0 W (211%) more power than with four MR sensors.

Localization using optical flow is overall a better method of localization. The main advantage of this localization method is that there is minimal extra hardware needed on the WSN node. The only additional hardware required on the WSN node is the small MR sensor, which is just a quarter of the size of its resonant coil. Furthermore, the optical flow camera can produce a stable hover, while the localization method with four MR sensors produces an oscillating hover. The MR sensors simply do not provide accurate enough range estimates to accurately estimate the position of the UAV.

The main disadvantage of both localization methods is that the MR sensor must use some energy from the sensor node to transmit range information over a short range radio to the centralized computer, but WSN nodes already have radios and can transmit at very low power settings when the UAV is nearby. Plus, communication with the UAV would enable the WSN nodes to transfer their data onto the UAV and empty the persistent data storage. Also, the MR sensor does not need to be active for the majority of the time. The MR sensor can sleep by default and only wake and starts
transmitting range measurements once it has detected that a power transfer UAV is near. While visual markers may be an easy alternative to using data from the MR sensor, our ultimate goal is to be able to recharge sensors underground, underwater, or embedded in some other material. In these environments, visual markers will be unavailable.
Chapter 7

Energy Optimal Flight

We are interested in maximizing the distance that a UAV can travel on a single battery charge to reach as many WSN nodes as possible. We do this in two ways. First we maximize the efficiency of the drone during flight by picking the best translational speed, and second we maximize the efficiency of the battery by adjusting its mass.

To maximize the efficiency of the drone during flight, we show that there exists a velocity which provides the optimal distance per unit energy. We have already discussed the background information on quadrotor UAVs in Chapter 3.3. Next, we develop a theoretical energy usage model of a UAV in flight and collect experimental data to develop a realistic model for our vehicle. Results show that by flying at the optimal speed of 7.3 m/s we can fly for 2.7 km more than flying at 9.5 m/s and 3.5 km more than flying at 3 m/s. We also show that using an optimal battery mass of 269 g our UAV can fly approximately 2.0 km more than with the standard 159 g battery that comes with the vehicle.

While these numbers are specific to our vehicle, the methods described in this section can be applied to any multi-rotor UAV by experimentally determining the relationship between their vehicles rotor speed (or thrust input) with the amount of
power it consumes. Alternatively, it is also possible to determine the optimal flight parameters through rigorous theoretical modeling. However, we find that an empirical model is not only easy to obtain but provides a good estimate for small multi-rotor UAVs.

Our goal is to find an optimal translational speed. The drag force on the body of the UAV while translating is defined as:

\[ F_D = \frac{1}{2} C_d \rho A_B v^2 \]  
\hspace{1cm} (7.1)

where \( C_d \) is the drag coefficient,
\( A_B \) is the area of the frontal body,
and \( v \) is the velocity.

We make the assumption that the air density \( \rho \) will be uniform, so by replacing constants with the term \( C_D \) we arrive at:

\[ F_D \approx C_D v^2 \]  
\hspace{1cm} (7.2)

We can then finally arrive at equations describing the translational and lift forces acting on the UAV:

\[ F_x = (\cos \psi \sin \theta \cos \phi + \sin \psi \sin \phi) K_T \sum_{i=1}^{4} \omega_i^2 - F_{D_x} \]  
\hspace{1cm} (7.3)

\[ F_y = (\sin \psi \sin \theta \cos \phi - \cos \psi \sin \phi) K_T \sum_{i=1}^{4} \omega_i^2 - F_{D_y} \]  
\hspace{1cm} (7.4)

\[ F_z = mg - (\cos \phi \cos \theta) K_T \sum_{i=1}^{4} \omega_i^2 - F_{D_z}. \]  
\hspace{1cm} (7.5)

Eqns. 7.3 and 7.4 are used to estimate the translational forces on the UAV given the
individual thruster input and the current vehicle attitude. Eqn. 7.5 represents the lift forces on the UAV. To simplify the results in the following sections, we assume it is at equilibrium in the $z$ axis.

### 7.1 Theoretical Energy Consumption

![Figure 7.1: Power consumed with respect to the thrust input.](image1)

![Figure 7.2: Average velocity of the vehicle with the drag on the body considered versus thrust.](image2)

![Figure 7.3: Max flight time available by consuming one battery versus thrust.](image3)

![Figure 7.4: Max distance traveled with on battery versus thrust.](image4)

![Figure 7.5](image5)

Now that we have described how the thrust produced by quadrotors relates to the translational trajectory, we describe how the produced thrust is related to the energy
consumed. The goal is to be able to fly between the sensor nodes as efficiently as possible. By relating thrust and energy, we can derive a power consumption model based on the UAV’s flight vector. In Section 7.2, we experimentally verify this model.

