Sensing Change: Distance Sensors for Rapid Deployment and Data Collection

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Executive Summary

Our sensor has the potential for rapid deployment and precise collection of sidewalk Level of Service (LOS) data, as well as measuring the turnover of parking spaces. For sidewalk level of service, our sensor provides an inexpensive way to collect voluminous data through strategic placement across the service area. Each sensor would be able to create accurate counts after a training dataset is provided. If adopted as a viable practice, the sensor could replace dozens of hours of manual counting by firms working to measure LOS for ULURP or other environmental analysis procedures. One drawback must be overcome: the sensor is not able to detect direction. It is plausible direction could be inferred if several sensors were placed along the same block face, although the accuracy of this would decrease as the number of people on the sidewalk increases. Because of this, it may be preferable to move toward an infrared or camera for sensing direction in the future. If direction is not critical, this sensor could be deployed, tended to, and recorded by one individual, producing the same data requiring several individuals doing manual counts. Measuring parking space turnover may be the best use of this sensor in its current configuration, as direction is not a subject of turnover analysis. However, this would require substantially more sensors (one per parking space), and would likely be achievable with significant scaling of production. Firms or agencies that produce parking studies would likely save in the long term through rapid deployment and low labor costs after a substantial investment in these sensors.

Introduction

This project was originally inspired by the possibility of improving upon standard parking sensors. Unfortunately, parking mismanagement is a major problem for cities. It is a root cause of traffic congestion and emissions, and straightforward mismanagement of resources that could provide ancillary benefits to businesses and the general public. For example, cities have begun adopting parking benefit districts as a way to implement demand pricing while creating a virtuous cycle of investment in their downtowns. A parking benefit district helps get the business groups on board, and patrons of the downtown feel better about paying a small fee for parking if it goes toward supporting local downtown businesses. After exploring these issues, we determined the pricing of parking was the root cause of parking issues. Being the pragmatic planners that we are, we decided not to pursue a permanent sensing device that would get people on their phones, racing to find parking. The more noble and just cause, if parking could ever be construed as noble and just, is to help cities find the right price for their parking spaces.

We intended to develop a sensor capable of identifying many different vehicles in parking spaces, where the current industry standard is only capable of identifying vehicles. This current standard is also more expensive and costly to implement, as they must be built into the pavement. Some standard sensors can be simply attached to the pavement surface, but all of the standard sensors we found used an electromagnetic field to detect metallic objects within a short range of the sensor. This was problematic as many municipalities allow scooters and smaller vehicles to park in car-sized parking spaces. We thought we could improve on this and develop a niche within cities that have mixed-vehicle parking and are interested in exploring demand pricing as a way to manage parking supply and demand.

Scenario: Old Pasadena, Allegory of America's Downtowns

Between 1930 and 1980, downtown Pasadena (Old Pasadena) featured struggling businesses, inadequate public spaces, and facilities, and was generally in decline. The community decided to name it a historic district and built a mall to try and increase patronage. Unsurprisingly, a mall did not rectify the situation. The downtown was struggling for two main reasons: a lack of investment, and a lack of available parking. A downtown parking benefit district was an innovative plan at that time and worked to solve the problem. Meters were installed in 1993 before which curbside parking only maintained a two-hour time limit. Employees would park in curbside spots, running out to move their car every two hours to avoid ticketing. Customers would hunt for parking for dozens of cumulative hours on the weekend, but more often the community would avoid traveling to downtown altogether. Meanwhile, businesses and landowners feared the $1 parking meter like the plague, fearing business would dry up altogether.

To get the community on board, the city earmarked parking revenue for reinvestment in downtown. The parking revenue exceeded $1.2 million by 2003, a big boost for a struggling downtown. The money was spent on walkability improvements such as street lighting and benches. The streetscape was improved, inviting more people to enjoy the downtown, and thus the virtuous cycle continued. Old Pasadena's sketchy alleys were transformed into functional urban fabric connecting businesses. Parking benefit districts (PBD) are becoming a widely-used tool, with cities across the U.S. seeing success:

- In 1997, the revenue from San Diego’s PBD was directed toward revitalizing their historic district through infrastructure investment and pedestrian-friendly improvements to the downtown.
- In 2008, Washington D.C.’s PBD maintained a consistent 85% parking spot occupancy rate, while funding sidewalk furniture, bike racks, improved lighting, and trash compactors.
- After implementation in 2011, Austin’s PBD saw a 10% increase in sales taxes combined with a 16% increase in mixed beverage receipts.
- One of Boulder, Colorado’s PBD investments includes transit passes for downtown employees to save parking spots.

