Automated Lamp-Type Identification for City-Wide Outdoor Lighting Infrastructures

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ABSTRACT

As cities ramp up the efforts to convert their aging lighting infrastructure to connected and energy-efficient Light-Emitting Diodes (LEDs), they are confounded by the lack of reliable information about their existing outdoor lighting bases. *In this paper, we propose a vehicle-mounted spectrom etry-based approach to scalably audit the roadway lamp types by driving across the city, thereby quickly and efficiently providing the basis for planning and executing LED conversion projects.* *LambdaSeek*, a mobile sensing system that can be mounted on a vehicle, is developed to reliably capture the Spectral Power Distributions (SPDs) of the light emitted by the luminaires on the light poles by driving around the city. The on-board illuminance sensor and the global positioning system receiver helps to localize the SPDs, which are then classified into the corresponding lamp types using a k-Nearest Neighbor classification algorithm. Validation experiments across four field trials are presented: the most commonly found High-Pressure Sodium, Mercury Vapor, Metal Halide and LED lamps were classified correctly with a recall rate of more than 95%.

Keywords

Mobile Information Processing Systems; Mobile Computing

1. INTRODUCTION

Roadway lighting is a crucial infrastructure for cities. In addition to helping us safely navigate after dark and reduce crime, street lights add to the vibrancy and livability of urban spaces. Over the years, outdoor lighting has evolved to be one of the most wide-spread and granular infrastructure in American cities. New York City (NYC) has about 262,000 streetlights and the entire United States (US) roadway lighting consists of about 52.6 million light fixtures. Operating such a large and complex infrastructure is expensive. Outdoor lighting consumes 52.8 TWh of energy annually, enough energy to power six million homes for a year, costing cities about $10 billion annually [19] and can account for up to 60 % of a city's electricity bill for public amenities [18]. Additionally, lighting systems have a significant carbon footprint [13].

Consequently, cities have been focusing on roadway lighting systems in the recent years. According to *the 288-city survey* [16], published jointly by the U.S. Conference of Mayors and Philips in 2014, 82% of the cities voted *Light Emitting Diodes* (LEDs) to be the most promising technology for reducing energy consumption and carbon emissions among 15 different technologies. Consequently, LEDs are the energy technology receiving the top priority from 29% of the cities. Moreover, modern LED-based lighting systems offer fine-grained intensity control and entail remote monitoring and control via wireless networking resulting in energy savings of more than 70% [1]. In January 2015, President Obama, in conjunction with the Department of Energy (DoE), launched the Presidential Challenge for Advanced Outdoor Lighting to encourage American cities to convert their conventional outdoor lighting systems to LEDs [19].

A critical question that needs to be answered before, and often during LED conversion projects, is: *What are the lamp types that are being operated on the various light poles in the city?* This question is the basis of planning a conversion project. Knowledge of different lamp types is needed to identify the requirements for the LED lighting system. For example, High-Pressure Sodium (HPS) lamps, the most commonly occurring urban lamp-type in the US, may require a different LED alternative from a Metal Halide (MH) or Mercury Vapor (MV) lamps [12]. Once the conversion project commences, progress can be tracked and reported to the citizens and other stakeholders in a transparent manner by monitoring the lamp types across the city. *In this paper, we propose a vehicle-mounted spectrometry-based approach to solve the lamp-type identification problem at a city-wide scale.* The approach, which is illustrated in Fig. 1, consists of *LambdaSeek*, a mobile sensing system for rapidly acquiring the Spectral Power Distributions (SPDs) of the light poles by driving across the city and then automatically classifying the spectra into the corresponding lamp types.