A torque about the rotor $Q$, is produced by converting electrical current $I$, to a motor torque. Energy consumption of a motor can be modeled by

$$Q = k_q I$$

(7.6)

where $k_q$ is a constant relating the current to torque. The voltage $V$ can be modeled by the motor speed $\omega$, the current $I$, the total armature resistance $R_a$, and a constant $k_e$ which relates motor speed to the electromotive force.

$$V = R_a I + k_e \omega$$

(7.7)

And the total power $P$ can be represented as

$$P = IV = \frac{Q}{k_q} V.$$

(7.8)

The question is, for a UAV, is it better to move slowly, as fast as possible, or somewhere in-between? We make a few assumptions to answer this question. First, we assume that the UAV can consume 100% of the battery’s total capacity. Next, we assume that the forces acting on the UAV are purely horizontal, given by $F_{x,y} = \sqrt{F^2 - F_z^2} - C_{D_{x,y}} v_{x,y}^2$ where $F$ is the total force exerted by the thrust, $C_D$ is the drag coefficient, and $v$ is the velocity (the equation is simply the total horizontal force minus the drag on the vehicle). This means that there is only translational motion and no rotational or vertical motion. These assumptions greatly simplify the problem for only a very small cost. Since hovering costs a lot of energy, it is most
likely that an optimal trajectory will not contain much excess vertical force than simply the vertical force required to stay level. Furthermore, since the vehicle can reach its terminal velocity in under 3 seconds for any thrust value, we do not consider the acceleration time of the vehicle or the rotational velocity during the acceleration phase. Aerodynamic forces such as rotor drag, rotor tip speed, and free stream speed are not considered. This level of precision is unnecessary for our applications, since we are only concerned with the macro-scale performance.

The non-linear relationship between power and thrust implies that the motors are most efficient when rotating slowly. For a ground vehicle, this would imply that moving slow is the most efficient way to travel. However, for a quadrotor UAV, a significant amount of thrust must be used to maintain a hovering state. The approximate power required is [22]:

\[ P \approx \frac{T^3}{2}K_p \]  

(7.9)

Fig. 7.1 shows the relationship between thrust and power consumption. Using the relationship between power and thrust from these equations, we can find an optimal velocity to maximize range. Fig. 7.5 shows the relationship between power consumption, average flight velocity, flight time, distance traveled, and flight time with respect to thrust values on the x-axis. These graphs begin at \( T = 60\% \) thrust since with less thrust the UAV does not have enough thrust to lift off, but when \( T > 60\% \) the UAV can begin to add force in the horizontal direction.

Fig. 7.2 shows the relationship between velocity and thrust. Initially, we can get large increases in velocity with very little extra thrust, but the rate of increasing velocity slows as thrust increases due to the drag on the vehicle. Therefore, increasing the thrust becomes less effective to increase the velocity. In addition, Fig. 7.3 shows
that as the thrust increases, the flight time will decrease with a similar curve.

Fig. 7.4 shows that there is an optimal thrust value that maximizes the range. This is the equilibrium point beyond which increasing the thrust becomes detrimental to the overall distance traveled because energy is wasted from fighting the intense drag. This graph shows that it is possible to calculate an ideal thrust that should be used to cover the most distance. For this example, it would be a thrust of 75%. Fortunately, as Fig. 7.4 shows, the optimal point is near the plateau of this function so even if the thrust value is off, the travel distance will not be impacted too much.

This shows that a theoretical understanding is important, but our goal is to use this type of UAV to recharge wireless sensor network nodes. For this reason, it is more important to know the details specific to our UAV to maximize its range. We now empirically measure the relationship between thrust, velocity, and power. We then confirm the relationship between thrust and distance seen in Fig. 7.4 with real flight data. From this, we experimentally determine the thrust that produces the optimal distance traveled.

