Sozu: Self-Powered Radio Tags for Building-Scale Activity Sensing

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ABSTRACT
Robust, wide-area sensing of human environments has been a long-standing research goal. We present Sozu, a new low-cost sensing system that can detect a wide range of events wirelessly, through walls and without line of sight, at whole-building scale. To achieve this in a battery-free manner, Sozu tags convert energy from activities that they sense into RF broadcasts, acting like miniature self-powered radio stations. We describe the results from a series of iterative studies, culminating in a deployment study with 30 instrumented objects. Results show that Sozu is very accurate, with true positive event detection exceeding 99%, with almost no false positives. Beyond event detection, we show that Sozu can be extended to detect richer signals, such as the state, intensity, count, and rate of events.

Author Keywords
Activity sensing; Battery-free; Wireless sensing; Context-Aware Computing; Internet-of-Things.

CSS Concepts
Human-centered computing → Ubiquitous and mobile computing → Ubiquitous and mobile computing systems and tools.

INTRODUCTION
Building-scale sensing of human activities has been a long-standing research goal. Of course, human environments are incredibly diverse, with potentially hundreds of facets that would be valuable to feed into intelligent systems that could enhance everyday tasks. Such systems may wish to monitor fixed infrastructure (e.g., doors, cabinet drawers, faucets, toilets), movable objects (e.g., kitchen utensils, personal hygiene items, tools) and larger appliances (e.g., microwave, refrigerator, stove, laundry machine, coffee maker).

Unfortunately, contemporary sensing approaches are ill-suited to the scale, diversity, and construction of homes and offices. For example, to achieve the ubiquity required for wide-area sensing, many systems use small, wireless, battery-powered "tags" (e.g., [12, 42, 51, 55, 56]). In general, sensing fidelity is limited due to tight power constraints, and even still, the batteries require periodic maintenance, which is undesirable for deployments with scores of sensors. Alternatively, sensors can utilize wall power, though this limits placement or requires wires to be run. Either way, both battery-powered and wired sensors typically cost between $10 and $100 each (e.g., [12, 55, 56, 58]), meaning a comprehensive, whole-building deployment might cost thousands of dollars. In response to these limitations, we define four properties an ideal sensing solution should embody:

Low Cost: The cost per sensor should be under $10, meaning a building could be outfitted with 100 sensors for under $1000. This price point would also permit integration with low-cost items, such as a plastic watering can.

Battery- and Maintenance-Free: The sensors should not require wall power or batteries, allowing for flexible placement and minimal (or no) maintenance.

Building Scale: The system should operate wirelessly, through walls and floors, and without line of sight.

Rich Sensing: Finally, beyond detecting the presence of activities, the system should also offer rich sensing opportunities, such as the state, intensity, count, and rate of activities.

SOZU
This paper presents Sozu, a building-scale sensing solution that achieves the above idealized constraints. A Sozu deployment consists of one antenna, which can be placed in an inconspicuous location, such as a basement. Users then attach Sozu "tags" to items and infrastructure of interest. To keep cost low, these tags are constructed from ultra-low-cost analog components, and thus cost only a few dollars each (i.e., no digital components, nor digital communication like Wi-Fi or Bluetooth).

Another key innovation is the battery-less design of Sozu tags, which instead harvest energy directly from the activities they sense. The tags convert and then broadcast this energy as radio frequency (RF) waves, acting like small radio stations. Each tag is given a unique frequency, allowing for recognition of many simultaneous events. Importantly, we selected a frequency range that readily penetrates common building construction types, offering whole-building sensing

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with just a single antenna. As we will discuss in detail, our tag design and software stack enable fine-grained sensing capable of supporting a wide range of end-user applications.

In addition to describing the implementation of our system, we also report the findings from several studies. First is a comprehensive survey of energy harvesting opportunities in common environments (Figures 1-7), which we used to inform the design of our tags. In our second study, we added Sozu tags to 30 objects across three, multi-story buildings and evaluated the recognition accuracy of our system over two weeks. Results show activity detection accuracies in excess of 99%. Simultaneously, we ran a separate one-month durability test of our tags, with no failures. Finally, we took all of our developments in hardware and software and created an easy-to-use Sozu Toolkit. We gave this toolkit to eight students, who created their own applications, which we summarize later in the paper.

In sum, Sozu describes a new approach for sensing human environments, at a cost and sensing range that enables comprehensive, whole-building deployments. By being self-powered, they should require near-zero maintenance, and can be placed on essentially any object that emits energy that we can harvest.

RELATED WORK

Activity sensing has been long sought after in the research domain and has seen some success in commercial products. All activity sensing systems require power, either from batteries, powerlines, backscatter, or energy harvested from the environment. We now review these different approaches.

Object-Borne Sensors

The most straightforward approach is to attach sensors directly to objects of interest, including users themselves. For example, Google's activity recognition API [28] leverages inertial sensor data captured by mobile devices. Researchers have created wearable sensors that collect a wide range of signals from a user's body for activity sensing [35, 37, 43, 46]. Thanks to advances in electronics and microprocessors, researchers have envisioned a future with ubiquitous sensor tags attached to objects [8, 60]. Today, many companies offer battery-powered sensor tags with wireless connectivity [12, 42, 51, 55, 56].

Wide-Area Sensing

Although per-object sensors can be very accurate, they have obvious scale limitations and maintenance implications. In addition, power constraints often limit their sensing fidelity (e.g., sampling rate, duty cycle). Thus, there has been considerable research looking into approaches where a single plugged-in sensor can monitor a large area, making deployments more practical and cost-effective.

Perhaps the largest body of work in this space falls under Infrastructure Mediated Sensing. Prior work has leveraged powerline [17, 31, 44], HVAC [45], gas lines [16], and plumbing [25, 26] to monitor activities in a building. Other efforts in wide-area sensing have focused on detached sensors, using cameras [36], laser vibrometry [62], ultrasound [52], EMI antennas [61], and multi-sensor-fusion boards [38] to achieve robust, wide-area sensing.

Backscatter Sensing

Backscatter technology offers the promise of using wireless signals (e.g., Wi-Fi) for power, compute, and/or sensing [13, 49, 54]. It is also possible to have ultra-low-cost passive tags, such as RFIDs. Researchers have used backscatter techniques to investigate activity sensing [11, 14, 39, 47, 53], detecting object grasp [27], 3D printing wirelessly-connected objects [34], localization [41] and even sound capture [9, 10, 48]. Unfortunately, backscatter techniques generally suffer from limited sensing range (<15m), precluding building-scale coverage unless multiple readers are deployed. There are battery-assisted RFIDs that achieve longer ranges, but these require periodic maintenance. Sensing concurrent objects and activities, as well as rich signal streams (beyond mere presence) are also challenging.

Self-Powered Sensing

Most related to Sozu are approaches that are self-powered – sensors that capture energy from the environment (e.g., solar) or human activities (e.g., tool use). Self-powered sensing has seen some commercial success, for example, battery-free switches [23]. Small solar cells are also popular for recharging small batteries, which can then periodically power microcontrollers with sensors and wireless connectivity [52]. In the research literature, PowerBlade [18] sits on and siphons energy from electrical plugs to monitor energy consumption of electrical appliances; WATTR [15] used variations in pipe water pressure for both sensing and energy harvesting, very much in the spirit of Sozu. Researchers have also harvested energy from powerlines [30], ambient temperature changes [63] and vibrations using the piezoelectric [50] and triboelectric [32, 40, 59] effect.

Although these sensors do not require maintenance (meeting one of our ideal criteria), they all rely on digital components (microcontrollers and wireless modules), which increases cost. Additionally, these prior systems are specialized, focusing on particular categories of events, whereas Sozu aims to be a flexible and universal sensing system.

DEVELOPMENT OVERVIEW

Sozu tags are essentially energy converters, turning energetic physical activities into wireless RF broadcasts. The system name – Sozu – comes from the traditional Japanese water feature, where a bamboo segment slowly fills with water, eventually causing its center of mass to shift, such that it pivots downwards, striking a rock (designed to scare away animals in gardens). This is similar in principle to our system, where one form of energy is converted into another for practical use.

The types of energy sources that Sozu can utilize dictates not only its RF emission strength, but also what facets it can sense in the environment. Therefore, our first step was to survey the environment for activities, classifying them into energy categories, and then investigating the effectiveness of harvesting implementations. Our next step was to determine how to best utilize this energy for radio broadcasts, taking into account our goals of long-range transmission without line of sight. We must also contend with, e.g., government regulations and background noise. This initial work informed our system implementation, which we describe in detail later.

INVESTIGATION ONE: ENERGY HARVESTING

We identified seven energy categories from which Sozu tags could be powered. For each category, we describe example activities, along with proof-of-concept implementations and estimated cost. Later in this section, we discuss energy harvesting in practice using measurements we collected from 50 unique everyday objects/activities.