Despite being critical to the grand challenge of LED conversion, *cities across the world are grasping with the problem of acquiring reliable information about their lighting inventory.* Consider the recent request-for-information published by the city of Chicago [3]. The city has requested a comprehensive inventory to be performed on about 20,000 lighting

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HotMobile '17, February 21-22, 2017, Sonoma, CA, USA

DOI: http://dx.doi.org/10.1145/3032970.3032980

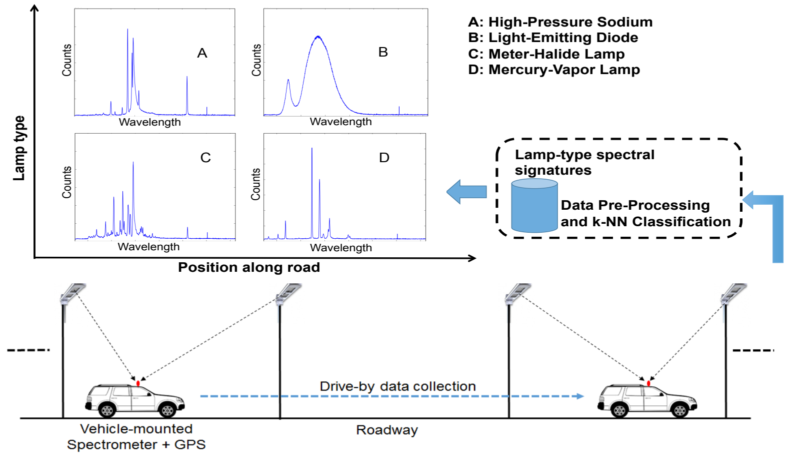


Figure 1: *LambdaSeek*: A vehicle-mounted mobile sensing approach for identifying the lamp types across a city's light poles.

fixtures in their parks as it transitions to LED-based smart lighting. Manual audits of light poles are very expensive, see [11] for details. Municipalities across the world urgently need scalable means of solving the lamp-type audit problem as they embark on large-scale LED conversion projects.

LambdaSeek consists of a spectrometer, an illuminance meter, and a Global Positioning System (GPS) receiver, which are managed by an embedded processor, and can be mounted on a vehicle using magnets. The vehicle is driven around the city at reasonable speeds to cover large areas relatively quickly. The locations of the light poles are assumed to be known apriori. The spectra collected at these locations are processed using a classification algorithm to infer the lamp types. The premise of the algorithm is that *different lamp types have characteristic SPDs that are consistent across product families.* In summary, the **main contributions** of our paper are:

- A vehicle-mounted spectrometer-based system is presented for rapid data acquisition by driving across the city. The details of engineering the system to reliably capture SPDs at speeds of up to 60 miles per hour (mph) are discussed.
- Four field experiments, consisting of HPS, MH, MV, and LED lamp types, were conducted after validating the system for accurate data acquisition.
- A classification algorithm, based on k-Nearest Neighbors (k-NN), is presented to classify the spectra to its corresponding lamp type.

The remainder of the paper is organized as follows. Sec. 2 presents background on *LambdaSeek*. Sec. 3 describes the system description and our validation efforts. Sec. 4 presents the validation and data collection experiments. Sec. 5 prese nts the k-NN algorithm for classifying the lamp spectra. Sec. 6 presents the results of the field trials. Sec. 7 discusses related work. Sec. 8 discusses the directions for future work and Sec. 9 presents our conclusions.

2. BACKGROUND

An SPD S is a mapping $S : \boldsymbol{\lambda} \rightarrow \mathbb{R}_{\geq 0}$, from a set $\boldsymbol{\lambda}$ of discrete wavelengths to real-valued intensities. $S(\lambda)$, for $\lambda \in \boldsymbol{\lambda}$ denotes the intensity of wavelength λ in the light.

A spectrometer, which is illustrated in Fig. 2, is a sensor that outputs the SPD of the incident light. An optical fiber of the appropriate diameter is used to feed the light into the spectrometer, which uses charged coupled devices, to generate the SPD. Each sample is generated by accumulating photons over the *integration time* interval. The sampling frequency dictates the rate of generating the sample.