### 7.2 Experimental Analysis of Energy Consumption

To experimentally analyze the energy consumption of our UAV and determine the optimal thrust to fly the farthest, we collected a dataset of over 15,000 data points (40 minutes of flight), coming from a set of flights with level horizontal trajectories at different thrust settings. The UAV reports the amount of thrust produced and a monitor attached to the battery records the power that is being consumed. Furthermore, we can also determine the speed of the UAV through the UAV’s GPS. Fig. 7.6
Figure 7.6: Thrust vs. Watts from flights and the least squares curve approximation.

shows the data along with a curve that is approximated using non-linear least squares method. The x-axis is the sum of the velocity of the four rotors, and the y-axis is the amount of power consumed. Examining Figs. 7.1 and 7.6 we see that the theoretical model exhibit similar characteristics to the empirical model (Note that the x-axis scale is from 60 – 100% in Fig. 7.1 and 0 – 100% in Fig. 7.6).

In our theoretical analysis we showed that with the rotor speed versus power relationship, we can compute an optimal speed to maximize distance (See Fig. 7.4). Using data from the previous experiment (Fig. 7.6) we can compute that the optimal range can be obtained by flying at 75 % of the maximum thrust. We tested this by using data from 54 flights where the UAV traveled in approximately a straight line along a horizontal trajectory at different speeds. The experiments were performed at an indoor football field to eliminate error due to wind. The UAV has a monitor attached to the battery which radios back the power consumed by the UAV during the flight. The UAV is placed on the zero yard line to begin. The experiment starts by changing the position of a switch on the UAVs controller. Once switched on, the computer sends signals to the drone to fly with a constant thrust value. When the UAV crosses the 70 yard line, the switch is turned to the off position. The amount
of time that it takes to fly this distance is within the data returned by the drone. We use this to computer velocity information. Fig. 7.7 shows data gathered from the 54 test flights. The $y$-axis represents the distance covered per Joule, and the $x$-axis represents the rotor speed. This graph shows that the optimal input thrust is about 66% of the maximum.

In Fig 7.7, the line is the mean energy usage at a given rotor speed and the error bars represent one standard deviation. The most significant source of error in this graph is the noisy GPS data, which was used to estimate vehicle speed. Comparing this figure to Fig. 7.4, we can see that they are nearly equivalent, only differing in that the peak distance per unit power is more pronounced in the empirical model. Table 7.1 shows the thrust and corresponding range (in meters) on a single battery charge for a select values based on the experimental data. This shows that at the optimal speed we can cover over 7km, whereas the worst setting will result in a flight distance of under 4 km.

This data is specific to the Asctec Hummingbird quadrotor. In order to determine these values for another vehicle they may follow these steps.

1. Obtain the input Thrust to Power ratio.

2. Obtain the input Thrust to Force ratio.

3. Estimate the drag constant $C_d = 1/2K_D\rho A$. The parameters $K_D = 1/2$ and $A = 0.6^2$ are representative of our system.

4. Calculate the terminal velocity for this thrust input by setting $F_{x,y} = 0$ and solving for $v_{x,y}$.

5. Calculate the flight time by dividing the battery’s power capacity by the power consumption for the corresponding thrust input.
6. Calculate the distance per battery by multiplying the flight time and the terminal velocity. (We can neglect the acceleration phase of the vehicle since it takes negligible time to reach terminal velocity).

The data is filtered by taking small time intervals from each of the experiments, measuring the distance traveled and watts used for that interval, then averaging all these points together for the given thrust input. More formally, each $y$ value is calculated as

$$y = \frac{\Delta d}{\bar{w} \cdot \Delta t}$$

(7.10)

where $\Delta d$ is the change in distance and $\bar{w}$ is the average watts consumed during time $\Delta t \approx 1\text{s}$. From Fig. 7.7, the most efficient usage of power can be obtained where thrust is 66% of the UAV’s maximum.

<table>
<thead>
<tr>
<th>Percent Thrust</th>
<th>Velocity (m/s)</th>
<th>Meters per Joule</th>
<th>Meters per Battery</th>
</tr>
</thead>
<tbody>
<tr>
<td>60 (Minimum)</td>
<td>1.9</td>
<td>0.053</td>
<td>4448</td>
</tr>
<tr>
<td>66 (Optimal)</td>
<td>7.3</td>
<td>0.087</td>
<td>7267</td>
</tr>
<tr>
<td>85</td>
<td>9.5</td>
<td>0.055</td>
<td>4615</td>
</tr>
<tr>
<td>100 (Maximum)</td>
<td>10.0</td>
<td>0.047</td>
<td>3944</td>
</tr>
</tbody>
</table>

Table 7.1: Energy consumption of a battery with respect to the distance that can be traveled.