Motion

Motion is generated by a wide range of activities, including opening a drawer, popping a pill bottle, and pruning plants. To convert these motions into electrical energy, we used magnets to induce current in a wire coil (example integrations shown in Figure 1). We found two commercial harvesters that worked well for our purposes: a self-powered bicycle light [2] ($2.70) and the ECO 200 energy bow made by EnOcean [22] ($6.95).

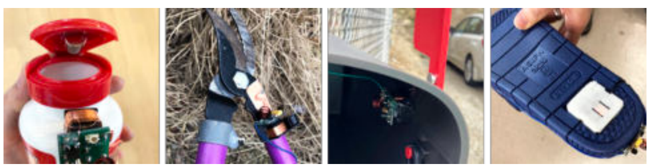

Figure 1. Four Sozu-augmented objects that use motion energy: pill bottle, garden pruner, mailbox, and slipper.

Vibration

Appliances such as food blenders and power tools generate vibrations that can be covered to electrical energy with piezoelectric materials. For this, we used a 50 mm piezo buzzer element [19] ($1.36) weighted with a small nut. This harvester can be attached to movable objects with double-sided tape (Figure 2, left and middle). For stationary appliances, such as a grinding wheel, we can place the harvester underneath one of the feet (Figure 2, right).

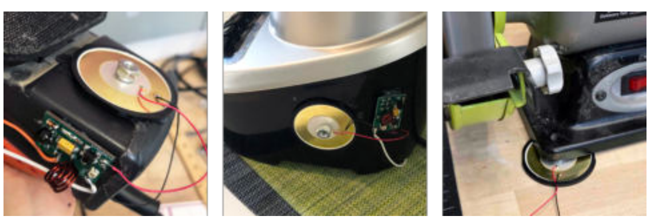

Figure 2. Sozu-augmented objects that convert energy from vibration: sander, blender, and grinding wheel.

Light

Light is another common form of energy, which can be used to infer events and activities. For example, illumination increases when room lights are turned on and refrigerator doors are opened (activating the internal light; Figure 3, left). Conversely, a car parking above a sensor or curtains being drawn decreases light level. To convert light energy, we use solar cells (58×55 mm Panasonic [20], $7.80).

Figure 3. Sozu can also be powered by light energy: refrigerator door light, overhead work lights, and sunlight in a garden and parking lot.

Thermal

Many devices generate heat when operating, for example, gas-powered tools, hot glue guns, stoves and fireplaces. Sozu converts this thermal energy with Peltier junctions [5] (~$2). We attach one side of a Peltier junction to an object of interest with thermal glue and tape, and on the other side, we use an aluminum heat sink to improve efficiency. Figure 4 shows four example instrumented objects.

Figure 4. Sozu can be powered by hot surfaces, such as those found on stoves, hot glue guns, fireplaces, and gas tools.

Electromagnetic Radiation

Electrical appliances often emit electromagnetic (EM) radiation when in use, due to e.g., motors and switched-mode power supplies. We harvest this energy using a 60 mm diameter, 1500-turn coil with a ceramic core (~$5). These harvesters can be stuck (often magnetically) to devices, ideally close to motor coils and power regulation circuits (Figure 5).

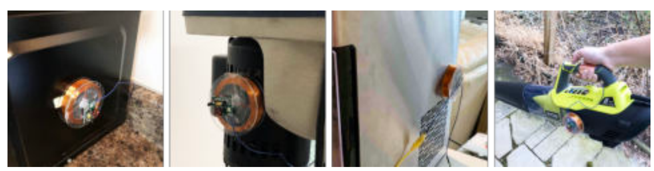

Figure 5. Sozu can be powered by EM radiation from objects such as a microwave, drill press, ice maker, and leaf blower.

Gas Flow

HVAC and machine exhaust generate flows of air and other gases, which can be easily harvested with DC brushless fans [21] ($3.30), as seen in Figure 6.

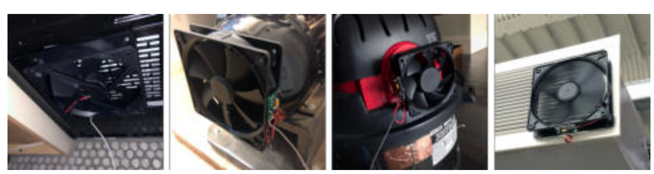

Figure 6. Sozu can be powered by gas flow from a kitchen hood, exhaust fan, ShopVac, and HVAC vent.

Water Flow
Finally, water flow is a high energy source, which Sozu can leverage to detect the use of faucets, showers, garden hoses, and even liquid containing vessels, such as watering cans (Figure 7). We selected two water-generators: one that fits US faucets [3] ($3.5) and another that can be added inline to half-inch NPT water lines [4] ($4).

Figure 7. Sozu can be powered by the flow of water from a sink faucet, garden hose, watering can, and showerhead.

Energy Harvesting in Practice
To better understand the energy budget for our Sozu implementation, we surveyed 50 objects (Table 1) to test energy harvesting in practice. For each test object, using harvesters described in the previous section, we recorded harvester output using an oscilloscope with a 10 kOhm load (close to the input impedance of our final Sozu tag design), which allowed us to estimate power output.

On average, our test objects yielded 2.7 mW of power (Table 1). We found our motion harvesters produced impulses, whereas other harvester types produced continuous output, either a constant signal (e.g., solar, thermal) or a periodic signal (e.g., vibration, EM radiation, gas and water flow). Overall, water flow produced the most power, followed by solar. Harvested power from the other energy categories was more variable, and more of a function of the object or activity. Finally, we found the Peltier junctions generated low voltages (<400mV), and thus we augmented these harvesters with a LTC3108 [7] boost converter ($6) to bring the output voltage up to a more usable 5V.

INVESTIGATION TWO: RF BROADCAST
With our power budget known, our next task was to identify an ideal frequency range for Sozu tag RF broadcasts. This was an iterative process, which we now describe.

Antenna Design & Broadcast Frequency
According to antenna theory, the optimal size of an antenna is proportional to the wavelength of the radio wave. A 1 Mhz RF signal has a wavelength of 300 meters, much too long for practical use, even with e.g., a quarter-wave monopole antenna. For this reason, we use frequencies above 30 MHz (i.e., 2.5 m quarter-wave monopole antenna), approaching the physical size of commonplace objects (e.g., perimeters of appliances).

The wavelength of an RF signal also impacts its ability to penetrate obstacles, such as walls, floors and furniture. High-frequency signals (shorter wavelength) have more energy reflected by obstacles, which limits transmission range and also introduces multipath effects [1]. Therefore, we decided to only consider broadcast frequencies below 200 MHz.

Object Name	Activity or State	Energy Type	Waveform	Power (μW)	Source
Faucet	Water running	Water flow	Periodic	26538.2	165 mL/s
Shower Head	Spraying water	Water flow	Periodic	23215.2	153 mL/s
Garden Hose	Spraying water	Water flow	Periodic	23105.2	151 mL/s
Gas Trimmer	Engine running	Thermal	Constant	11700.0	112 °C
Powered Drill	Drill spinning	EM radiation	Periodic	7227.1	310 μT
Window Sunlight	Sunlight	Solar	Constant	4027.1	5906 Lux
Refridgerator	Door open / light on	Solar	Constant	3804.3	4250 Lux
Parking Spot (light)	Lit by sun	Solar	Constant	3609.8	4400 Lux
Floor Lamp	On	Solar	Constant	3287.5	4768 Lux
Garden Sunlight	Lit by sun	Solar	Constant	3164.0	3922 Lux
Ice Maker	Making ice	EM radiation	Periodic	3071.6	301 μT
Work Light	On	Solar	Constant	2759.0	1724 Lux
Hedge Trimmer	Trimmer on	EM radiation	Periodic	2736.7	293 μT
Hot Glue Gun	On	Thermal	Constant	2599.8	90 °C
Toilet	Flushing	Motion	Impulse	1771.6	1.5 m/s
Hairdryer	Blowing hot air	Gas flow	Periodic	1634.5	5.8 m/s
Kitchen Hood	Fan exausting	Gas flow	Periodic	1521.1	4.5 m/s
ShopVac	Vacuuming	Gas flow	Periodic	1519.7	15.1 m/s
Hand-Held Vacuum	Vacuuming	Gas flow	Periodic	1190.4	3.6 m/s
Mitersaw	Blade spinning	EM radiation	Periodic	1176.1	277 μT
Microwave	Running	EM radiation	Periodic	684.0	280 μT
KitchenAid Mixer	Mixing	EM radiation	Periodic	466.0	275 μT
HVAC Vent	Vent blowing	Gas flow	Periodic	390.2	6.8 m/s
Pruner	Cutting	Motion	Impulse	362.1	0.7 m/s
Watercan	Watering	Water flow	Periodic	348.8	50 mL/s
Leaf Blower	Blowing air	EM radiation	Periodic	266.5	271 μT
Air Purifier	Filtering air	Gas flow	Periodic	241.8	3.5 m/s
Drill Press	Drill on	EM radiation	Periodic	225.1	266 μT
Projector	Projecter on	Solar	Periodic	218.5	142 Lux
Sander	Sander on	Vibration	Periodic	217.5	218 m/s^2
Exhaust Fan	Exhausting	Gas flow	Periodic	205.3	3.4 m/s
Reciprocating Saw	Running	Vibration	Periodic	160.5	182 m/s^2
Fireplace	Fire lit	Thermal	Constant	119.4	95 °C
Pill Bottle	Opening lid	Motion	Impulse	116.4	1.1 m/s
CNC	Router spinning	EM radiation	Periodic	115.7	172 μT
Toaster	Toasting	Thermal	Constant	113.7	82 °C
Battery-Powered Drill	Dill spinning	EM radiation	Periodic	106.6	128 μT
TV	On	Solar	Periodic	81.0	101 Lux
Coffee Grinder	Grinding coffee	EM radiation	Periodic	43.9	68 μT
Sliding Door	Opening / closing	Motion	Impulse	43.8	0.4 m/s
Blender	Blending	EM radiation	Periodic	41.9	142 μT
Kettle	Boiling water	Thermal	Constant	41.0	96 °C
Slipper	Walking	Motion	Impulse	29.2	0.2 m/s
Drawer	Opening / closing	Motion	Impulse	23.7	0.3 m/s
Mailbox	Indicator flag raised	Motion	Impulse	23.7	0.3 m/s
Grinding Wheel	Grinding	Vibration	Periodic	14.7	11 m/s^2
Solder Iron	On	Thermal	Constant	10.4	149 °C
Blender	Blending	Vibration	Periodic	6.8	18 m/s^2
Gas Stove	Stove lit	Thermal	Constant	4.8	67 °C