As James Howard Kunstler says, “We have to do better if we are going to continue the project of civilization in America.” While he was referring to civic design, I would like to extend the notion to include what is obviously efficient and effective management of parking, arguably one of the most oversupplied and mismanaged resources in the country.

Since you have already been privy to the parking study I conducted in Gainesville, I have attached the pictures from this study in Appendix A. These small-town scenarios are abundant in America, and we think we can do our part to reduce emissions one parking meter at a time (it would be better than doing ULURP all day).

Local Interactions

After moving toward the noble and practical objective of developing sensors for finding the right price for parking for cities, we started looking at parking studies to uncover how these were conducted in standard practice. The example we found was from the City of Santa Rosa, where the city was conducting a demand study based on the location of parking (Figure 0). That is to say, parking availability was examined and classified based on the percentage of parking spots available on one block face. The study involved 25 study areas, each receiving an occupancy count at 5 am, 9 am, 12 pm, 4 pm, and 8 pm on one day only. We immediately thought this was not at all a rigorous approach, and the implementation of ongoing sensors would produce data much more temporally robust.

Figure 0. City of Santa Rosa parking study based on just a few data points.

The interactions could be described as those that are spontaneous and those that are intentionally sought out. The intentional interactions we would have would include starting a conversation with a community about the current parking situation and the related issues people of different walks of life are experiencing. We would seek out local government administrators and explore policy ideas with them. We would look to business owners and business groups to gain their support as their livelihoods would be directly affected (and most likely benefit) from any change of parking policy. We would also seek out natural community leaders, nonprofits and centers of design activity that tend to exist in cities and often grapple with public policy surrounding the built environment. These intentional interactions would not be simply interactions but would seek to build relationships as the sensor is intended to spark a long term policy conversation and movement around a problem.

Unintentional interactions would include the physical damage individuals could do or could experience themselves if they aggressively “messed with” the sensor, or otherwise tripped over the sensor. When we tested the sensor at the park, some individuals were curious about what we were doing, as the sensor was obviously more than just a cone because of its location and us hovering around it. People would likely want to know who gave us approval as well (we were asked this), so we would need to be explicit with our communication to the community, as well as prepared to navigate the local government apparatus.

Principally, the interactions we decided to measure were the level of service of sidewalks as well as the existence of cars in parking spaces. In order to measure these, we go in-depth more in the next section, but we went with the simplest possible sensor that would achieve our vision of understanding how these two, people and cars, occupy space. These principal interactions take place within a 10 m range or less for sidewalks, and a 5-6 m range depending on the size of parking spaces.

Technologies Used

In order to measure parking space turnover and count individuals passing along the sidewalks, we wanted to develop a sensor that would both fit well within the context and urban environment and would be simple and inexpensive. The sensor we landed on was the Maxbotix Ultrasonic Rangefinder (Figure 1). This sensor is quite inexpensive, small, simple, and has a range of 650 cm, perfect for car parking spaces. The range is a bit short for very wide sidewalks but works well for the standard sidewalk width.