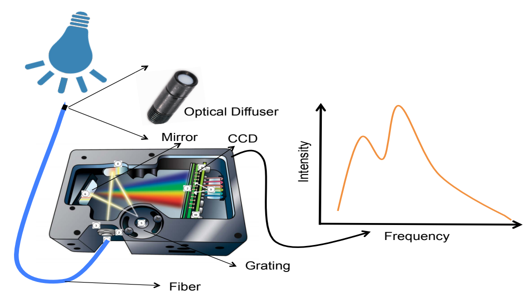


Figure 2: Working principle of a spectrometer.

Fig. 1 shows the typical spectral signatures for the four lamp types of interest in the paper: HPS, LED, MH, and MV. These are the most commonly found lamp types in cities across the world. The intensity is plotted as a function of the wavelength. The four spectra are visibly distinct from each other. The challenge, which is addressed in the further sections, is to acquire the SPDs reliably and automatically classify them.

The intensity of light is measured using illuminance, a fundamental photometric quantity that measures the photometric flux per unit area of a surface. Photometric flux is the amount of energy emitted by the light source per unit time over the visible frequencies of light. Illuminance is measured in lux ($lumen/m^2$) or footcandles ($lumen/ft^2$) using an illuminance meter, which is more commonly known as a light meter. Given the typical inter-pole distances in urban areas, an appropriately engineered vehicle-mounted light meter will record intensity peaks as it drives under and/or near the light poles.

3. SYSTEM DESCRIPTION

LambdaSeek, which is illustrated in Fig. 3, consists of the following components: i) an Oceanoptics USB 2000+ spectrometer, ii) a Konica Minolta T10a illuminance meter, iii) a Novatel FLEX-G2L-BPR-TTN GPS receiver equipped with GPS-702-GG antenna, and iv) A Raspberry Pi (RPi) B+

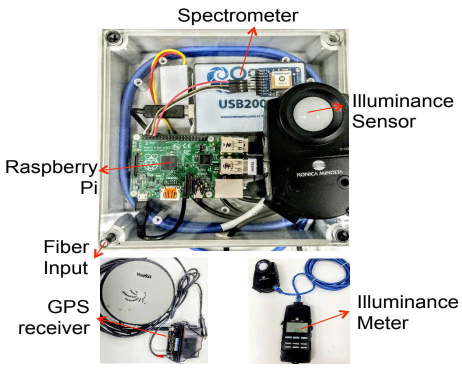


Figure 3: LambdaSeek: system description.

to manage the sensors. The RPi was interfaced to the sensors using the USB. Data acquisition programs were written to manage the sensors in a Debian Linux environment. We describe the system parameters of the sensors and the implementation details of the data collection routines below.

Oceanoptics USB 2000+ spectrometer: The diameter of the optical fiber used by the spectrometer dictates the intensity of the spectral measurements and thus is a critical parameter for data collection at night. After experimentation, we chose the 1000 μm QP1000-2-UV-VIS fiber, with the CC-3-UV-S cosine corrector for *LambdaSeek*.

After careful experimentation, the integration time was set to 500 ms. Lower values result in spectra with very low intensities leading to the loss of morphological features, which are crucial for the classifier. Higher values may result in saturation and also cause the spectra to loose critical features. The sampling rate, which cannot be less than the integration time, was set to 1 Hz. Each sample is a vector of intensities of length 2029 for wavelengths that are uniformly distributed in the range of 200 - 1100 nm in accordance with the product specifications [14].

Konica Minolta T10a Illuminance Meter: The communication protocol for the meter [8] was implemented for data collection. Adaptive ranging was enabled to handle the varying intensities of outdoor lighting that is encountered in typical urban areas. The sampling rate was set to 1 Hz.

Novatel Flexpak GPS Receiver: This receiver enables submeter accuracy using the Satellite-Based Augmentation System (SBAS). The RTKLib open source program package [17] was modified for the receiver and the RPi platform: the SBAS mode was enabled and the `sbas.conf` configuration file was changed to increase the sampling rate to 10Hz.