Table 1. Mean energy generated by 50 activities we tested.

Environmental Noise
To identify "quiet" parts of the RF spectrum in the range we identified previously, we used a USRP and ran a wide spectrum collection test from 1-200 MHz (62.5 kHz steps) using a wideband omnidirectional antenna. We collected data at six locations (two commercial buildings, two apartments, and two detached single-family homes, all in a large US city) for 8 hours each. Figure 8 illustrates the power spectrum, which we computed by comparing the received power at each frequency with the noise floor (min within the current frame of powers). The range from ~90-100 MHz is densely occupied by FM radio stations, while ~30-35 MHz is used by mobile communication equipment. This left three relatively quiet bands: 15-30, 35-85, and 105-160 MHz. We dropped 15-30 MHz, as it did not provide much bandwidth for many tags, leaving us with two candidate ranges.

FCC Compliance
Sozu must also comply with FCC regulations, which permits low-power RF transmission in unlicensed frequencies [24]. There are, however, there are many restricted frequencies that must be avoided. This eliminated the promising 105-160 MHz range from consideration, as it was mostly restricted. Thus, we ultimately selected the 35-85 MHz range for Sozu. In this frequency range, transmitters are limited to a field

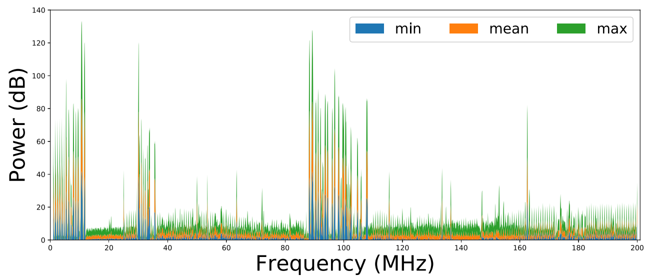

Figure 8. RF power density from 1 to 200MHz.

strength of 100 µV/m at 3m, which is equivalent to 3 mW transmitter power assuming isotropic radiation. This means, with an *ideal* passive antenna design (Power Gain = 1, impedance = 50 Ohm), the peak voltage (Vpeak) of a sinusoidal RF signal has to be lower than 0.54 V. We strictly followed this in the Sozu RF circuit design to meet FCC guidelines.

Building Penetration

From theory and literature, we knew our selected frequency range should have good building penetration. Nonetheless, we wished to measure this directly with our own equipment and across typical construction styles. We tested five walls: brick (30 cm thick), drywall + metal studs (15 cm), glass (2 cm), stone/masonry (65 cm), and precast concrete (20 cm). To capture data, we transmitted a swept-frequency signal from 35-85 MHz on one side of the wall, and measured the signal strength on the other side (symmetric 5 m separation between transmitter and receiver). We did not find significant differences in attenuation across frequencies, and so we average these results. Across all wall construction types, we found a mean attenuation of -12.04 dB (SD=7.83). The concrete wall had the most attenuation (-20 dB), whereas glass and drywall + metal studs had little effect (-4.10 and -3.30 dB respectively).

SOZU IMPLEMENTATION

A Sozu deployment consists of two main components: Sozu tags and an antenna receiver with attached computer. Sozu tags are distributed in the environment, transforming energy from activities into radio broadcasts. The antenna receiver is deployed at one central location (e.g., basement of a house), which monitors tag broadcasts. We now describe these components in detail.

Sozu Tags

Sozu uses a custom tag (Figures 9 and 10) which connects to an energy harvester (see Investigation One) and an antenna (discussed subsequently). The board itself is responsible for managing energy and generating an RF signal with a power consumption of 2.05 mW.

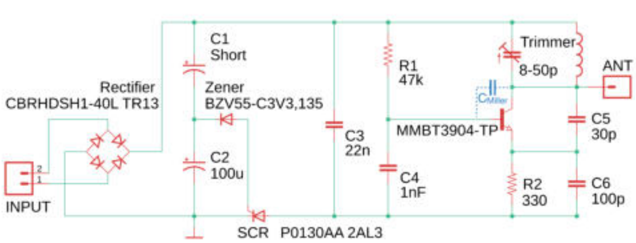

Figure 9. Sozu tag circuit schematic.

Energy Management: As discussed previously, most of our energy harvesters provided periodic signal, which we rectify with an ultra-low-forward-voltage rectifier. As the incoming power may not be enough energy to run our circuit, we designed an energy storage and latch mechanism to store small amounts of energy, which can later be released. We use two capacitors (C_1 and C_2) in series to store rectified energy (Figure 9); the voltage at the junction between the two capacitors controls the gate of a silicon-controlled rectifier (SCR). A trigger voltage of 1.5 V activates the SCR, which then passes the stored energy to the RF oscillation circuit. The SCR turns off once the RF oscillation consumes all energy, and then the tag begins to store energy again for the next activation. Releasing the stored power results in an RF chirp lasting roughly half a second (e.g., Figure 13 right). We note that some activities provide sufficient continuous energy (e.g., water faucet, HVAC vent) that the SCR is always on, resulting in a continuous RF output (e.g., Figure 14 right).

Different transmission strengths and broadcast chirp durations are achievable by tuning the capacitance of C_1 and C_2. The ratio between C_1 and C_2 sets the initial voltage that powers the RF front end when the SCR is on. A smaller C_1:C_2 produces a higher initial voltage, which yields stronger signal strength and extended transmission range. However, we note that C_1:C_2 must be higher than 0.39 so that the FCC requirement is not exceeded.

To increase the duration of RF broadcasts, larger capacitors can be used. For our later evaluation, we used a C_2 of 100 µF and a shorted C_1. This was because all of our activities generated sufficient power, which did not need further energy storage. With this configuration, the minimum energy to generate one RF broadcast is 0.12 mJ, which is roughly the amount of energy needed to charge C_2 up to 1.5 V (i.e., the trigger voltage). This configuration also had the effect of limiting transmission power to below the FCC regulation.

RF Oscillation: To generate RF broadcasts, Sozu tags use an oscillation circuit based on a single-transistor LC oscillator. The output frequency can be calculated by:

$$f = \frac{1}{2\pi\sqrt{LC}}$$

where L is the inductance of a coated copper coil which measures 420 nH. C is the capacitance that is dominated by a user-adjustable capacitor (range of 8-50pF), which permits a tag to be set to a specified frequency. One version of our

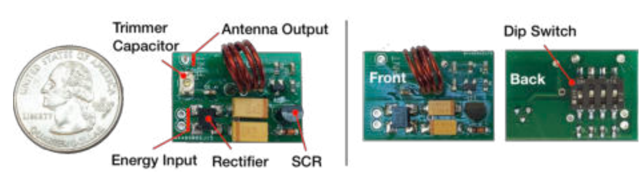

Figure 10. Two Sozu tag designs, one with broadcast frequency tuned with a trimmer capacitor (left) and one with a dip-switch (right).

tag used a simple trimmer capacitor (adjustable with a screwdriver, Figure 10, left), while our second design used a 4-bit dip switch to connect/disconnect four capacitors (1, 2, 4, and 8 pF) in series with a 30 pF capacitor, treating frequency more like a binary ID (Figure 10, right).