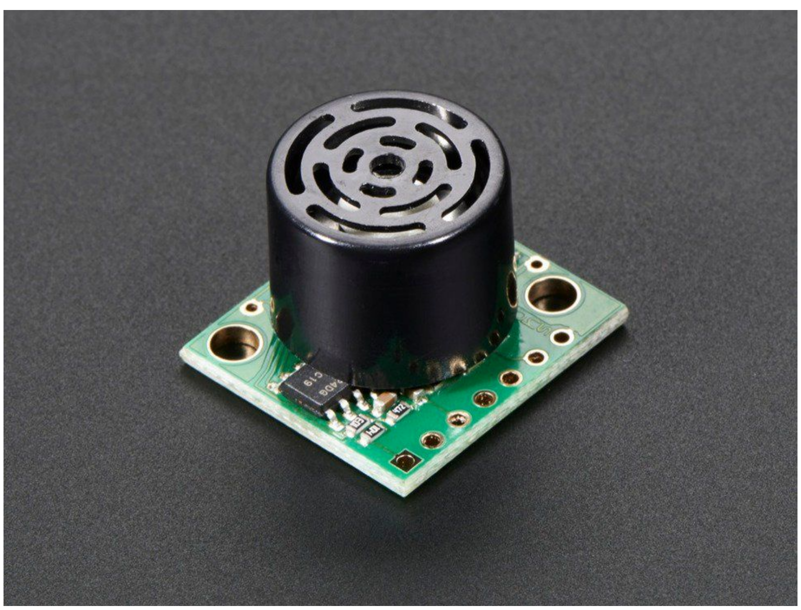


Figure 1. Maxbotix Ultrasonic Rangefinder. Image Credit: Adafruit.com.

This sensor would work well for determining when a car is in a space or not, as the distance would be far below 650 cm. It would perform the same function for indicating when individuals were on the sidewalk, as the distance measurement would also be far below 650 cm. The range and “cone” of the sonar for this rangefinder is shown in Figure 2. Our sensor is the D category, with the longest range. The width is only two ft, which we touch on later as possibly problematic.

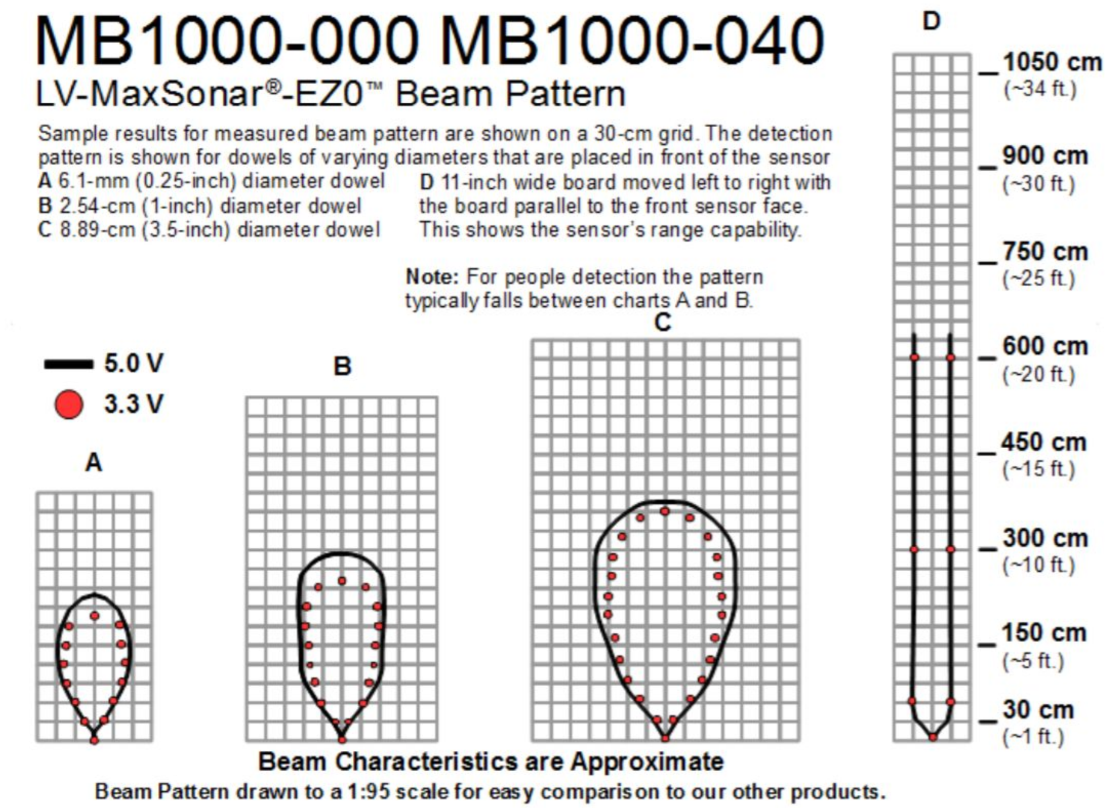


Figure 2. “Cone” of rangefinder sonar. We worked with sensor D.