### 7.3 Optimal Battery Weight and Capacity

In addition to flying at the most efficient speed, it is also important to carry the optimal size battery. Carrying a larger battery may increase flight time, but at some point the added weight will make the UAV too heavy to fly efficiently. In this section we analyze the weight and capacity of the UAV’s battery using the empirical energy usage information from the prior section. The battery provided by the manufacturer is a 2100 mAh, 12 V LiPo battery that weighs 159 g. Let us assume that we can
add or remove mass from the battery, which will in turn add and remove energy from the battery. We will assume that the energy density is fixed and is $\epsilon = 2.1 \text{Ah} \cdot 12 \text{V}/159 \text{g} = 570.6 \text{J/g}$. We assume that the UAV can consume 100% of this total energy. The goal is to optimize the weight of the battery to maximize the distance that the UAV can cover before discharging the entire battery.

The acceleration of the system at time $t$, $a(t)$, in the horizontal direction for a given overall thrust, $r$, can be rewritten from Eqns. 7.3 and 7.4 as:

$$a(t) = \sqrt{r^2 - \left(9.81 \cdot (m_{\text{uav}} + m_b)\right)^2 - C_D \cdot v(t)^2}.$$  \hspace{1cm} (7.11)

The approximate amount of energy that the UAV is using for this input has been experimentally determined (see Fig. 7.6) and is given in terms of overall thrust, $r$, by:

$$e(r) = 12.09 + 1.629 \cdot 10^{-4} \cdot r^{2.236}.$$  \hspace{1cm} (7.12)
Total energy capacity of the UAV is $E = \epsilon \cdot m_b$, where $m_b$ is the mass of the battery, and $\epsilon$ is the energy density of the battery. The mass of the entire system is the mass of the UAV plus the mass of the battery, $m = m_u + m_b$.

From these equations, we can solve the optimization problem to fine the best battery to maximize the range:

$$\text{Maximize } \int_0^x v(t) dt$$

subject to $\epsilon \cdot m_b \leq e(r) \cdot x$. (7.13)

Fig. 7.8 plots the relationship between battery mass and total range. The green dot shows that the maximum achievable range is 9.3 km with the optimal battery mass of 269 g. The orange dot is the battery mass of 159 g given by the manufacturer, yielding a flight range of 7.3 km, so the addition of 110 g increases the flight range by approximately 2 km or 29%. At the optimal point, the UAV is using 66% of its overall thrust capability.

The fact that there is an optimal battery mass is intuitive because if we assume the battery has no mass, the resulting energy of the battery is 0, meaning that the UAV cannot cover any distance. As the mass rises, we gain total usable energy, but we either lose top speed or thrust efficiency. The trade-off between maximum speed and mass is given in Fig. 7.9. As the battery mass continues to rise, the top speed of the UAV slowly decreases and then falls sharply, causing the overall distance covered to shorten. Finally the total distance traveled becomes zero when the UAV can no longer provide the necessary force to lift the payload. Looking back at Eqn. 7.11 we can see that a lower top speed means less parasitic drag, meaning that less energy is being wasted due to drag forces. By increasing the battery mass (and therefore overall energy) will continue to increase the overall range of the UAV until the UAV’s
thrust capabilities have been reached. The range is maximized when the battery’s mass gives an optimal thrust value equal to the maximum thrust capacity of the UAV. This phenomena is also intuitive because as we increase mass, although we need more thrust, the maximum velocity is decreased, and therefore less thrust is wasted due to drag on the body of the UAV. Also, as we add battery mass, although the acceleration of the UAV is slower, the optimal velocity does not significantly decrease until the UAV is at its maximum thrust capability.

7.4 Summary

In this chapter, we developed an energy usage model for UAVs and experimentally measured this for our UAV. We found that by flying at the optimal speed of 7.3 $m/s$ we can fly for 2.7 $km$ more than flying at 9.5 $m/s$ and 3.5 $km$ more than flying at 3 $m/s$. We also analyzed the trade-off between battery capacity/weight to flight range and found that using the optimal battery can increase the flight range by an additional 2.0 $km$.

To our knowledge, quadrotor manufacturers have not yet considered increasing the mass of the battery to extend range. However, incorporating both the mass of the battery and the speed of flight can double the flight range of the UAV. This shows how critical these factors are to multi-rotor UAV operation. In our application this means that we can either transfer more power to sensors or we can charge more sensors on a single flight.
Figure 7.8: Curve showing the relationship between battery mass and total range, or distance the UAV is able to travel with the given battery. The green dot is the maximum value at 269 g and the orange dot is the current mass given by the manufacturer at 159 g.

