Title
EffiSenseSee

Authors
Yen, Alex
Shah, Zeal
Ochoa, Benjamin
et al.

Publication Date
2022-11-09

DOI
10.1145/3563357.3564062

EffiSenseSee: Towards Classifying Light Bulb Types and Energy Efficiency with Camera-Based Sensing

Alex Yen
alyen@ucsd.edu
UC San Diego

Zeal Shah
zshah@umass.edu
University of Massachusetts, Amherst

Benjamin Ochoa
bochoa@eng.ucsd.edu
UC San Diego

Pat Pannuto
ppannuto@ucsd.edu
UC San Diego

Jay Taneja
jtaneja@umass.edu
University of Massachusetts, Amherst

ABSTRACT

EffiSenseSee is a means to identify energy-inefficient lighting infrastructure lingering in our built environment. When light bulbs convert incoming AC power into visible light, a carefully designed camera can "see" some of the original AC signal in the varying light intensity. Using a large corpus of over 60 bulbs, we show that based solely on analysis of subtleties in observed light output, previously unseen bulbs can be classified as energy-efficient or energy-inefficient with over 95% accuracy. With 89% accuracy, EffiSenseSee can group bulbs into incandescent, halogen, CFL, or LED—the four primary categories measured by regulatory bodies. We then investigate how to bring this technology "out of the lab." In an outdoor setting with a commodity camera, EffiSenseSee identifies inefficient bulbs with 74% accuracy.

CCS CONCEPTS

• **Human-centered computing** → *Ubiquitous and mobile computing systems and tools*; • **Computer systems organization** → *Embedded and cyber-physical systems*; • **Computing methodologies** → Computer vision.

KEYWORDS

Light bulb classification, Energy efficiency, Sensing with cameras

ACM Reference Format:
Alex Yen, Zeal Shah, Benjamin Ochoa, Pat Pannuto, and Jay Taneja. 2022. EffiSenseSee: Towards Classifying Light Bulb Types and Energy Efficiency with Camera-Based Sensing. In *The 9th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation (BuildSys '22), November 9–10, 2022, Boston, MA, USA.* ACM, New York, NY, USA, 10 pages. https://doi.org/10.1145/3563357.3564062

1 INTRODUCTION

One of the greater successes in policy and global energy reduction is the transition to energy-efficient lighting technologies. Down from 15-25% in 2011, today lighting accounts for just 8% of the energy use across the residential and commercial sectors in the United States [1, 2]. For commercial buildings, their limited incandescent population has fallen to under 5%. However, they also have a limited LED penetration of only 17%; older, fluorescent tube lighting still represents nearly 70% of commerical building lighting power [3]. Residential surveys suggest that 45-52% of their fixtures are now powered by energy-efficient CFL or LED bulbs [4, 5]. At the same time, these same studies estimate 28-43% of residential lighting still comes from inefficient incandescent or halogen bulbs.

This lingering population of inefficient bulbs may not necessarily be as bad as it sounds. The incandescent bulb in the home attic or rarely-visited machine room likely sees well-under 1% on-time. Replacing such bulbs would actually be an environmental net-negative, as the carbon spent to manufacture the new bulb would take decades to be surpassed by the efficiency gains of such a lightly-used item [6].

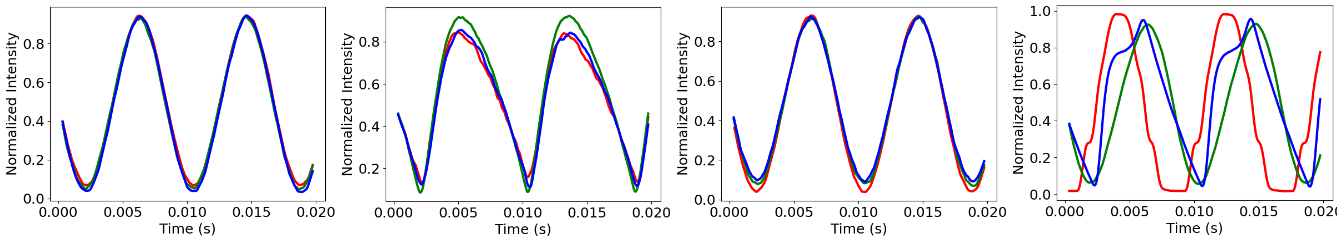
Today, then, we must ask two questions to guide replacement policies and incentives: where are the inefficient bulbs that remain, and how much are they actually used? Answering this first question is labor-intensive. The state-of-the-art approach is a mix of consumer self-reporting, opaque supply-side monitoring, and costly surveys where highly trained operators inspect representative samples of residential and commercial buildings [3–5]. Answering the usage question is intractable with such a manual approach. Indeed, the "uncertainty about the baseline and the need for ongoing research" is explicitly identified as a challenge in NREL's Residential Lighting Evaluation Protocol [7].