We note that the transistor Miller capacitance (C_{Miller}) between base and common also contributes to C, through being in series of C_4 and C_3, and parallel to the trimmer capacitor. Considering the Miller capacitance, the C component of the oscillation circuit is calculated by:

$$C = \frac{1}{\frac{1}{C_{Miller}} + \frac{1}{C_3} + \frac{1}{C_4}} + C_{trimmer}$$

This Miller capacitance is affected by the supply voltage, resulting in very basic frequency modulation (FM). We observed a variance of Miller capacitance (C_{Miller}) of around 1 pF with a supply voltage from 1.5 to 5 V, resulting in a frequency shift of ~0.5 MHz. This effect allows us to demodulate analog signals on the receiver end, enabling richer sensing opportunities, which we discuss later.

Transmit Antenna

We investigated a wide variety of antennas for our Sozu tags, including chip antennas and PCB antennas. Ultimately, we selected simple monopole antennas, which can be easily integrated into many objects. We varied our antenna lengths (from 5 to 100 cm) for different objects, depending on their output power. In general, objects that produce less energy require longer antennas to help maintain broadcast range. We used generic 18-gauge braided wire for our antennas, which was easily trimmed to a desired length.

Our wire antennas can often be hidden by making clever use of an object's geometry (e.g., running down a mailbox post), or simply be tucked behind larger objects and infrastructure. For smaller and mobile objects, where long antennas are more problematic, we found two alternatives. First, for objects with metallic enclosures (e.g., kitchen appliances), we can use the shell itself as an antenna. Second, the human body can be co-opted as a large antenna; for this, we connect our RF output to a copper patch where the user would grasp an object (example shown in Figure 14).

Bandwidth & Concurrent Signals

In order to support detection of many concurrent activities, Sozu requires each tag to operate at a unique frequency. The frequency stability (i.e., bandwidth) of Sozu tags therefore decides the maximum number of concurrent activities that the system can sense simultaneously. To quantify this, we measured the frequency shift of a Sozu tag while varying the supply voltage from -5 to +5 V. We observe an average bandwidth of 0.52 MHz (SD=0.12). This suggests that Sozu could support up to ~96 tags (i.e., (35-85 MHz) / 0.52 MHz bandwidth). In practice, we found that moisture and temperature can affect the capacitance of our LC oscillator circuit, which further shifts the registered frequency. To account for this, we suggest using a 1 MHz bandwidth, especially for outdoor objects and activities (e.g., mailbox, parking spot).

Environmental Hardening

Outdoor placements, such as a garden or parking lot, require resilience to moisture and temperature change. To survive these environments, we fully encased some of our tags in clear epoxy resin (examples in Figure 3). The only external element was our wire antenna. This solved tag failures from moisture and extreme temperatures, but it did not solve small shifts in our LC oscillator circuit from temperature changes.

Sozu Receiver

To capture RF signals emitted by Sozu tags, we used a HackRF One software defined radio (SDR) [29] connected to a wideband omnidirectional antenna [6]. We recommend this antenna be placed in a discrete, but central location, such as an attic, closet or basement (Figure 11). The SDR streams data to a laptop over USB, after which it is processed by GNU Radio [57], which computes FFTs (non-overlapping windows, 8192 samples). This yields a stream of ~2400 FFT results per second (i.e., FPS), which are streamed over a local socket to a custom Java program for further computation and interactive control.

Activity Recognition

Detecting the presence of activities (i.e., on/off) can immediately power a wide variety of smart building applications, including automatic lighting with occupancy detection, alerts for unattended stoves, and medication reminders with smart pill bottles. As noted previously, detecting the presence of activities is equivalent to detecting the presence of RF signals at registered frequencies. Specifically, for each registered frequency, we find the min and max FFT bin within a ±0.5 MHz window and compute the difference. We found this range value compensates for varying antenna sensitivity across frequencies and interference from wide-band environmental noise (e.g., fluorescent light). To increase stability, we smooth this value with an exponential moving average, and then use a basic threshold to decide if an activity is on or off. This decision is further stabilized with a majority voter (300 ms history).

Open Source

To facilitate replication and deployment, we have open sourced our Sozu tag PCB design files and deployment software: https://github.com/FIGLAB/Sozu

ACCURACY EVALUATION

We deployed Sozu tags at three locations – an apartment, a detached house, and a commercial building. These

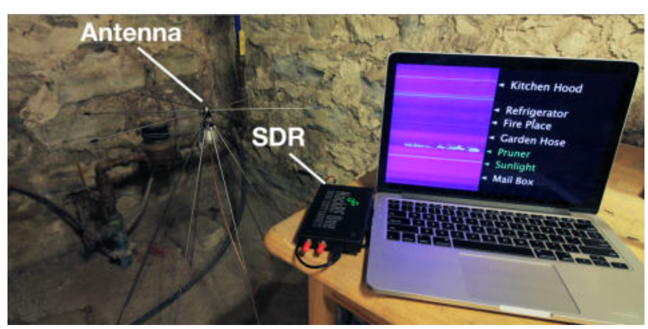

Figure 11. Sozu receiver setup deployed in a basement.

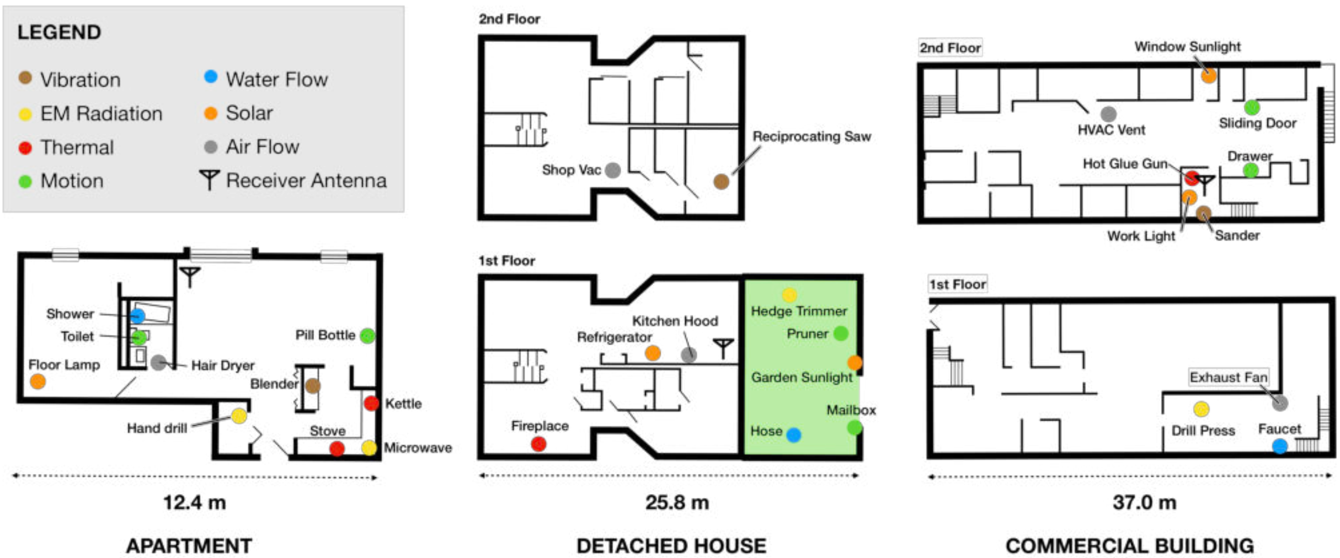

Figure 12. We deployed Sozu at three test locations. Objects in our accuracy evaluation are denoted by colored-coded circles.

environments offered different objects, room functions, and construction types. At each location, we deployed our Sozu receiver in an inconspicuous location, and augmented ten commonplace objects with Sozu tags (Figure 12).

Of the 30 activities we chose to evaluate, 22 have been identified as important in prior work [26, 31, 38, 62]. The eight "new" items are pruner, hedge trimmer, drawer, mailbox flag, pillbox, hot glue gun, garden sunlight, and window sunlight. The aforementioned papers were unable to sense unpowered handheld items (e.g., pruner) and distant unpowered objects (e.g., mailbox flag), and thus these items help to underscore Sozu's new capabilities.