We decided to use a traffic cone in order to fit the cone within the context of traffic studies and transportation, hoping to embody an “official” version of the sensor that people would be less inclined to damage. We are not sure this is entirely the case, but hopefully many distributed cones with a communication of the department “traffic study, DOT” painted on the side might deter individuals from disrupting a study.

We then decided to cut a hole in the traffic cone in order to fixate the sensor with hot glue. The sensor is connected to the Arduino, SD datalogger, and a 9v battery in a Tupperware that is also fixated with hot glue inside the cone. This setup is short-term weatherproof. The circuit is shown in Figure 3, and the complete cone sensor is shown in Figure 4 and 5.

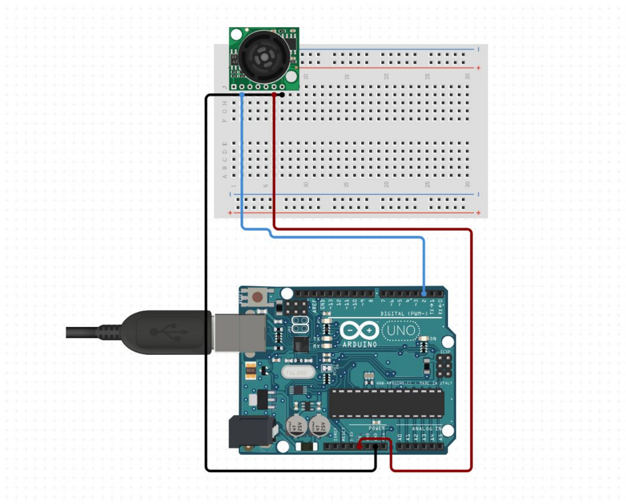


Figure 3. Basic Circut. The Arduino is powered by a 9V battery and a datalogger sheild is fixated on top of the Arduino board.


Figure 4. The cone with a written indication of the Columbia University project, and the sonar extruding from the front.

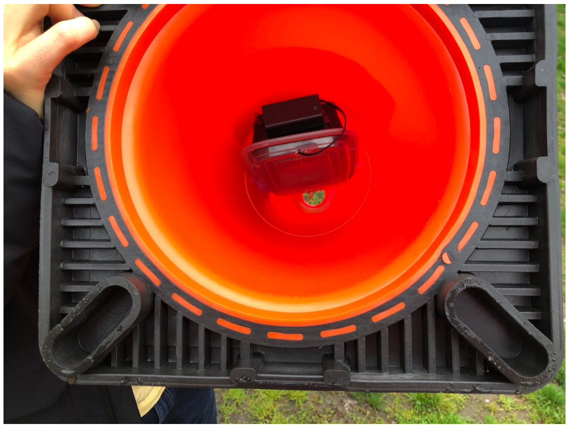


Figure 5. Arduino is held with double-stick tape inside a plastic container, with wires connecting to the sensor. This setup is short-term weatherproof and would need significant upgrades for long-term use. As a prototype, it was completely functional and would be reconfigured with considerations when developed at scale.