What if instead we could automate these measures? Imagine if all the cameras in Smart City infrastructure could tell whenever and wherever an inefficient bulb is running. As a first step, we present EffiSenseSee, a classification engine that uses commodity cameras to automatically identify energy-inefficient bulbs. EffiSenseSee tackles the first of the two challenges – autonomously identifying powered-on inefficient bulbs. This is a critical building block towards future wide-area measures of the penetration and longitudinal utilization of inefficient bulbs in our built environment.

The key idea in EffiSenseSee is the analysis of "Bulb Response Functions" (BRFs). First discussed by Sheinin et al., BRFs are a description of how a light bulb transforms incoming AC power into light [8]. BRFs are stable, intrinsic properties of bulbs. Prior work has shown they can act as "fingerprints" to uniquely identify a bulb. Indeed, if a bulb's BRF is known, it can even be reversed to infer properties of the incoming AC based on light output [9]. With EffiSenseSee, we consider the case that BRFs are not known a priori.

BuildSys '22, November 9–10, 2022, Boston, MA, USA

ACM ISBN 978-1-4503-9890-9/22/11.
https://doi.org/10.1145/3563357.3564062



(a) BRF of incandescent. **(b) BRF of CFL.** **(c) BRF of halogen.** **(d) BRF of LED.**

Figure 1: Example of smoothed Bulb Response Functions (BRFs) for three different bulbs of each type we study: incandescent, compact fluorescent light (CFL), halogen, and LED. While similar to the eye, differences among electronic components and manufacturing details can cause reliable patterns that identify bulb fingerprints.

We aim to discover new, previously unseen bulbs and autonomously identify them as efficient or inefficient bulbs.

We posit that design of energy efficient bulbs means they will have characteristically different BRFs. Consider the operation of an incandescent bulb. At its heart, it is simply a resistor periodically impeding grid power, getting hot while doing so, and as a consequence emitting light. In contrast, a CFL must charge a ballast and ionize gases, which emit ultraviolet light, which causes the coating on the bulb to fluoresce and emit visible light. LEDs are similarly complex, usually with solid state power electronics converting AC into constant voltage or constant current sources. As Figure 1 shows, BRFs of different types of bulbs do look distinct.

The next question, then, is how to build a classifier that can autonomously label BRFs. We consider signal processing, statistical, and machine learning methods and find that k-Nearest Neighbors (kNN) is a suitable approach. While we are predominately interested in the binary question, 'is this an inefficient bulb?,' we also attempt more nuanced bulb type detection. When the Energy Information Administration (EIA) and other bodies survey lighting infrastructure, they report four bins: incandescent, halogen, CFL, and LED [10]. As a secondary goal then, we investigate whether our classifier can autonomously collect this data. While it is reasonably good at distinguishing efficient bulbs (i.e. separating CFLs from LEDs), in outside-the-lab settings, the difference between incandescent and halogen bulbs proves too subtle to reliably distinguish.

With the classifier in hand, we have two other challenges to form a complete system. First, we must find a means to collect BRFs. Here, we lean on prior work. To collect high-resolution BRFs for training, we capitalize on oscilloscope-collected data from Shah et al. [9], while for inference in the wild we leverage the rolling-shutter-based ACam from Sheinin et al. [11]. We discuss the tradeoffs in these two collection methods in Section 4.1. In our evaluation, we demonstrate empirically that it is possible to harmonize these two approaches, and that normalized BRFs can be used interchangbly, without retraining, no matter how they were collected.

The second challenge is to adapt to new environments (i.e. prevent double counting and recognize unprecedented BRFs). As a first exploration in this space, we do not attempt to handle continuous motion; a system to reliably extract BRFs in a moving scene is (at least) one whole paper of its own merit. However, we do expect that the camera may move between BRF captures. This means we must be able to distinguish between a new bulb and one that EffiSenseSee has previously seen. To identify bulbs over time and across scenes, we can use BRF fingerprints. As we do not have a database of fingerprints a priori, however, we must construct one on-the-fly. For this, we develop a novelty detection engine, which is able to answer the question, 'is this a new bulb?' with 85% accuracy.