Procedure

Our 30 tags were deployed for three weeks. At the end of each week of operation, the experimenter visited each location to check the durability of the Sozu tags, as well as test detection accuracy. To start, all activities were turned off (sunlight powered tags were covered), after which the experimenter collected ten instances of Sozu detections, spaced apart by one minute. Activities were then manually activated one at a time (random order), and a single instance was captured. The experimenter then turned the activity off (or waited for the activity to naturally end, e.g., toilet flush and refill) and repeated the collection process nine more times for that activity. Note that every "on" instance for a particular activity gave us nine "off" instances for all other activities. In sum, for each activity, we collected 30 "on" trials (10 instances × 3 weekly collections) and 300 "off" trials (10 instances × 3 weekly collection when all objects were "off", plus 9 other "on" objects per location × 10 instances × 3 weekly collections). In total, across all 30 activities we studied, we collected 9,900 on/off instances.

Result

All tags were functional at the end of the deployment (including those placed outside. The overall accuracy of on/off activity detection was 99.94%, with an even split of false positives and false negatives. Though this high accuracy is encouraging, we caution that further long-term deployment studies (multiple months, more locations) are required.

Latency

For all harvesting methods, other than thermal, the time between activity actuation and RF broadcast is under 500 ms. Our thermal harvesters required at least a 30 °C temperature differential before generating sufficient voltage, and the large thermal mass of our test objects simply required time to heat up.

BEYOND ON/OFF DETECTION

While on/off activity detection is a powerful building block, smart building applications can also benefit from fine-grained information, such as directionality and rate of activities. Sozu can offer such information with simple extensions of its detection process.

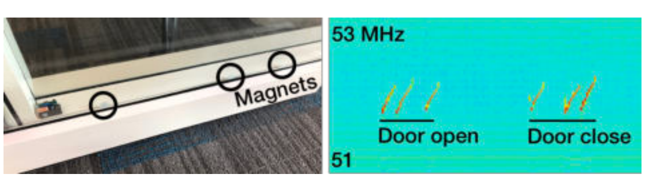

Figure 13. Strategic placement of magnets on a door frame allows the direction of a sliding door to be sensed.

Figure 14. By including the user in the LC oscillator circuit via a conductive grip (copper tape), Sozu can detect user grasp, which manifests as a characteristic frequency shift.

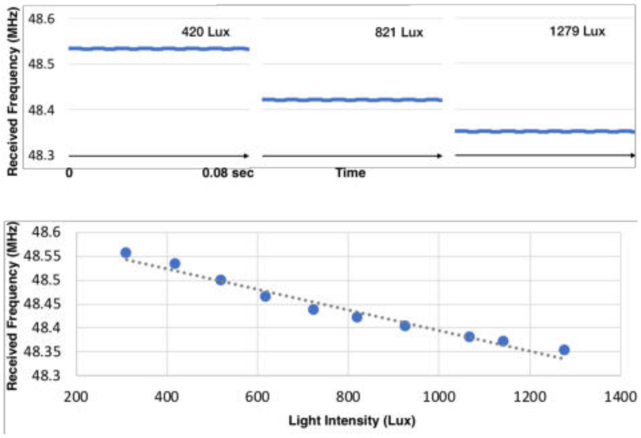

Figure 15. Top: received Sozu tag frequency at different light intensities. Bottom: mean received frequency vs. light intensity with linear regression plotted.

Directionality

Some objects have complex states with directional activities. Doors are a quintessential example, as a closed door has a very different function and meaning than an open one, and simply knowing "door moved" is not sufficient. As an example implementation of direction sensing, we strategically mounted magnets on the rail of a sliding door (Figure 13). This asymmetry results in two sets of chirps (a pair and a single chirp), the order of which can be used to infer direction, and thus door state.

Grasp Detection

Sozu can also detect when a user is grasping an object. We achieve this by connecting the user's body to our LC oscillation circuit with a conductive patch, which characteristically lowers the broadcast frequency. As an example, we augmented a hot glue gun (Figure 14), allowing Sozu to not only know if the glue gun is on, but also if the user is actively using it. With this data, we could e.g., alert a user if they have left a glue gun on without use for more than 15 minutes.

Intensity

We can also leverage frequency modulation to encode analog signals. Specifically, we calculate the frequency difference between the current frequency (f_{curr}) and the registered frequency (f_{base}) of a tag. This frequency shift correlates to the output voltage of the harvester, which can be associated with an analog dimension of the activity. As a demonstration, we placed a light meter (for ground truth) side-by-side with a Sozu tag powered by a solar cell (f_{base} = 48.6MHz). We used a dimmable light to vary the environmental illumination from 312 to 1279 Lux. We recorded both the measured light intensity and the received tag frequency. Figure 15 (top) plots some example signals, and further shows that it is fairly straightforward to correlate frequency shift with light intensity (Figure 15, bottom; see also Video Figure).

Rate

Sozu can also detect the rate of activities, such as water flow volume and motor RPM. In these cases, the energy harvesters provide periodic signals that correlate with the rate of the activity. This manifests as an oscillating frequency shift (see Figure 16, top), the rate of which can be measured by counting zero crossings.

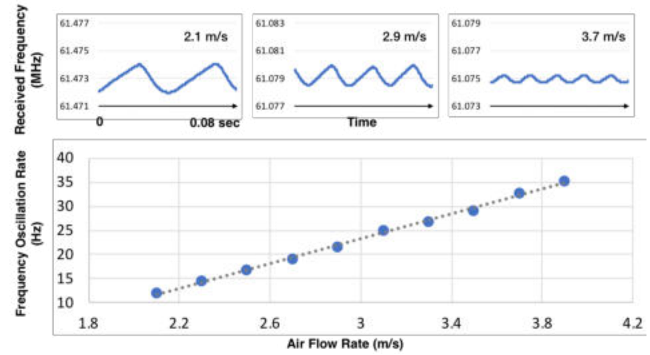

Figure 16. Top: received Sozu tag frequency at different wind speeds. Bottom: the linear correlation between Sozu-detected frequency oscillation rate and actual wind speed.

As an example, we captured data from a gas-flow-powered Sozu tag at different wind speeds using a DC fan (placed next to an airflow meter for ground truth). The raw FM signal can be seen in Figure 16 (top), as well as the linear relationship between the detected frequency oscillation rate and actual wind speed (bottom). We performed a similar experiment for water flow; Figure 17 shows the linear correlation between the frequency oscillation rate and true water flow rate.

TAG LOCALIZATION

Knowing the location of activities would also be useful for smart buildings systems. For example, a shop manager may wish to track the location of power tools for safety reasons, while facilities staff may want to see what rooms have been vacuumed recently. Additionally, in multi-occupant environments (e.g., apartment buildings), a personal Sozu system should only decode a user's activities and not neighbors'. This could be also achieved by using different tags (with different registered frequencies) in different rooms (e.g., each faucet is unique), but this approach does not scale or work for movable devices, such as power tools and vacuum cleaners. Instead, one could use tags registered to the same frequency (e.g., all faucets use the same frequency), and their location serves as extra bits of information for disambiguation. This approach would also expand the number of tags we could support in our 35 – 85 MHz frequency range.

Since RF broadcasts attenuate while propagating through space, we used multiple antennas to triangulate broadcasts

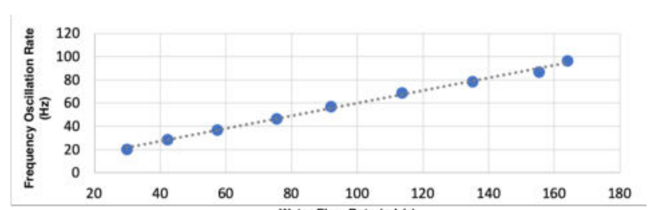

Figure 17. The linear correlation between Sozu-detected frequency oscillation rate and water flow rate.

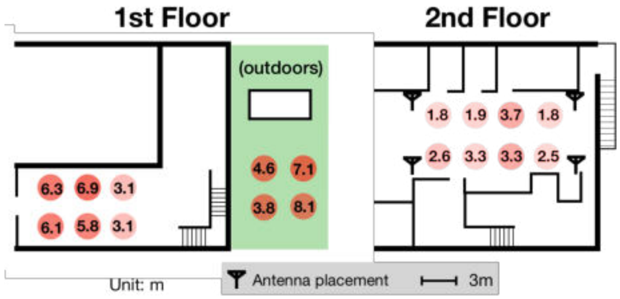

Figure 18. Locations (circles) tested in our localization study, with mean Euclidian error (meters) provided inside circles.

and thus localize tags. Specifically, we used four receiver antennas and the Wentzel-Kramers-Brillouin (WKB) approximation [33] to model RF propagation:

$$P_R(q, b_i) = P_T(q) + L(q, b_i) + \gamma \sum_j d_j \eta_j$$

where $P_R(q, b_i)$ denotes the received signal power at the i-th antenna for the tag q, $P_T(q)$ denotes the transmission power, $L(q, b_i)$ is the path loss power, and $\gamma \sum_j d_j \eta_j$ is the shadowing term, which captures the impact of the attenuation because of the wall type (η_j) and thickness (d_j). These factors were calculated using data from our previous Building Penetration study. We then corrected the signal power with a shadowing term, inferred the distances between the tag and the base stations using the path loss power, and used a least square error approach to compute the location.