Power management: A SMAKN step-down transformer was used to convert the 12 V supply of a car's cigarette charger to 5V/3A output to power the RPi, which powers the spectrometer and the Adafruit GPS. An internal battery was used for the illuminance meter. The Novatel GPS receiver was powered directly from the car's cigarette charger.

Mounting: Ten disc-shaped N48 neodymium magnets of size $1/2 \times 1/4$ inches were riveted to metal bars at the bottom side of the polycarbonate enclosure.

System validation

We designed experiments to test the following hypothesis: *Drive-by data collection using LambdaSeek at reasonable speeds preserves the morphological features of the lamp spectra and offers requisite spatial separation to distinguish the signals from adjacent poles.*

We selected a road segment of two identical LED luminaires at the campus of Philips Lighting Research in Briarcliff Manor, NY in the summer of 2015. The road has two lanes and the light poles are located on one side of the road. A thirty-point grid was laid on the road between the two poles. The spectrometer was mounted on a six-foot-tall cart to mimic the height of a typical car. Spectral measurements were taken across the grid by aligning the cart at the gird point. After the stationary measurements, *LambdaSeek* was mounted on a sedan and driven on the road three times at speeds ranging from 10 - 30 mph. Fig. 4 illustrates the experiment setup.

Fig. 4b shows the stationary measurements of the LED spectra at various points on the grid. These compare well with the measurements made by *LambdaSeek* in the drive-bys, as shown in Fig. 4d. Moreover, the spectra for the two adjacent poles can be easily separated. Based on these observations, we concluded that *LambdaSeek* can be used to collect reliable data for lamp-type identification and proceeded for large-scale field trials.

4. FIELD TRIALS

Four field trials were conducted to test the reliability of data acquisition and collect training and testing samples for the lamp-type classifier. All the tests were conducted after dark to minimize the effects of ambient lighting and ensured that the spectra for all the four lamp types were consistently captured at speeds of 20 - 60 mph.

The town of *Rosendale in NY* conducted an assessment of streetlights in 2014 and has released this data to the public [6]. *LambdaSeek* was tested in the town and the survey data was used as the ground truth. The poles locations (latitude/longitude pairs) were manually recorded by driving past them during day time because the town's survey included approximate human-readable locations, like intersections. Drive-bys were conducted over two nights at speeds of 20 - 40 mph to collect the spectra and illuminance peaks for 100 light poles. The spectra were localized using the illuminance peaks and assigned to the corresponding poles.

Pleasantville road, in Ossining NY, consists of about 70 poles that span all the four lamp types of interest. Moreover, the road cuts across both residential neighborhoods and the town center. A drive-by test was conducted at approximately 35 mph to collect spectral and illuminance measurements. The spectra were localized to the corresponding poles using illuminance data. The ground truth for the lamp types was established using visual inspection.

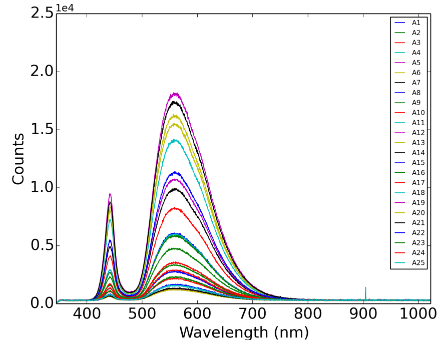
The *Governor Malcolm Wilson Tappan Zee Bridge* in NY crosses the Hudson river and is part of a major thruway. The bridge consists of 70 HPS lamps on both sides and is ideal to test the *LambdaSeek* at high speeds. Data collection drives were conducted at 50 - 60 mph on all the lanes of both the east and west-bound sides of the bridge.

LambdaSeek was tested as part of a larger lighting audit on the campus of Clemson University. The system was mounted on a golf cart to cover pedestrian walkways and bylanes in the university. A total of 956 spectra were collected to test the scalability of data acquisition and the accuracy of the classifier. All the spectra were labeled by hand.

