DeepInfra: Deep Learning-based Wireless Infrared Charging for Unmanned Aerial Systems

Abstract: We propose a novel wireless charging framework, which can charge unmanned aerial systems (UAS) during their mission/flight when there is line of sight between a UAS and charging station. The proposed charging mechanism, called DeepInfra, utilizes infrared beamforming to transfer energy from charging station to the UAS. However, alignment of the infrared beamforming should be updated frequently according to the movement of UAS to maintain efficient energy transfer. DeepInfra utilizes software based radios in order to track the movement and determine the location of the UAV accurately. In this manner, DeepInfra offers deep learning techniques integrated with GnuRadio and flight control software to estimate future position of the UAV so that energy transfer can be maintained without any degradation. In the scope of this challenge, DeepInfra will be implement to a specific drone model, Freefly Alta 8, which capable to cry payloads up to 20 lbs. As baseline performance, Freefly Alta 8 (with two 10Ah batteries) can fly 13, 10 and 8 minutes while carrying 10lbs, 15 lbs and 20lbs payload configuration respectively. This performance can be advanced into 37, 24 and 18 minutes for 10lbs, 15 lbs and 20lbs payloads respectively with constant reception of 1.5KW power at the UAV during its flight.

1 Introduction

Unmanned Aerial Systems (UAS) are becoming indispensable in assisting military and first responders in relief efforts for man-made or natural disasters owing to their increased cost-effective availability and easy deployment in any environment. In every search and rescue (SAR) mission, ensuring the longest possible flight time is of paramount importance and can directly impact human lives. However, UAS are power hungry devices with limited battery capacities. A single UAS weighs approximately 6lbs and requires more than 150W power during flight. Thus, it is able to fly for about 25 minutes under default battery/payload configurations. Therefore, a UAS must frequently return to a ground station to re-charge or swap its batteries.

• **Problem.** Landing on a charging station or hovering above a charging pad is time consuming, requires complex maneuvering for correct landing, and also costs actual mission time. There can also be cases where there is no feasible solution, especially if the charging station is far away resulting in excessive energy consumption in the travel alone, or if the disruption in the monitoring task during its travel time to the station is prohibitive. To address the above challenges, we propose a novel infrared charging system called DeepInfra, which aims at proposing a network-supported UAS architecture enabled by over-distance wireless charging capability that can potentially extend the flight time by a factor of two.

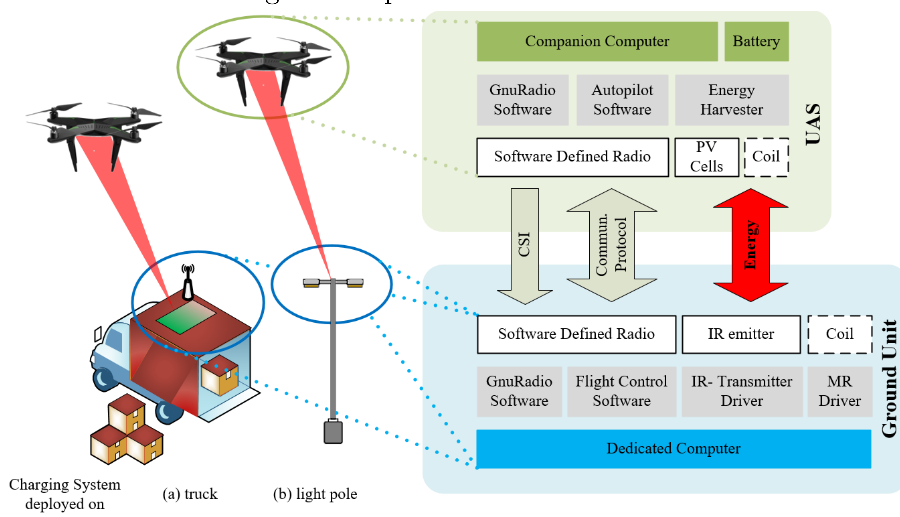


Figure 1: DeepInfra Architecture with software defined infrared chargers and multiple pole-and vehicle-mounted transmitters.