Procedure

For testing, we deployed antennas at the four corners of a 13×5 m office space (illustrated in Figure 18). We first calibrated antenna sensitivity by collecting data from a Sozu tag of a known power on a 1 m grid on the first and second floors, as well as outside of the building.

After calibration, we used a gas-flow-powered Sozu tag powered by a small DC fan (simulating a vacuum cleaner) and collected data at 18 locations (8 points on the second floor, 6 points on the first floor and 4 points outside the building – see Figure 18). At each location, we collected 20 seconds of data, yielding 14,400 data points in total. We then calculated the Euclidian distance error between the true location and Sozu's estimated location to quantify the performance of our localization approach.

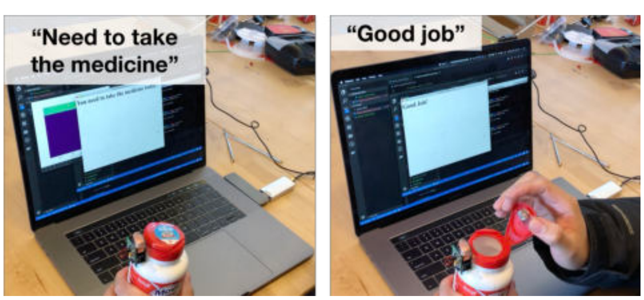

Figure 20. A Sozu-augmented pill bottle can detect when its lid is opened, or not opened, in which case an alert is sent.

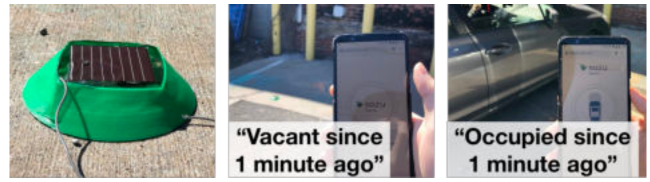

Figure 19. Sozu tag used for parking occupancy detection.

Results

Sozu was able to localize tags with an average error of 4.1 m (SD=1.9). Figure 18 breaks this result out across the 18 locations we tested. Although coarse, it is sufficiently accurate for room-level localization. This means if there are several e.g., faucets in a house, they could use a common frequency and be disambiguated by location data. We also used our study data to simulate zone-level localization (i.e., first floor, second floor, and outside), and in this case, all points were correctly localized.

SOZU TOOLKIT

To lower the barrier of entry in applying Sozu to activity sensing applications, we created a toolkit that consists of a Sozu tag connected to a solar cell, an RTL-SDR, a set of antennas, and demo code. We also wrote a quick start guide on how to set up the software, deploy Sozu tags, and receive signals. All materials can be found in the Sozu repository: https://github.com/FIGLAB/Sozu/tree/master/toolkit

User Study

To evaluate our Sozu toolkit, we conducted a user study with 8 students taking classes in Human-Computer Interaction at our institution (6 undergraduate and 2 graduate students). Among these students, four rated themselves as having little hardware development experience. Each student was given a Sozu toolkit and provided with any harvester they requested for their project. Students were responsible for generating an application concept, implementing their idea, and documenting their project with a video (see Auxiliary Materials). The students were given one week and were compensated $50 for their time. We recorded how long it took participants to set up the Sozu sensing pipeline, from receipt of the toolkit package to displaying signal on their laptop. We also kept track of bottlenecks, failures and successes with daily interviews.

Results

All participants successfully deployed Sozu tags and finished their projects within the one-week deadline. On average, it took 36 minutes (max 2 hours) to set up Sozu on their personal computers. We note that most of the time was spent on

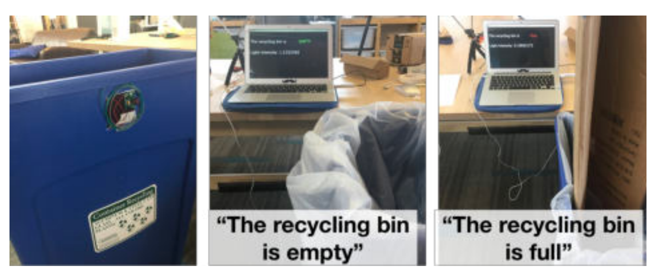

Figure 21. A recycling bin that alerts facilities staff when full.

Figure 22. A door could automatically open when a wheelchair approaches.

Python environment configuration. Participants found the solar cell we included in the toolkit package particularly helpful in getting started (i.e., "signal out of the box", no soldering needed). Participants also found our guide on how to harvest energy from different sources useful, though it was still the most challenging part of the project according to their feedback.

Example Student Projects

We now briefly describe the student projects, which both illustrate potential uses of Sozu and also the ease at which our approach can be deployed. See also Auxiliary Materials for student-made videos of their projects.

Parking Occupancy: One student made a parking sensor with Sozu, which is powered by a solar cell. When the output frequency dips (or turns off entirely), it is inferred that a car has parked at the spot above the sensor (Figure 19).

Medication Reminder: Another student used Sozu to build a smart pill bottle that can detect if its lid is opened. If the lid is not opened when medication is scheduled to be taken, an alert can be sent to the user (Figure 20).

Smart Recycling Bin: In this project, a student used Sozu to detect if a recycling bin was full, based on whether a solar-powered tag near the top was blocked by refuse (Figure 21).

Automatic Door for Wheelchairs: One student attached a motion-powered Sozu tag to a wheelchair and placed a receiver antenna by a doorway. The idea was to automatically open the door once a wheelchair's presence was detected. The sensitivity and orientation of the receiver antenna was tuned such that wheelchairs were only detected when ~1 m away (Figure 22).

Consumables Monitoring: One of our student participants instrumented a bin in the lab containing tapes with a motion-powered Sozu tag. This allowed for automatic tracking of how often the bin was accessed. After a certain threshold, a reminder is sent to the shop manager to check on supplies (Figure 23).

Foot Traffic: In this student project, a solar-powered Sozu tag was used in concert with a wall-powered laser pointer to count how many people passed through a doorway.

Meeting Room Occupancy: This project had a student place a solar-powered Sozu tag at the corner of a projection screen to detect when the digital projector was turned on, inferring meeting room occupancy.

Figure 23. A Sozu-augmented storage bin can alert a shop manager to check on supplies after repeated access.

Work Hour Monitoring: Lastly, a student made a chair occupancy sensor using a solar-powered Sozu tag cut into the back of a chair. Light is blocked or attenuated when someone is seated, and the student used it to track how long they are seated for work.

CONCLUSION

Future smart homes and offices will rely on robust, wide-area activity sensing to power intelligent and context-sensitive end user applications. In pursuit of this vision, we developed Sozu, a low-cost, self-powered, building-scale activity sensing approach. Instead of batteries, Sozu utilizes energy produced as a byproduct from many everyday activities. We optimized Sozu's implementation by first investigating energy harvesting opportunities. We then conducted a series of RF investigations to explore how to best utilize harvested energy. Results from a multi-week evaluation across three multistory buildings and 30 activities suggest our approach offers very high detection accuracy, with few false positives. We also discuss how Sozu can be used to sense rich signals, such as direction, user grasp and rate of events. Finally, we put together a toolkit and had eight students participate in a week-long study. All participants were able to get Sozu running on their personal computers and build simple, yet illustrative example applications of their choosing, underscoring the ease-of-use and flexibility of Sozu.

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REFERENCES

[1] Achmad Affandi, Ghais El Zein, and Jacques Citerne. Investigation on frequency dependence of indoor radio propagation parameters. In Gateway to 21st Century Communications Village. VTC 1999-Fall. IEEE *VTS 50th Vehicular Technology Conference* (Cat. No. 99CH36324), vol. 4, pp. 1988-1992. IEEE, 1999.