5. LAMP-TYPE CLASSIFICATION USING SPECTRUM DATA

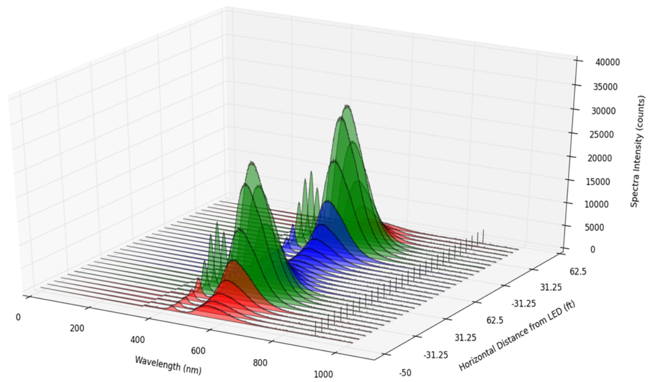
In this section, we describe the classification algorithm for

(a) Cart-top measurements for reference.



(b) Spectra measured atop the stationary cart.

(c) Daytime view of LambdaSeek mounted on a car.



(d) Spectra collected by LambdaSeek after multiple drive-bys.

Figure 4: System validation: LambdaSeek preserves the morphology of lamp spectra.

labeling the spectra obtained in the aforementioned field trials. The lamp-type classification problem is: *Given a spectrum $S(\lambda)$, assign it a class label l from $\mathcal{L} = \{$High Pressure Sodium (HPS), Metal Halide (MH), Mercury Vapor (MV), Light-Emitting Diodes (LED)$\}$.* The spectrum $S(\lambda)$ is a vector of non-negative real-valued intensities collected by *LambdaSeek*. The goal of classification is to use the morphology of the spectra to assign the lamp type.

The similar spectral patterns for the same lamp type can be captured using distance metrics:*two spectra of the same type will be "closer" to each other than the spectra of other lamp types*. Thus, an unlabeled spectrum can be classified by looking at the labels of the nearest known spectra.

We applied this observation to build a *k-NN classifier* to identify the lamp types. The k-NN classifier, a supervised learning algorithm, works as follows. In the *learning phase*, a representative sample of labeled spectra is used to build a library $\{(S_1^*(\lambda), l_1), (S_2^*(\lambda), l_2), \dots, (S_M^*(\lambda), l_M)\}$; $S_i^*(\lambda)$ and l_i denote the spectrum and the class label of the i^{th} sample. Ideally, the sample must capture the diversity across all the classes. In the *testing phase*, the class label l for the spectrum $S(\lambda)$ is assigned by

$$l = l_{\hat{j}}, \text{where } \hat{j} = \underset{j \in 1,2,\dots,M}{\text{argmin}} \left(d(S(\lambda), S_j^*(\lambda))\right), \tag{1}$$

where $d(.,.)$ is the distance metric of choice. Next, we describe the implementation details of this idea.

Preprocessing: The spectra collected by the system need to be pre-processed before learning and testing the classifier. $S(\lambda)$ was scaled such that the intensities lie in $[0, 1]$. All the spectra collected by *LambdaSeek* show a peak around 900 nm. This peak is an artifact due to the heat emitted by a human present in the vicinity of the spectrometer, both during manual measurements and car-top collection. The peak was removed from the spectra using a low-pass filter.

Learning the k-NN Classifier: A library $\mathcal{L}$ of 25 representative samples of HPS, MH, MV, and LED was created. The library spanned different types and brands of lighting products. The Lamp Spectral Power Distribution Database (LSPDD) [7] was used to pick the samples for the class MH and MV. The validation experiment at Briarcliff Manor was used for LED samples. The data collected during the Rosendale field trial was used to extract HPS samples based on the results of the street light assessment survey by the officials of the town of Rosendale, NY [5, 6].