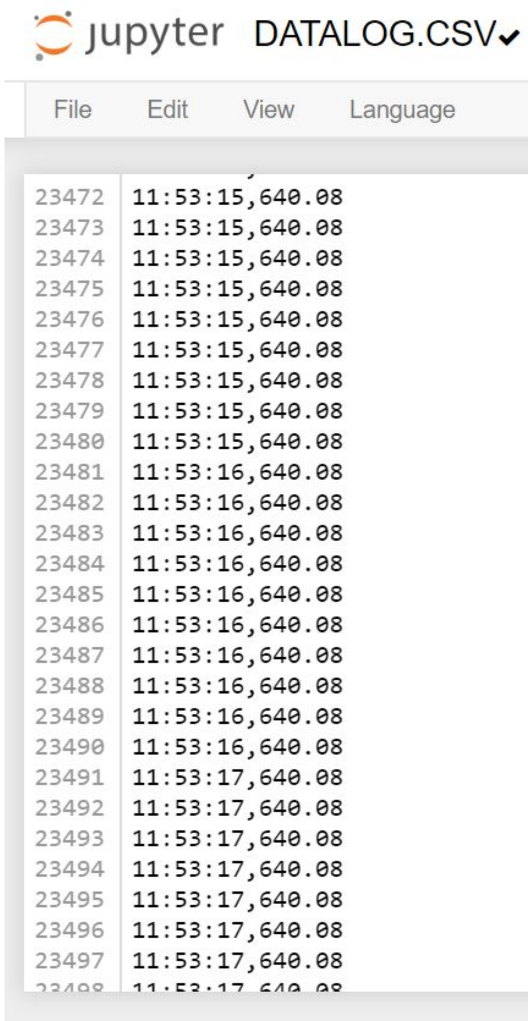
Pilot

We did not pursue sensing cars, as it was assumed we could readily achieve this and in order to sense a car changing place we might end up waiting all day because of low turnover. We instead worked with counting individuals as the more challenging aspect of the project and in an effort to see if measuring sidewalk LOS was feasible.

We deployed the sensor at Starlight Park in the Bronx on Saturday, May 4th. We placed the sensor to face across a walkway and detect people crossing the path by their closer distance than the maximum distance of 650 cm (Figure 6). This was not a busy day at the park, so the majority of our sensing measurements were actually us, the researchers, crossing the path of the sensor in an effort to achieve a viable dataset to operate on.

Figure 6. Beam faces perpendicular to the path so individuals will cross the path and trigger a lower distance measurement.

The counts were then pulled into python as a csv, and the processing of the data became the main issue. We found a few bugs with our methods that could be improved upon in future deployment.




```
23472 11:53:15,640.08
23473 11:53:15,640.08
23474 11:53:15,640.08
23475 11:53:15,640.08
23476 11:53:15,640.08
23477 11:53:15,640.08
23478 11:53:15,640.08
23479 11:53:15,640.08
23480 11:53:15,640.08
23481 11:53:16,640.08
23482 11:53:16,640.08
23483 11:53:16,640.08
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23492 11:53:17,640.08
23493 11:53:17,640.08
23494 11:53:17,640.08
23495 11:53:17,640.08
23496 11:53:17,640.08
23497 11:53:17,640.08
```

Figure 7. Raw data csv.

```
In [1]: import pandas as pd
        import numpy as np

In [175]: data = pd.read_csv('DATALOG.CSV', names = [ "timeStamp", "distance"])

In [176]: data.head()

Out[176]:
```

	timeStamp	distance
0	11:43:1	642.62
1	11:43:1	642.62
2	11:43:1	642.62
3	11:43:1	642.62
4	11:43:1	642.62

Figure 8. Pulling the data into a pandas data frame for operating on.

```
In [178]: data['sensorTrigger'] = (data.distance < 550).astype(int)
```

```
In [192]: data.head()
```

Out[192]:

	timeStamp	distance	sensorTrigger	switch
0	11:43:1	642.62	0	NaN
1	11:43:1	642.62	0	0.0
2	11:43:1	642.62	0	0.0
3	11:43:1	642.62	0	0.0
4	11:43:1	642.62	0	0.0

Figure 9. Creating a trigger column with a value of 1 if the distance measure is below 550 cm. This will indicate when something is within the range of the sensor.

```
data['switch'] = (data.sensorTrigger).diff()
```

```
data.head()
```

	timeStamp	distance	sensorTrigger	switch
0	11:43:1	642.62	0	NaN
1	11:43:1	642.62	0	0.0
2	11:43:1	642.62	0	0.0
3	11:43:1	642.62	0	0.0
4	11:43:1	642.62	0	0.0

```
data.switch.unique()
```

```
array([nan,  0.,  1., -1.])
```

Figure 10. Creating the switch column by using the .diff() function. This measures the difference between each row in the sensorTrigger column, so the times that a person moves in and out of the sensor field is identified.

```
In [195]: data2 = data.loc[data['switch'] == 1]
          # df.loc[df['column_name'] == some_value]
```

```
In [187]: data2 = data2.drop_duplicates(['timeStamp'])
```

```
In [185]: data2.head(100)
```

Out[185]:

	timeStamp	distance	sensorTrigger	switch
1654	11:45:45	17.78	1	1.0
1788	11:45:58	251.46	1	1.0
1790	11:45:58	246.38	1	1.0
1794	11:45:58	226.06	1	1.0
1796	11:45:58	205.74	1	1.0
1816	11:45:59	203.20	1	1.0
1859	11:46:4	304.80	1	1.0
1861	11:46:4	292.10	1	1.0
1863	11:46:4	276.86	1	1.0

Figure 11. A switch column is made to identify rows where the trigger column is equal to one, indicating something has entered the sensor field and is being measured.