Figure 7.9: Curve showing the relationship between the battery mass and the optimal velocity of the UAV. As the battery mass increases, the UAV must travel more slowly, however, the energy capacity is increased. The orange dot shows where the optimal battery mass lies.
Chapter 8

Conclusion

Wireless sensor networks have many applications because of the large amount of data that they are able to collect. However, the WSN nodes will eventually run out of energy and require maintenance. Fortunately, WSN nodes are low-powered devices which can generally last weeks or months with just a small amount of energy. Furthermore, some WSN nodes may be difficult to access or in remote locations, such as under a bridge or under water.

This thesis presents a unique solution to these problems. A small, quadrotor UAV is equipped with a wireless power transfer system which allows it to recharge a node in the WSN at up to $6.1\, W$.

The main problems with this approach are that the UAV has very limited energy, so it must fly efficiently out to the network. And secondly, the UAV must be within 30 cm of the WSN node in order to transfer sufficient power, however, GPS does not provide this level of accuracy.

This thesis addresses the energy constraints of the UAV in two ways. First, we develop a model of the UAV dynamics and analyze the energy usage. The model shows that an optimal translational speed exists which maximizes the range of the
UAV. The theoretical model is then confirmed with empirical data that shows that we can achieve a 38% increase in distance with a single battery by flying at an optimal velocity. Results show that by flying at the optimal speed of 7.3 m/s, we can fly for 2.7 km more than flying at 9.5 m/s, and 3.5 km more than flying at 3 m/s. Furthermore, the mass of the battery that the UAV carries is optimized to give the UAV the most range, while keeping the same energy density. The results show that by using an optimal battery mass of 269 g, our UAV can fly approximately 2.0 km more than with the standard 159 g battery that comes with the vehicle.

The power transfer system cannot transfer significant power to the sensor node until it is within 30 cm of the power transfer receiver. Since GPS is insufficiently precise, we develop two methods of localization which allows the UAV to get close enough to the sensor to charge it. Both localization methods utilize the magnetic field emitted by the wireless power transfer system on the UAV.

The first localization method uses one MR sensor and a simulated optical flow camera. The optical flow camera gives a short-term position estimate of the UAV, while a minimization function computes the estimated position of the sensor relative to the UAV. Results show that we can localize to within 21 cm over 36 seconds to transfer 3.38 W to the WSN node.

The second method uses four magnetic resonant (MR) sensors to estimate the position of the UAV. Results show that the position of the UAV can be measured with 39.5 cm of accuracy. Using either method, the UAV can either hover while transferring power to the node, or it is able to safely land on the node to transfer an average of 1.8 W and 3.38 W, respectively.

While the current system works well, there are many improvements that can be made to the wireless power transfer system and the dedicated hardware. First, the current system has too many communication channels. The Rx board, MR sensor,
Tx board, and UAV all have their own channels. This model can be compressed down into two communication channels, one combining the Rx board and MR sensor, and the other combining the Tx board and UAV.

In this system, the UAV must communicate with the MR sensor to position itself. This means that the WSN node needs to communicate with the UAV. However, we envision that the WSN node will transfer all the data that it has collected to the UAV while it is being charged. Plus, the MR sensor only needs to transmit the data a short distance, allowing it to use a low powered radio.

Ideally, in the future we would like to use data from the Tx board (such as voltage and current) to replace the MR sensor. However, results show that the data from our current Tx board does not provide the level of resolution necessary for localization.

Future work includes more testing outdoors. Preliminary testing as well as related work shows that, even in outdoor conditions, the localization method using optical flow should be used over the localization method using an array of MR sensors.

Finally, we have optimized the parameters of the power transfer coils for efficiency on a small UAV. This improves the coils of our system, but the focus of this research is localizing, not maximizing the power transfer capabilities. However, research has shown that power transfer can be greatly increased using similarly sized coils [63]. This research inspires us to improve the UAV’s power transfer system in our future work.

In conclusion, the presented system allows for long-term deployment of sensors, potentially underwater, underground, or embedded in materials, without the need for large batteries, solar panels, or fixed cabling. We have shown that this method of recharging a network is feasible and even suitable for some wireless sensor networks. Networks which implement this system may be able to survive indefinitely.
Bibliography


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