• **Solution.** Our core idea is to integrate low-cost infrared beamforming/charging capability within a UAS. While there are a few recent solutions by companies that provide limited, contact-based (such as magnetic resonance) and over-distance charging with laser/RF, the existing solutions either require manual involvement (during the landing process) or are not designed for challenging environmental conditions typically associated with SAR situations, such as lack of a visual range, thick smoke, clouds, fog, structural barriers, among others. The high mobility and continuous hovering motion of the UAVs makes it difficult to keep energy beams correctly aligned. We tackle these problems holistically in our proposed approach by adopting an end-to-end charging architecture, and demonstrating the outcomes with off-the-shelf Freefly Alta 8 UAS. Figure 1 shows a sample target scenario, where infrared chargers are placed in light poles and vehicles on the ground. A software defined network controls multiple transmitters and identifies the UAS to be charged in priority if multiple candidates are present in a common range. The UAS are equipped with a custom-designed energy harvesting circuit that has PV cells as well as a RF-transceiver in the 900MHz/2.4GHz range, which periodically sends 3-axis accelerometer and location coordinates to the ground-bases chargers. The charging infrastructure tracks the movement of the UAS and emits the infrared light beam accordingly in order to maximize the energy gain at the target UAS.

2 Team

The team is composed of two Northeastern faculty with significant research background in designing energy-efficient UAS architectures, systems building, wireless communications and robotics.

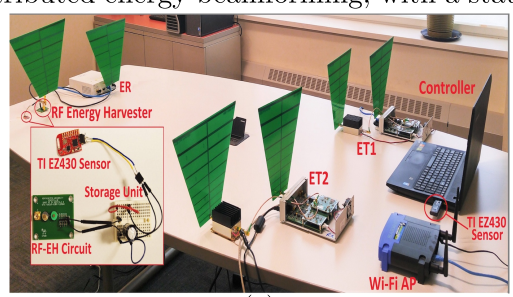
• Prof. Chowdhury is associate professor at Northeastern University, Boston. He has over twelve years of experience in the area of wireless and software defined networks. He was awarded the Presidential Early Career Award for Scientists and Engineers (PECASE) in Jan. 2017 by President Obama at the DoDs nomination, the ONR Director of Research Early Career Award in 2016, and the NSF CAREER award in 2015. He has won three best paper awards in IEEE ICC (in 2009, 2012 and 2013). The PI has authored numerous papers on intelligent radio and energy harvesting architectures which are directly relevant to this proposal. His overall h-index is 33 with over 8800 cumulative citations.

• Prof. Singh is a professor at Northeastern University. He was earlier in the Scientific Tenure Track Staff at Woods Hole Oceanographic Institution rising to Senior Scientist. He has been the principal architect behind the Seabed class of AUVs which are in wide use around the world and more recently was also responsible for the design of the Jetyak USV. He has designed and flown UAS extensively including in Greenland, the Arctic and the Antarctic. He and his students have multiple awards including the ICRA Best 2006 Paper Student Award and IEEE King Sung-fu Memorial Best Transaction on Robotics Paper award He has been on more than 50 research expeditions in all the world's oceans using his robotic and imaging techniques for applications in Marine Geology and Geophysics, Marine Archaeology, Coral Reef Ecology, Fisheries, and Polar Studies.

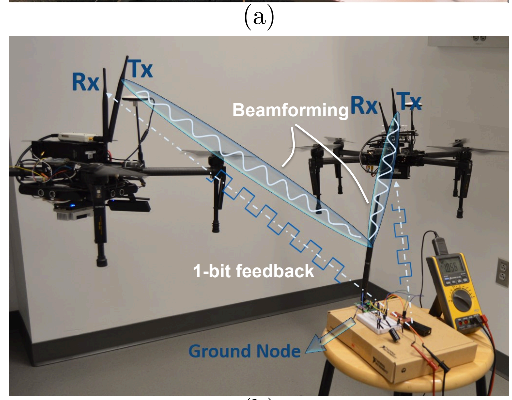
3 Preliminary Experimental Results

Our work is based on our considerable experience in distributed energy beamforming, with a static setup shown in Figure 2a.