In [188]:
```
count = data2.switch.cumsum()
c = pd.DataFrame(count)
c["count"] = count
c['switch'] = data2.switch
c['timeStamp'] = data2.timeStamp
c.head(100)
```

Out[188]:

	switch	count	timeStamp
1654	1.0	1.0	11:45:45
1788	1.0	2.0	11:45:58
1816	1.0	3.0	11:45:59
1859	1.0	4.0	11:46:4
1885	1.0	5.0	11:46:5
1965	1.0	6.0	11:46:13
1987	1.0	7.0	11:46:14
2073	1.0	8.0	11:46:22

Figure 12. A new dataframe is made to count the data by operating the cumulative sum function on the switch column.

In [200]:
```
counts = c
counts.max()
```

Out[200]:
```
switch             1
count            165
timeStamp    12:6:48
dtype: object
```

The counts dataframe is operated on by the .max() function to get the total number of counts for the time period.

In the future, the sensors would ideally have code like this built into their firmware with a function to create counts without writing endless data to a csv. These counts could be then automatically uploaded with unique identifiers based on their locations, with time stamps so vehicle turnover could be measured. It is important to record the entire timestamp as well. We tried to have an abbreviated time stamp to reduce the size of each recording, but this backfired and proved too difficult to parse because we could not figure out how to change these timestamps in pandas.

We also noticed the counts were quite high for the number of crossings we had, and we believe this is due to the low level of the sensor. The sensor sits near the top of the cone, which may be bouncing the sonar off people’s legs and subsequently not counting when there is a gap between their legs. If it were at torso level, there would likely be no issue.Additionally, it became obvious the sensor is heavy and a bit awkward. We will discuss a new design in the next section.

Future!

If this type of sensor were to be pursued in the future, the design would likely change to something cheaper and more capable of maintaining multiple rangefinders across a wider length. For this, we think a movable parking block would be useful (Figure 13).

Figure 13. Curb stop available for ~ $23. Globalindustrial.com.

We think a wider object such as this parking block would be more useful, as two sensors could be used to help detect not only cars but smaller vehicles (Figure 14) since the “cone” of sonar is only two feet. So if there were two of them, a total of four feet would increase to possibility of detecting a a vehicle. If we wanted to be quite diligent, we would even have three rangefinders, one in the center and two on the ends to create a thorough sweep of the spot.

Figure 14. Smaller vehicles may not show up on the rangefinder distance readings if they are parked on one side of a space or the other. Image: The American River Current.

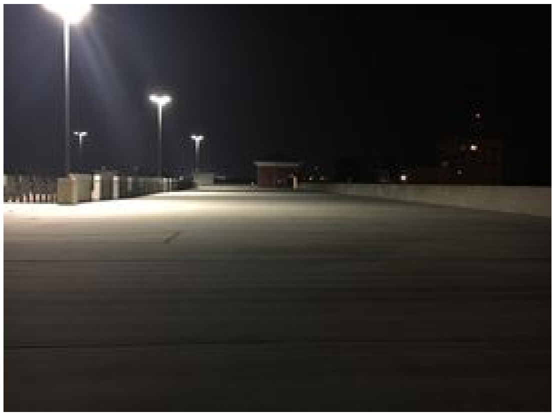
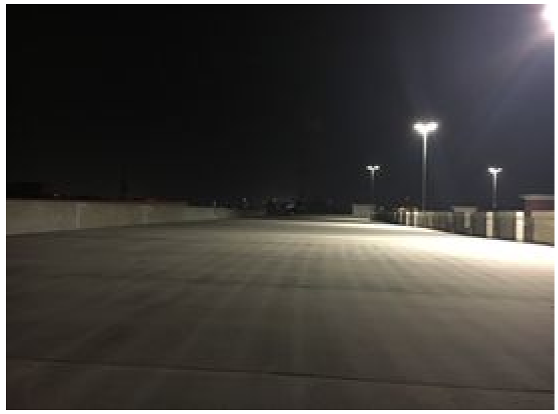
For these to be deployed, the total price would have to come down significantly in order to compete with the price of (intern) labor. These would also have to be a quantity where one person could deploy and keep an eye on all of the sensors at once, which may be limited to a number along the lines of 100, so keeping track of them would be feasible. We think these sensors would make the most sense for larger firms that conduct many parking studies. The scale of their operation would benefit from rapid deployment and voluminous data collection because the frequency of their studies would be high enough for this method to make sense and justify the capital expenditure. Watry Design is a good example, where this is a firm whose niche is parking and would benefit from more precise parking data and conduct studies frequently enough to be interested in trying out these sensors.

