

Opo: Characterizing Human Interactions To Model Disease Transmission

William Huang, Prabal Dutta
Electrical Engineering and Computer Science Department
University of Michigan
Ann Arbor, MI 48109
{wwhuang, prabal}@umich.edu

ABSTRACT

Capturing the spatial and temporal aspects of human interactions allows for better informed disease transmission models. Various smart badge type solutions have been devised to capture these parameters, but their real world deployability is minimal. The key problem stems from the unpredictability of mobile neighbors, which makes synchronization and neighbor discovery difficult, resulting in either bulky, high powered nodes or infrastructure heavy systems. In this paper, we present Opo, a small, ultrasonic wakeup circuit that draws $16 \mu\text{A}$ when no neighbors are present, allowing nodes to remain asleep most of the time and be asynchronously awoken when other nodes are present. This solves the synchronization problem without requiring large batteries or infrastructure nodes, enabling easily deployable systems to characterize the spatial and temporal aspects of human interactions.

1. INTRODUCTION

It is estimated that the flu season results in an average annual loss of 610,660 life-years lost, 3.1 million hospitalized days, 31.4 million outpatient visits, \$10.4 billion in direct medical costs, and \$87.1 billion in terms of total economic impact for the United States [4].

Models for aerosol transmissions, or droplets expelled during coughing or breathing, are used to better understand influenza outbreaks. These models are quite sensitive to input parameters such as the frequency, orientation, duration, and distance of human interactions.

Surveys are the most common approach for discerning these human interaction parameters for epidemiological models [1, 7, 3]. However, surveys depend on subjective, self-reported measures of interactions, and scaling such studies is problematic. More automatic, objective and scalable methods have been devised, but none of them have been able to provide the necessary parameters in a deployable manner [5, 6, 2].

RF/ultrasonic time difference of arrival (TDoA) schemes have come the closest to solving this problem by providing high ranging resolution and orientation data. TDoA transmits two signals with different propagation speeds,

such as RF and ultrasonic, with the receiver calculating the speed based on the difference in arrival time of the two signals. Traditionally, TDoA have been difficult to deploy due to the aforementioned synchronization problem, which has led to infrastructure heavy systems.

In this paper, we present Opo, the a small, light, and ultra low power wearable sensor that can capture the spatial and temporal aspects of human interactions with zero infrastructure nodes. Opo achieves high ranging resolution by directly ranging neighbors using the TDoA between RF and ultrasonic pulses, and high collectively at 1 Hz between two nodes. The key to allowing this to be done in an infrastructure free manner while only drawing tens of micro-amps is a $16 \mu\text{A}$ ultrasonic wakeup radio built from commercially-available components. This allows Opo to shrink to a *lapel pin* scale sensor node with a high battery life. We claim that this will enable unprecedented capture of the physical aspects of human interactions.

2. ARCHITECTURE

2.1 Opo Circuitry

The key enabler of Opo is a $16 \mu\text{A}$ ultrasonic wake up circuit, which allows the ultrasonic transceiver to serve as an always on receiver, eliminating the need for synchronizing infrastructure nodes.

To analyze the viability of an always on, ultra low power ultrasonic receiver, we examined 11,000 op amps from the DigiKey database which would run off a typical sensor mote power supply. The results of this analysis are summarized in Figure 1. We found two op amps which could provide adequate stable amplification for our 40 kHz transducers at a low enough power to be always on: the MIC861 and MIC863.

Opo uses three $10\times$ gain op amp stages, a 900 nA comparator, and an integrator circuit, resulting in a power efficient, noise resistant, and digitized receive circuit.

2.2 The Opo Protocol

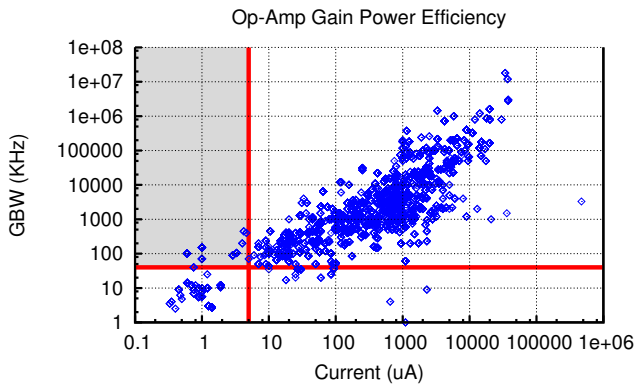


Figure 1: Analysis of current vs op amp gain. The shaded gray region highlights op amps with sufficiently high gain and sufficiently low current.

Opo nodes can dynamically choose to be a transmitter or receiver using a single ultrasonic transducer. At minimum, the transmission only requires a PWM module from the MCU.

2.2.1 The Transmit Protocol

First, an ultrasonic wake up pulse is sent, waking up and synchronizing neighboring nodes to the transmitter. Next, a radio packet and ultrasonic pulse are simultaneously transmitted.

2.2.2 Receive Protocol

Upon hearing an ultrasonic pulse, the Opo receive circuitry generates a wake up interrupt. The Opo software layer then disables ultrasonic interrupts and turns on the radio.

The receiver then waits for the SFD pin to assert, signifying a packet reception, captures the assertion time, and re-enables interrupts from the ultrasonic receive circuitry. The receiver captures the time of arrival of the next ultrasonic pulse, and uses the time difference of arrival between the SFD assertion and this ultrasonic pulse to calculate the distance between the receiver and transmitter. Each ms time difference corresponds to approximately $.34 m$.

3. DISCUSSION

Microbenchmarks validate the ranging accuracy of the Opo subsystem, as seen in Figure 2. Our current implementation weighs $16.4 g$ with a battery, and has a volume of only $5.4 cm^3$. Small experiments with students have proven successful, but many research challenges remain.

With regards to the protocol, the backoff mechanism and transmission frequency are open questions. In areas of high ultrasonic noise, RF interference, or node density, the Opo nodes should clearly back off their transmission frequency. However, if the backoff is

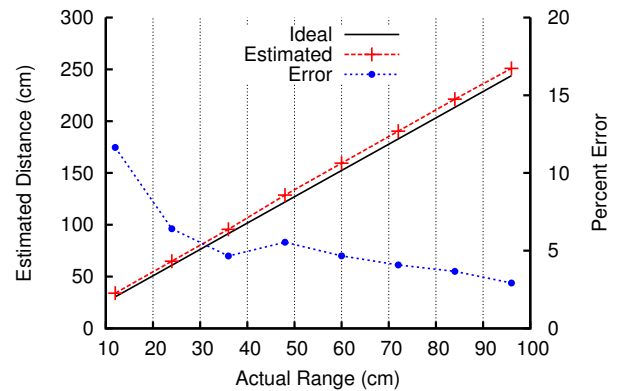


Figure 2: Head-on evaluation where two nodes directly face and range against one another. We find Opo consistently reports the distance as slightly too far, but within 5% error for ranges over $.6 m$.

too aggressive, we risk missing important interactions. Transmission frequency trades off temporal fidelity and power usage, and it is unclear what the correct balance of longer term study vs more intensive data is.

From a big data standpoint

4. REFERENCES

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