It has the following components: 1) programmable energy transmitter (ET) based on a USRP SDR from Ettus Research, 2) feedback-generator receiver, and 3) controller software. The GNURadio software plane in the USRP implements the beamforming algorithm for phase and frequency synchronizations and transfers high power energy signals toward the desired receiver using a power amplifier. Each ET also uses an extended Kalman filter to estimate and correct the frequency offset between its carrier frequency and the feedback as a reference signal. The receiver estimates the received signal strength (RSS) of the net incoming signal and broadcasts a single bit to all the ETs to indicate whether this value is higher or lower than that measured in the previous time slot. Figure 2b shows our experimental efforts used to demonstrate the beamforming in a practical UAS scenario which runs on the DJI−matrice 100. The system setup consists of two USRP B200MINI-I SDRs with the NVIDIA Jetson TX1 serving as the host controller, which are contained



(a)



(b)

Figure 2: Experimental setups.

on-board the UAS. In our setup, each USRP radio drives a separate transmitter and receiver boards, also connected with the Ettus VERT900 and VERT2450 antennas. The former is used for the beamforming operation in the 900MHz band, while the latter is used to receive feedback from the ground node at 2450 MHz.

4 DeepInfra: Deep Learning-based UAS Wireless Charging

We propose to implement the charging system upon a Firefly ALTA 8 UAS, which can carry 20lbs payload with a $(2 \cdot 10\text{mAh})$ battery configuration, as shown in Figure 1. It will contain the following components 1) programmable RF as feedback-generator, 2) controller software, and 3) infrared receiver panel composed of an array of photovoltaic cells. Our charging station setup will integrate charging mechanisms with the ground control software to provide seamless charging during the entire mission.

The charging station/module contains 1) Freefly SYNAPSE flighter controller, 2) high power far-infrared laser source with optical amplifier which can transfer energy in order of hundred watts, and 3) programmable RF radio. In the far-infrared laser source, we use an electro-optic modulator (EOM) as a shutter to turn off the infrared beam in nanoseconds if needed for any safety reasons. This module could pulse the laser or alter the transmitted power at a very high frequency. It sends the infrared beam through a crystal with acoustic vibrations that alters the refractive index of the material so turn off the beam in a very short time.

DeepInfra addresses the main bottleneck of infrared beamforming, which is direction and delay of beam alignment in SAR scenarios where we do not have LoS, through integration of RF feedback containing UAS location and Channel State Information

If the position of the charger and UAS remain fixed, the CSI shows slow variation during coherence time of the infrared beam signal. Then, only reception of the feedback with CSI is enough for beam alignment. However, the position of the UAS changes rapidly in typical SAR scenarios, and thus, can cause the variation in CSI within coherence time. Ultimately, this results in poor infrared beamforming. Figure 3(a) shows the incident received signal strength measured at a ground node for three different scenarios: static, indoor-UAS, and outdoor-UAS, based on our setup depicted on Fig. 2b. Figure 3(b) shows small variation in CSI due to movement of the UAV. With the real-time (RT) CSI reception, beam alignment mechanism should satisfy critical deadlines to maintain constructive energy transfer. To address this limitation, we propose to use the obtained CSI with additional sensor readings from the UAS combined with deep learning techniques to accurately estimate the future location and CSI of the UAS by the ground station. In particular, instead of increasing the feedback from the receiver, we will predict the CSI by tracking the movement of the UAV. In the DeepInfra we propose to use Convolutional Neural Networks (CNNs) composed of two parts: the convolution

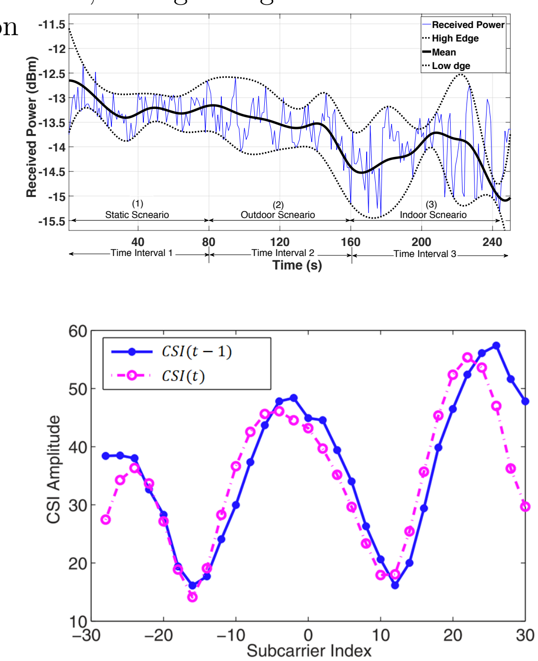


Figure 3: Experimental results for variations in received power and feedback CSI due to UAV movements.