With these challenges addressed, we implement and evaluate EffiSenseSee. We develop a feature-engineering-based approach to classify and distinguish between highly similar, sinusoidal waveforms from light bulbs. EffiSenseSee is a methodology to distinguish between bulb types and their relative efficiency, which no system to-date can do from BRFs. We first establish that we can build a classifier, which is able to accurately classify bulbs solely from their BRFs. We then show that a model trained on in-lab, cleaned oscilloscope data can be used directly to identify inefficient bulbs using BRFs collected with a camera, in both indoor and outdoor settings. Finally, we test the novelty detection engine. While it is reasonably accurate, a system implemented at-scale will likely need to supplement novelty detection with metadata such as GPS location and magnetometer orientation for robustness. We then close with a discussion of future directions for EffiSenseSee and the most promising paths for improving performance.

In sum, this paper makes the following contributions:

- We validate prior work in BRF capture and then newly demonstrate that captures from high-fidelity oscilloscope data and cleaned rolling-shutter data can be interchanged in machine learning models.
- We develop a classification engine to accurately label previously unseen bulbs as inefficient or efficient, based solely on BRF data; we also demonstrate type classification across incandescent, halogen, CFL, and LED bulb classes.
- We create a new novelty detection algorithm, which can distinguish between previously unseen bulbs and bulbs which have simply moved in the observed scene to enable robust accounting.

2 RELATED WORK

Most prior work that analyzes light bulb output targets localization applications. Bulbs in the built environment form a sort of star chart, with buildings mapped and labeled during system setup. Devices in the space extract various features as labels to infer which 'stars' they are looking at.

For example, Kuo et al. label bulbs directly. They show that "smart" LED lights can be programmed with high-frequency flicker (2-7 kHz) which is imperceptible to the human eye but recoverable by exploiting the "rolling shutter" used by most CMOS cameras [12]. We do not control the bulbs we study and cannot inject such labels.

Newer approaches show that labels can be inferred from intrinsic, physical properties unique to each bulb. Zhu et al. use RGB values from camera sensors to fingerprint the irradiance characteristics of light bulbs [13]. While this no longer requires bulb modifications to provide labels, it is still only capable of *re*-identifying bulbs. The approach does not provide a means to classify unseen bulbs.

While classification is not the purpose, the LiTell localization system does give a classification primitive. Zhang et al. found that most fluorescent bulbs have a weak-but-unique, per-bulb characteristic flicker; the rolling shutter can be used here as well to capture oscillations between 80 and 160 kHz as labels [14]. Unfortunately, non-fluorescent bulbs do not have such flicker. As we are interested in classifying all bulbs, we seek a different approach.

Ladeira et al. use and test various machine learning algorithms to predict a light bulb's type, brand, and power from light bulb characteristics [15]. Here, they rely on spectrometry to capture bulb intrinsics (and only from a range of 2-5 m). This technique is not easily adaptable to general purpose devices for cost-effective, wide-area measurement. Additionally, the work primarily targets mercury and sodium bulbs. Again, we seek a more general approach across all bulb types.

3 BULB RESPONSE FUNCTIONS

At a high level, light bulbs take as input a periodic, time-varying signal (i.e., AC power) and output a periodic, time-varying signal (i.e., light). That is, there exists a *Bulb Response Function* (BRF) that expresses how each bulb transforms input power into output light.

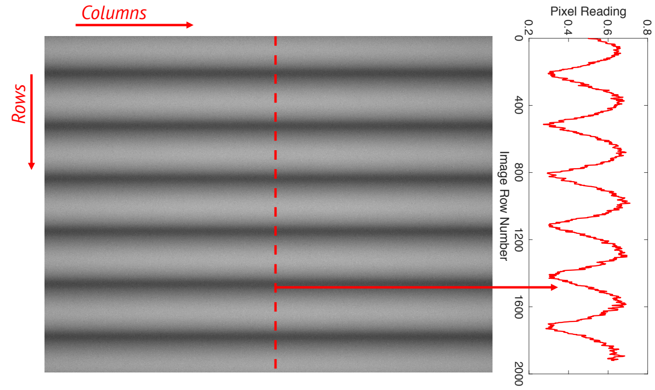
Sheinin et al. first described BRFs in their Computational Imaging work, where they showed that BRFs are consistent over time and used them to build a database of bulbs to match [8]. While used only for fingerprinting specific bulbs, they observed that BRFs tended to 'look different' for different bulb types. This observation is the foundation of our work. As example, Figure 1 shows BRFs we captured from four different bulb types. We ask whether there is sufficient consistency in BRFs for a given class of bulbs that new, previously unseen bulbs can be accurately classified.