Testing the k-NN Classifier: There are several choices for the distance metric d in Eq. 1. The Euclidean (L2), and Manhattan (L1) distances, obtained by $p = 1$ and $p = 2$ respectively the in Eq. (2), were the initial choices.

$$d_p(\bar{S}(\lambda), \bar{S}_i^*(\lambda)) = \sum_{\lambda} (|\bar{S}(\lambda) - \bar{S}_i^*(\lambda))|^p)^{1/p}, \tag{2}$$

for $\bar{S}_i^*(\lambda) \in \mathcal{L}$. The cosine distance was also employed:

$$d_c(\bar{S}(\lambda), \bar{S}_i^*(\lambda)) = 1 - \frac{\bar{S}.\bar{S}_i^{*T}}{((\bar{S}.\bar{S}^T)(\bar{S}_i^*.\bar{S}_i^{*T}))^{1/2}}, \tag{3}$$

where the superscript T denotes the transpose of the spectrum vector and the subscript c denotes cosine distance.

The choice of the parameter k affects the ability of the classifier to generalize across the library: $k = 1$ and $k = 2$ were tested, as discussed in the next section.

Table 1: Results for the Rosendale field trial.

	HPS (89)	MV (11)	LED (0)	MH (2)	MIX (0)
HPS (87)	87 (100%)	0	0	0	0
MV (13)	2	11 (84.6%)	0	0	0
LED (0)	0	0	0	0	0
MH (0)	0	0	0	0	0
MIX (0)	0	0	0	0	0

Table 2: Results for the Tappan Zee Bridge field trial.

	HPS (70)	MV (0)	LED (0)	MH (0)	MIX (0)
HPS (70)	70 (100%)	0	0	0	0
MV (0)	0	0	0	0	0
LED (0)	0	0	0	0	0
MH (0)	0	0	0	0	0
MIX (0)	0	0	0	0	0

Table 3: Results for the Pleasantville Road field trial.

	HPS (26)	MV (35)	LED (7)	MH (2)	MIX (0)
HPS (26)	26 (100%)	0	0	0	0
MV (35)	0	35 (100%)	0	0	0
LED (6)	0	0	6 (100%)	0	0
MH (2)	0	0	0	2 (100%)	0
MIX (1)	0	0	1	0	0 (0%)

Table 4: Results for the Clemson University field trial.

	HPS (777)	MV (2)	LED (142)	MH (34)	MIX (0)
HPS (782)	777 (99.4%)	2	2	1	0
MV (0)	0	0	0	0	0
LED (130)	0	0	130 (100%)	0	0
MH (33)	0	0	0	33 (100%)	0
MIX (11)	1	0	10	0	0

6. RESULTS

In this section, we present the results of the k-NN lamp-type classifier on the data collected at the three field trials. The performance was measured using the *recall rate*, which is the fraction of the samples of a class classified correctly, and $k = 1$. Lamp-type audits conducted by the cities are often interested in ensuring high recall rates.

Tables 1 - 4 present the confusion matrices for the four case studies presented in the Sec. 4. The first column represents the ground truth in terms of the number of the test samples for each of the four classes. The first row represents the total number of samples that were classified into the four lamp types. The $(i, j)^{th}, i, j \in 1, \ldots, 6$ entry shows the number of samples of class label i that were classified as class j by the k-NN classifier.

In addition to the four lamp types, we also present results for a fifth class: Mix. This class captures the spectra that are combinations of two spectra of different lamp types. Such samples are acquired by *LambdaSeek* at locations where two poles with different lamp types are located close to each other and had to be manually labeled.

Fig. 5 is an example of a mixed spectrum that results from an HPS and an LED lamp situated close to each other. Note that our classifier is currently not trained to classify such spectra as these instances are very rare in cities.

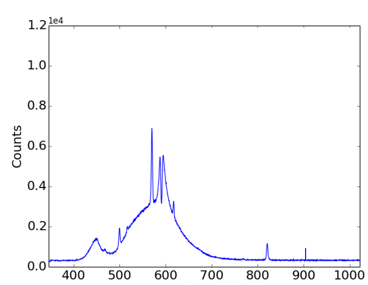


Figure 5: A mixed spectrum.