[2] Alibaba.com. Self-Powered Waterproof Bicycle Rear Light. Retrieved July 10, 2019 from https://alibaba.com/product-detail/Self-powered-Waterproof-Bicycle-Rear-Light_60624644563.html?spm=a2700.details.maylikeexp.13.38f15352VMlUkI

[3] Alibaba.com. Hydraulic Generator. Retrieved July 10, 2019 from https://www.alibaba.com/product-detail/ChaoLi-Small-AC-Hydraulic-Generator-CL_60620611210.html?spm=a2700.7724857.normalList.12.74a34b35oBxGqv

[4] Alibaba.com. Hydro-Power Generator. Retrieved July 10, 2019 from https:// alibaba.com/product-detail/SEA-DB-168-Three-phase-AC0_60830877215.html?spm= a2700.details.maylikehoz.1.2c107156vTldX6

[5] Amazon.com. Peltier. Retrieved July 10, 2019 from https://amazon.com/dp/B01IT8SAZG/ref= cm_sw_em_r_mt_dp_U_DxUPCbKYPV7AK

[6] Amazon.com. Tram 1410 Broad Band Discone/Scanner Base Antenna. Retrieved July 10, 2019 from https://www.amazon.com/Tram-1410-Discone-Scanner-Antenna/dp/B00QVPGKHU

[7] Analog Devices. LTC3108-1. Retrieved July 10, 2019 from https://www.analog.com/media/en/technical-documentation/data-sheets/31081fb.pdf

[8] Giuseppe Anastasi, Alessio Falchi, Andrea Passarella, Marco Conti, and Enrico Gregori. Performance measurements of motes sensor networks. In *Proceedings of the 7th ACM international symposium on Modeling, analysis and simulation of wireless and mobile systems*, pp. 174-181. ACM, 2004. DOI: http://dx.doi.org/10.1145/1023663.1023695

[9] Nivedita Arora, Steven L. Zhang, Fereshteh Shahmiri, Diego Osorio, Yi-Cheng Wang, Mohit Gupta, Zhengjun Wang, Thad Starner, Zhong Lin Wang, and Gregory D. Abowd. 2018. SATURN: A Thin and Flexible Self-powered Microphone Leveraging Triboelectric Nanogenerator. In *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*. 2, 2, Article 60 (July 2018), 28 pages. DOI: https://doi.org/10.1145/3214263

[10] Nivedita Arora and Gregory D. Abowd. 2018. ZEUSSS: Zero Energy Ubiquitous Sound Sensing Surface Leveraging Triboelectric Nanogenerator and Analog Backscatter Communication. In *The 31st Annual ACM Symposium on User Interface Software and Technology* Adjunct Proceedings (UIST '18 Adjunct). ACM, New York, NY, USA, 81-83. DOI: https://doi.org/10.1145/3266037.3266108

[11] Rahul Bhattacharyya, Christian Floerkemeier, and Sanjay Sarma. Low-cost, ubiquitous RFID-tag-antenna-based sensing. *Proceedings of the IEEE 98*, no. 9 (2010): 1593-1600.

[12] Bosch. XDK Cross Domain Development Kit. Retrieved July 10, 2019 from https://xdk.bosch-connectivity.com

[13] Michael Buettner, Richa Prasad, Alanson Sample, Daniel Yeager, Ben Greenstein, Joshua R. Smith, and David Wetherall. 2008. RFID sensor networks with the Intel WISP. In *Proceedings of the 6th ACM conference on Embedded network sensor systems* (SenSys '08). ACM, New York, NY, USA, 393-394. DOI: http://dx.doi.org/10.1145/1460412.1460468

[14] Michael Buettner, Richa Prasad, Matthai Philipose, and David Wetherall. Recognizing daily activities with RFID-based sensors. In *Proceedings of the 11th international conference on Ubiquitous computing*, (UbiComp '09). ACM, New York, NY, USA, 51-60. DOI: https://doi.org/10.1145/1620545.1620553

[15] Tim Campbell, Eric Larson, Gabe Cohn, Jon Froehlich, Ramses Alcaide, and Shwetak N. Patel. 2010. WATTR: a method for self-powered wireless sensing of water activity in the home. In *Proceedings of the 12th ACM international conference on Ubiquitous computing* (UbiComp '10). ACM, New York, NY, USA, 169-172. DOI: https://doi.org/10.1145/1864349.1864378

[16] Gabe Cohn, Sidhant Gupta, Jon Froehlich, Eric Larson, and Shwetak N. Patel. 2010. GasSense: Appliance-Level, Single-Point Sensing of Gas Activity in the Home. In *Pervasive Computing: 8th International Conference*, Pervasive 2010, Helsinki, Finland, May 17-20, 2010. Springer. 265-282. DOI=http://dx.doi.org/10.1007/978-3-642-12654-3_16

[17] Gabe Cohn, Erich Stuntebeck, Jagdish Pandey, Brian Otis, Gregory D. Abowd, and Shwetak N. Patel. 2010. SNUPI: sensor nodes utilizing powerline infrastructure. In *Proceedings of the 12th ACM international conference on Ubiquitous computing* (UbiComp '10). ACM, New York, NY, USA, 159-168. DOI: https://doi.org/10.1145/1864349.1864377

[18] Samuel DeBruin, Branden Ghena, Ye-Sheng Kuo, and Prabal Dutta. 2015. PowerBlade: A Low-Profile, True-Power, Plug-Through Energy Meter. In *Proceedings of the 13th ACM Conference on Embedded Networked Sensor Systems* (SenSys '15). ACM, New York, NY, USA, 17-29. DOI: https://doi.org/10.1145/2809695.2809716.

[19] Digikey.com. Buzzer Element Piezo. Retrieved July 10, 2019 from https://www.digikey.com/short/pjr574

[20] Digikey.com. Solar Cell. Retrieved July 10, 2019 from https://www.digikey.com/short/p999mh

[21] Digikey.com. DC Brushless Fan. Retrieved July 10, 2019 from https://www.digikey.com/product-detail/en/sunon-fans/HAC0251S4-000U-999/259-1620-ND/3694187

[22] EnOcean. ECO 200 Energy Bow. Retrieved July 10, 2019 from https://www.enocean.com/en/enocean-modules-24ghz/details/eco-200-6/data-sheet-pdf

[23] EnOcean. GmbH. Retrieved July 10, 2019 from https://www.enocean.com/products

[24] FCC Regulation on Unlicensed Low-Power Radio Frequency Transmitter. Last Retrieved July 10, 2019 from https://www.fcc.gov/media/radio/low-power-radio-general-information#UNLICENSED

[25] James Fogarty, Carolyn Au, and Scott E. Hudson. 2006. Sensing from the basement: a feasibility study of unobtrusive and low-cost home activity recognition. In

Proceedings of the 19th annual ACM symposium on User interface software and technology (UIST '06). ACM, New York, NY, USA, 91-100. DOI: http://dx.doi.org/10.1145/1166253.1166269

[26] Jon E. Froehlich, Eric Larson, Tim Campbell, Conor Haggerty, James Fogarty, and Shwetak N. Patel. 2009. HydroSense: infrastructure-mediated single-point sensing of whole-home water activity. In *Proceedings of the 11th international conference on Ubiquitous computing* (UbiComp '09). ACM, New York, NY, USA, 235-244. DOI: http://dx.doi.org/10.1145/1620545.1620581

[27] Chuhan Gao, Yilong Li, and Xinyu Zhang. 2019. LiveTag: Sensing Human-Object Interaction Through Passive Chipless Wi-Fi Tags. *GetMobile: Mobile Comp. and Comm.* 22, 3 (January 2019), 32-35. DOI: https://doi.org/10.1145/3308755.3308766

[28] Google. ActivityRecognition API for Android. Retrieved July 10, 2019 from https://developers.google.com/android/reference/com/google/android/gms/location/ActivityRecognition

[29] Great Scott Gadgets. HackRF One. Retrieved July 10, 2019 from https://greatscottgadgets.com/hackrf/

[30] Manoj Gulati, Farshid Salemi Parizi, Eric Whitmire, Sidhant Gupta, Shobha Sundar Ram, Amarjeet Singh, and Shwetak N. Patel. 2018. CapHarvester: A Stick-on Capacitive Energy Harvester Using Stray Electric Field from AC Power Lines. In *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*. 2, 3, Article 110 (September 2018), 20 pages. DOI: https://doi.org/10.1145/3264920

[31] Sidhant Gupta, Matthew S. Reynolds, and Shwetak N. Patel. 2010. ElectriSense: single-point sensing using EMI for electrical event detection and classification in the home. In *Proceedings of the 12th ACM international conference on Ubiquitous computing* (UbiComp '10). ACM, New York, NY, USA, 139-148. DOI: https://doi.org/10.1145/1864349.1864375

[32] Xu He, Yunlong Zi, Hua Yu, Steven L. Zhang, Jie Wang, Wenbo Ding, Haiyang Zou, Wei Zhang, Canhui Lu, and Zhong Lin Wang. An ultrathin paper-based self-powered system for portable electronics and wireless human-machine interaction. *Nano Energy* 39 (2017): 328-336. DOI: http://dx.doi.org/10.1016/j.nanoen.2017.06.046

[33] Chitra R. Karanam and Yasamin Mostofi. 2017. 3D through-wall imaging with unmanned aerial vehicles using wifi. In *Proceedings of the 16th ACM/IEEE International Conference on Information Processing in Sensor Networks* (IPSN '17). ACM, New York, NY, USA, 131-142. DOI: https://doi.org/10.1145/3055031.3055084

[34] Vikram Iyer, Justin Chan, and Shyamnath Gollakota. 2017. 3D printing wireless connected objects. *ACM Transactions on Graphics* (TOG) 36, 6, Article 242 (November 2017), 13 pages. DOI: https://doi.org/10.1145/3130800.3130822