layer and fully connected or dense layer. The input to the convolution layer are sensory data from the UAS (e.g. change in positions) and previous CSIs. The convolution layer can be considered as a spatial filter which performs spatial convolution of the input data. A ReLu activation function is used in the convolution layer to introduces non-linearity to the CNN. ReLU is an element-wise operation, which gives output max(x,0) for an input x, replacing all negative inputs to zeros. The convolution layers can be followed by a max pooling layer which reduces the dimensionality of the data. After the spatial features have been extracted, a fully connected traditional Multi Layer Perceptron (MLP) at the CNNs end performs prediction based on the output of the convolution layer. This output is the next estimated CSI, which is then used by the UAS for infrared beamforming.

5 Deliverables and Preliminary Results

A preliminary performance of DeepInfra is evaluated through numerical simulations with three vital metrics such as maximum payload, harvested power and flight time. The maximum payload highly depends on environmental conditions and UAS capabilities, though it drastically increases power consumed during flight thus reduces flight time and overall energy transmission. Secondly, as amount of harvested power increases, theoretically, flight time can be potentially prolonged for perennial operation. However, harvested power on UAS-side depends on multiple parameters like path loss, optical to electrical conversion efficiency and UAS alignment. Thus, it should be dynamically adjusted according to the payload and target flight time/plan in order consume energy efficiently. As a result, we measure the overall flight time with respect to harvested power and payload on the UAS. In order to present further insights, we theoretically calculated the flight time of Freefly Alta 8 drone with two 10Ah batteries under several scenarios according to the specifications provided in its datasheet. Figure 4a shows the baseline capability of the UAS in terms of flight time with different payload configurations and how much 200W and 500W charging power on the UAS prolongs the flight time with respect to the payload of the UAS. Figure 4b presents how much charging power should be harvested at the UAS during the entire flight in order to extend overall flight time to 30, 40 and 60 minutes of flight time respectively.

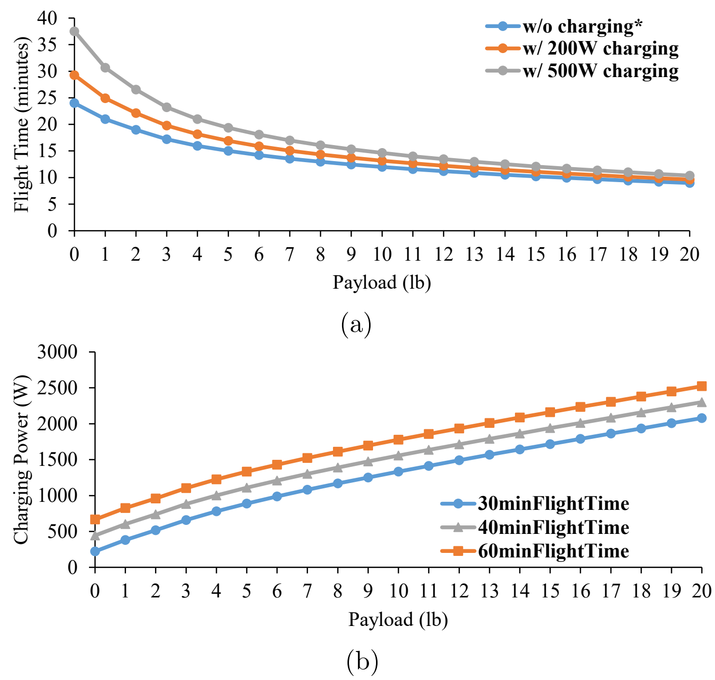


Figure 4: (a) Maximum estimated flight time w/ and w/o charging (b) Charging power requirement to maintain defined flight time.

*Based on the information retrieved from https://freeflysystems.com/alta-8/specs on January 2018.