Across the four case studies, the classifier recalled more than 95% of the samples into the correct lamp type. The large number of HPS samples in our test data reflects the typical distribution of lamp types across American cities, many of which have recently begun LED conversion. The recall rate for MV lamps is slightly lower: 96% due to the relatively low number of training samples in the library. HPS, LED, and MH were classified with high recall rates across the trials. The high number of HPS lamps results in diverse spectra that may be confused for the other lamp types, but this error rate was negligible in the Clemson University trial. Finally, the Tappan Zee Bridge field trial established *LambdaSeek*'s ability to collect SPDs at speeds of up to 60 mph.

7. RELATED WORK

The system in [9, 10] entails using vehicle-mounted cameras and GPS receivers to map the roadway lighting infrastructure. The authors develop a Kalman filtering approach to recover from gaps in the GPS data to localize the light poles. The system has been augmented with thermal imaging to map heat-emitting infrastructure atop light poles, like transformers. The authors have not extended their work to lamp-type identification.

Measuring illuminance and other optical performance metrics across the city is an important problem for the cities, as it enables the cities to periodically monitor the street lights. Vehicle-mounted approaches to this problem include [20, 15] and [2] presents a recent stationary approach. Light intensity, on its own, can not be used for lamp-type identification. *LambdaSeek* uses a spectrometer to capture spectral signatures of lamp-types to enable city-wide lighting audits.

In [11], the authors propose a vehicle-mounted system to measure illuminance and an anomaly detection algorithm to mine faulty street lights from the data. The geo-spatial patterns of light intensities are stored in so-called *Imaps* to enable algorithms that detect dark patches that correspond to faulty light poles. *LambdaSeek*, on the other hand, focuses on collecting spectral data.

The work of [4] focuses on identifying the lamp types, and is most closely related to our work. The authors propose to use a library of spectra to identify lamp types across the cities, but do not propose a scalable data acquisition system. Authors allude to satellite images as a possible source of spectral data. Despite being scalable, satellite imaging is prone to occlusions from trees and resolution-related accuracy issues. *LambdaSeek*, on the other hand, can provide precise insights about each light pole in the city.

8. DIRECTIONS FOR FUTURE WORK

We plan to extend our work on *LambdaSeek*-based large-scale lighting audits by augmenting the system with additional sensors and improving the data analytics pipeline.

System augmentation would involve expanding the set of sensors on board *LambdaSeek*. The goal is to adapt the spectral sensing rate to the speed of the vehicle. The Raspberry Pi can be interfaced with the on-board diagnostic system of the car to sense the vehicle speed and modify the sampling rate accordingly.

Improved Data Analysis: The existing data analytics pipe line suffers from the following shortcomings. The classifier is not trained to identify instances of spectral mixing, which occurs when two lamps of different types are located close to each other. An optimization-based scheme will be developed to handle this case. Spatial locality of lamp-types will also be exploited. The analytics engine is also agnostic to ambient lighting, which is very common in busy urban areas like Manhattan in NYC. Filtering algorithms will be developed to reduce the noise in the measurements.

Wider Implications: *LambdaSeek* will be used to build an end-to-end system to aid LED conversion projects. A visualization module will be added to create heatmaps of the light poles across the city and monitor the progress of conversion and the status of the luminaires.

9. CONCLUSIONS

We presented an approach, based on vehicle-mounted spectroscopy, to solve the problem of identifying roadway lighting lamp-types across cities, and thereby aid the planning and execution of LED conversion projects. The system was validated against data collected by a stationary cart. A k-NN classifier was developed using a library of 25 representative spectra. The cosine distance metric with $k = 1$ gave recall rates of more than 95% for HPS, LED, MV and MH lamp types across three field trials. The high degree of separability of the distinct spectral signatures, along with the reliable and scalable data acquisition enabled by *LambdaSeek*, provides an easy-to-use efficient solution for the cities to manage their lighting infrastructure.

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