The big-picture dream is for these sensors to be cheap and user-friendly enough to make parking studies an easy conversation to start and explore with a community. It would take the “sexiness” of data and sensing, and create precise, reliable data where there previously was not. We also think that this technology is not necessarily going to be a “silver bullet’ because we also think there are not many technological solutions to political problems, and demand pricing is definitely a political process. We think this sensor is much more about starting a conversation around a problem and contributing data to express the issue to an exact degree.

Appendix A: Pictures from one high-demand night in Gainesville, FL

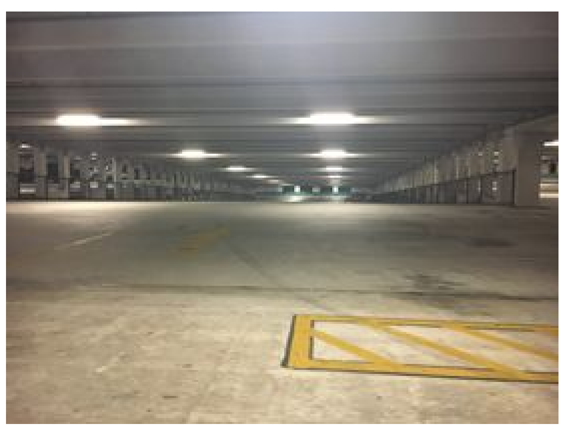
Notice the garage is thoroughly empty. The city spends upwards of $8 million on it, and it will recoup its value in approximately 300 years if a demand pricing program is not adopted.

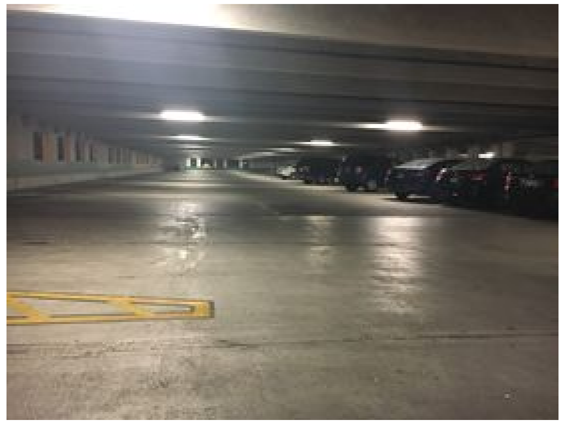
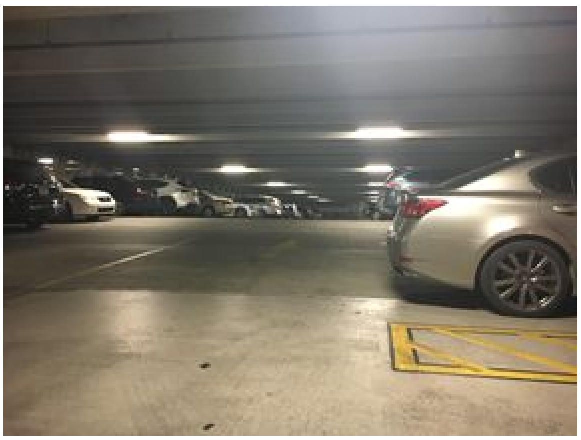

S. Main







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