4 EffiSenseSee DESIGN

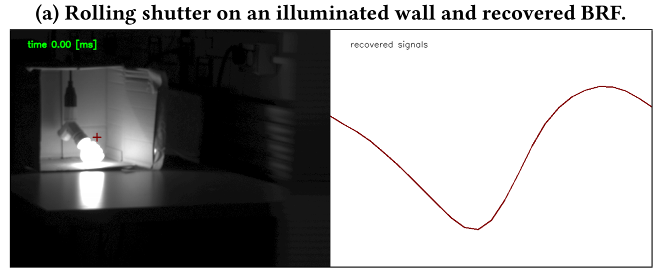
EffiSenseSee has three steps that present design questions. The first is BRF acquisition, where we explore both high-fidelity oscilloscope-based capture and a rolling-shutter design suitable for commodity cameras. The second is predictive labeling, where we identify and select characteristics of BRFs to classify bulb type. The third is where we must determine whether we have encountered a given BRF before to avoid double-counting of bulbs in the real world.

4.1 BRF Capture

To capture BRFs, we explore both high-fidelity, oscilloscope-based collection and deployment-friendly, rolling-shutter-based design. We begin with a database of BRFs from Shah et al. [9] to simplify implementation and enable reproducibility of our results. In Section 6, we discuss our process for transitioning from indoor to outdoor data collection and analysis with Sheinin et al.'s camera setup [11].



(a) Rolling shutter on an illuminated wall and recovered BRF.



(b) Video-based acquisition for when the light covers a small proportion of the scene and recovered BRF.

Figure 2: Working demonstration of BRF extraction using a rolling shutter camera in two different scenarios. In (a), the BRF is extracted from the image of a smooth wall illuminated by a bulb [9, 11]. In (b), a video-based approach enables BRF recovery when the bulb is in the scene through temporal sampling [11].

4.1.1 Oscilloscope. We discuss in detail how Shah et al. extracts BRFs, which is originally based on Sheinin et al.'s work [11]. To "see" AC, the system must capture the fluctuations in light emitted by a bulb. This requires quantizing the analog intensity of a light bulb powered by the electric grid. A phototransistor-based chip—Sparkfun's TEMPT6000—can convert light into voltage. This voltage is then sampled through an oscilloscope to quantize the light.

The post-bulb views of an AC waveform are Bulb Response Functions (BRFs). This is shown in the incandescent, CFL, halogen, and LED examples in Figure 1. Each waveform shown in Figure 1 represents two and a half cycles; each color represents a unique bulb. For each unique light bulb, the dataset contains approximately ten different instances of two-and-a-half cycle waveforms. There are over 60 unique light bulbs recorded [9], which we utilize in this study. In total, the dataset contains over 600 waveforms.

4.1.2 Rolling Shutter Camera. High fidelity collection of BRFs is also possible using images captured by a rolling shutter camera. In a rolling shutter camera, consecutive rows of the image sensor are exposed after a specific inter-row delay, which is of the order of 20-30 microseconds. This inter-row delay provides a temporal sampling rate high enough to capture a bulb's BRF in a single image as shown in Figure 2. This figure shows an image of a smooth wall illuminated by a CFL bulb, which is captured using a rolling shutter camera. The vertical wave pattern in the image corresponds to the BRF of the bulb illuminating the scene and can be recovered by extracting a single column of pixels as shown in Figure 2. However, the method in Figure 2 cannot collect BRF data without a large, diffuse surface; i.e., it cannot look straight at a bulb or small fixture.

Instead, we build on the capability of another imaging model proposed by Sheinin et al. [11], which also leverages the high frame rate capturing mechanism of imaging devices—video. A working demonstration of the new technique is shown in Figure 2, where a bulb is directly visible in the scene. We can now recover the BRF of that bulb using multiple images captured at a high frame rate. The new technique allows us to record BRFs of street lights and distant light sources present as small, point sources in a scene.

4.1.3 Data Cleaning. We perform all our initial tests and experimentation on Shah et al.'s oscilloscope-collected BRFs. While the oscilloscope offers the capture of high resolution data, the BRFs are not noise free. To generate clean BRFs, we apply a Savitzky-Golay filter, apply a moving average filter, an finally normalize each BRF. The Savitzky-Golay filter mitigates noise and retains the relative "shape" of each waveform. The moving average filter further smooths noise, and normalization ensures equivalent BRF intensity for the classification process. We found that the window sizes of 31 and 50 samples work well for the Savitzky-Golay and moving average filters, respectively. Each oscilloscope-based waveform is roughly 2,000 samples long. We truncate the waveforms to approximately begin and end at the nadir.