[35] Gierad Laput, Chouchang Yang, Robert Xiao, Alanson Sample, and Chris Harrison. 2015. EM-Sense: Touch Recognition of Uninstrumented, Electrical and Electromechanical Objects. In *Proceedings of the 28th Annual ACM Symposium on User Interface Software & Technology* (UIST '15). ACM, New York, NY, USA, 157-166. DOI: https://doi.org/10.1145/2807442.2807481

[36] Gierad Laput, Walter S. Lasecki, Jason Wiese, Robert Xiao, Jeffrey P. Bigham, and Chris Harrison. 2015. Zensors: Adaptive, Rapidly Deployable, Human-Intelligent Sensor Feeds. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems* (CHI '15). ACM, New York, NY, USA, 1935-1944. DOI: https://doi.org/10.1145/2702123.2702416

[37] Gierad Laput, Robert Xiao, and Chris Harrison. 2016. ViBand: High-Fidelity Bio-Acoustic Sensing Using Commodity Smartwatch Accelerometers. In *Proceedings of the 29th Annual Symposium on User Interface Software and Technology* (UIST '16). ACM, New York, NY, USA, 321-333. DOI: https://doi.org/10.1145/2984511.2984582

[38] Gierad Laput, Yang Zhang, and Chris Harrison. 2017. Synthetic Sensors: Towards General-Purpose Sensing. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems* (CHI '17). ACM, New York, NY, USA, 3986-3999. DOI: https://doi.org/10.1145/3025453.3025773

[39] Hanchuan Li, Can Ye, and Alanson P. Sample. 2015. IDSense: A Human Object Interaction Detection System Based on Passive UHF RFID. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems* (CHI '15). ACM, New York, NY, USA, 2555-2564. DOI: https://doi.org/10.1145/2702123.2702178

[40] Long Lin, Yannan Xie, Sihong Wang, Wenzhuo Wu, Simiao Niu, Xiaonan Wen, and Zhong Lin Wang. Triboelectric active sensor array for self-powered static and dynamic pressure detection and tactile imaging. *ACS nano* 7, no. 9 (2013): 8266-8274. DOI: https://doi.org/10.1021/nn4037514

[41] Rajalakshmi Nandakumar, Vikram Iyer, and Shyamnath Gollakota. 2018. 3D Localization for Sub-Centimeter Sized Devices. In *Proceedings of the 16th ACM Conference on Embedded Networked Sensor Systems*, pp. 108-119. DOI: https://doi.org/10.1145/3274783.3274851

[42] Notion. Notion Sensor. Retrieved July 10, 2019 from http://getnotion.com

[43] Katsunori Ohnishi, Atsushi Kanehira, Asako Kanezaki, and Tatsuya Harada. Recognizing activities of daily living with a wrist-mounted camera. In *Proceedings of*

the IEEE Conference on Computer Vision and Pattern Recognition, pp. 3103-3111. 2016. DOI: http://dx.doi.org/10.1109/CVPR.2016.338

[44] Shwetak N. Patel, Thomas Robertson, Julie A. Kientz, Matthew S. Reynolds, and Gregory D. Abowd. 2007. At the flick of a switch: detecting and classifying unique electrical events on the residential power line. In *Proceedings of the 9th international conference on Ubiquitous computing* (UbiComp '07). 271-288. DOI: https://doi.org/10.1007/978-3-540-74853-3_16

[45] Shwetak N. Patel, Matthew S. Reynolds, and Gregory D. Abowd. 2009. Detecting Human Movement by Differential Air Pressure Sensing in HVAC System Ductwork: An Exploration in Infrastructure Mediated Sensing. In *International Conference on Pervasive Computing*. 1-18. DOI: http://dx.doi.org/10.1007/978-3-540-79576-6_1

[46] Matthai Philipose, Kenneth P. Fishkin, Mike Perkowitz, Donald J. Patterson, Dieter Fox, Henry Kautz, and Dirk Hahnel. Inferring activities from interactions with objects. *IEEE pervasive computing* 4 (2004): 50-57. DOI: http://dx.doi.org/10.1109/MPRV.2004.7

[47] Matthai Philipose, Joshua R. Smith, Bing Jiang, Alexander Mamishev, Sumit Roy, and Kishore Sundara-Rajan. Battery-free wireless identification and sensing. *IEEE Pervasive computing* 4, no. 1 (2005): 37-45. DOI: http://dx.doi.org/10.1109/MPRV.2005.7

[48] Vaishnavi Ranganathan, Sidhant Gupta, Jonathan Lester, Joshua R. Smith, and Desney Tan. 2018. RF Bandaid: A Fully-Analog and Passive Wireless Interface for Wearable Sensors. In *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*. 2, 2, Article 79 (July 2018), 21 pages. DOI: https://doi.org/10.1145/3214282

[49] Alanson P. Sample, Daniel J. Yeager, Pauline S. Powledge, Alexander V. Mamishev, and Joshua R. Smith. Design of an RFID-based battery-free programmable sensing platform. *IEEE transactions on instrumentation and measurement* 57, no. 11 (2008): 2608-2615. DOI: https://doi.org/10.1109/TIM.2008.925019

[50] Edward Sazonov, Haodong Li, Darrell Curry, and Pragasen Pillay. Self-powered sensors for monitoring of highway bridges. IEEE Sensors Journal 9, no. 11 (2009): 1422-1429. DOI: https://doi.org/10.1109/JSEN.2009.2019333

[51] Sen.se Inc. Cookie Sensor. Retrieved July 10, 2019 from https://sen.se/store/cookie/

[52] Oliver Shih, Patrick Lazik, and Anthony Rowe. 2016. AURES: A Wide-Band Ultrasonic Occupancy Sensing Platform. In *Proceedings of the 3rd ACM International Conference on Systems for Energy-Efficient Built Environments* (BuildSys '16). ACM, New York, NY, 157-166. DOI: https://doi.org/10.1145/2993422.2993580

[53] Joshua R. Smith, Kenneth P. Fishkin, Bing Jiang, Alexander Mamishev, Matthai Philipose, Adam D. Rea, Sumit Roy, and Kishore Sundara-Rajan. RFID-based techniques for human-activity detection. *Communications of the ACM* 48, no. 9 (2005): 39-44. DOI: https://doi.org/10.1145/1081992.1082018

[54] Joshua R. Smith, Alanson P. Sample, Pauline S. Powledge, Sumit Roy, and Alexander Mamishev. 2006. A wirelessly-powered platform for sensing and computation. In *Proceedings of the 8th international conference on Ubiquitous Computing* (UbiComp'06). 495-506. DOI: http://dx.doi.org/10.1007/11853565_29

[55] STMicroelectronics. SensorTile. Retrieved July 10, 2019 from https://www.st.com/content/ccc/resource/technical/document/data_brief/group1/be/f2/a1/a7/d9/a5/4a/e5/DM00372460/files/DM00372460.pdf/jcr:content/translations/en.DM00372460.pdf

[56] Texas Instruments. SensorTag. Retrieved July 10, 2019 from http://www.ti.com/tools-software/sensortag.html

[57] The GNU Radio Foundation, Inc. GNURadio. Retrieved July 10, 2019 from https://www.gnuradio.org

[58] Matrix. Matrix Creator. Retrieved July 10, 2019 from https://www.matrix.one/products/creator

[59] Zhong Lin Wang. Triboelectric nanogenerators as new energy technology and self-powered sensors –Principles, problems and perspectives. *Faraday discussions* 176 (2015): 447-458. DOI: https://doi.org/10.1021/nn404614z

[60] Brett Warneke, Matt Last, Brian Liebowitz, and Kristofer SJ Pister. Smart dust: Communicating with a cubic-millimeter computer. *Computer* 34, no. 1 (2001): 44-51. DOI: https://doi.org/10.1109/2.895117

[61] Yang Zhang, Chouchang (Jack) Yang, Scott E. Hudson, Chris Harrison, and Alanson Sample. 2018. Wall++: Room-Scale Interactive and Context-Aware Sensing. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems* (CHI '18). ACM, New York, NY, USA, Paper 273, 15 pages. DOI: https://doi.org/10.1145/3173574.3173847

[62] Yang Zhang, Gierad Laput, and Chris Harrison. 2018. Vibrosight: Long-Range Vibrometry for Smart Environment Sensing. In *Proceedings of the 31st Annual ACM Symposium on User Interface Software and Technology* (UIST '18). ACM, New York, NY, USA, 225-236. DOI: https://doi.org/10.1145/3242587.3242608

[63] Chen Zhao, Sam Yisrael, Joshua R. Smith, and Shwetak N. Patel. 2014. Powering wireless sensor nodes with ambient temperature changes. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing* (UbiComp '14). ACM, New York, NY, USA, 383-387. DOI: https://doi.org/10.1145/2632048.2632066