4.2 Bulb Classification

To detect energy inefficient bulbs, we first need to acquire knowledge of what type of BRFs we are looking at. We attempted a variety of approaches before arriving at a feature engineering solution for light bulb classification. This section first discusses approaches which did not work (i.e. direct statistics, signal processing, and Principal Component Analysis) and why. We show how pieces of these techniques were incorporated in our final feature-engineering.

4.2.1 Statistics & Signal-Processing. We first considered classifying bulb types via statistical and signal processing methods. For our statistical approach, we compute the cross correlation of the unknown BRF with reference bulbs of each type. The resulting correlation coefficient should show how closely related two compared waveforms are. However, this method was not useful. The correlation coefficients between similar and dissimilar waveforms overlapped; no threshold value could accurately distinguish between identical or different bulb types (e.g. comparing two incandescent waveforms versus an incandescent and a halogen waveform). Indeed, as seen in Figure 1, the waveforms between similar bulb types—especially halogen and incandescent—are challenging to distinguish.

Our second approach tries classic signal processing with frequency analysis. We sought to find characteristic frequencies in the upper kHz range after computing the Fast Fourier Transform on a BRF, as done by Zhang et al. to label lights [14]. We discovered no characteristic frequencies in our data. We theorized that double the grid frequency (i.e. 120 Hz in the United States) and its harmonics dominate all other possible characteristic frequencies. To remedy, we added a band-stop filter for 120 Hz and its harmonics and then take the inverse Fourier transform to yield new, time-series data. However, the resulting waveforms were identical; removing the 120 Hz signal and its harmonics removed the characteristic pattern of each waveform. We believe this is because light bulbs behave as transfer functions, such that the amplitude of the 120 Hz sinusoidal frequency—or *shape* of the waveform—is modulated. Thus, removing the 120 Hz frequency and its harmonics would remove the component that characterizes and displays the unique pattern of each waveform. We then tried to subtract a normalized sinusoidal waveform at 120 Hz from BRFs. This attempt did not work either because resulting BRFs are not perfectly periodic like a synthesized sinusoid; alignment with a BRF and a 120 Hz sinusoid is imperfect.

4.2.2 Feature Engineering with PCA. As signal processing techniques do not distinguish light bulbs given our BRF data, we next try a feature engineering approach. A typical approach to feature engineering uses a methodology called Principal Component Analysis (PCA) [16]. This is the dimensionality reduction of the number of samples, or dimensions. For our dataset, this reduced roughly 1600 dimensions into 10 features. However, our initial results from PCA were not promising. From dimensionality reduction, the resulting features could not accurately distinguish between different bulb types. While there is potential with a PCA-based approach, we instead find success with handpicked features.

4.2.3 Manual Feature Extraction. In lieu of autonomous feature extraction, we can use domain-specific knowledge to manually derive features that describe and characterize each BRF. To classify BRFs, we devise a small set of features that describe BRF waveforms via statistical analyses. We use these features for supervised learning to classify BRF bulb types. These features are:

- *Integral Average*: The integral of a single cycle divided by the length of the cycle.
- *Rising-Falling Ratio*: The quotient of the rising-edge sum divided by the number of samples in the rising edge, divided by the quotient of the falling-edge sum divided by the number of samples in the falling edge.
- *Angle of Inflection*: The angle measurement of the nadir.
- *Peak Location*: The relative position of the peak with respect to the length of the cycle.
- *Crest Factor*: The ratio of the peak value to the RMS value.
- *Kurtosis*: Measurement of the waveform's tail distribution.
- *Skew*: The deviation of the waveform's distribution with respect to the normal distribution.

Using a supervised learning approach, we found that these features perform well and use them for the analyses presented next. The only other feature that we experimented with was the linearity measurement of the rising or falling edge; we omit this feature due to imperfections in the measurement process.

4.2.4 Supervised Classification Approach. A primary contribution of this remaining work is to distinguish between energy-efficient and energy-inefficient light bulbs. From the data collected by Shah et al. in 2019, we perform some brief wattage statistics of the four primary light bulbs listed in Table 1. While this does not represent the real-world distribution of light bulbs, we use these statistics to

Table 1: Light bulb wattage statistics from the light bulb database by Shah et al. We can observe that halogen and incandescent bulbs generally consume more energy than CFL and LED bulbs.

	# Unique Bulbs	Mean	STD	Min	Max
Halogen	9	69.89	33.03	39	150
Incandescent	10	87.6	43.57	60	200
CFL	16	19.25	7.34	9	32
LED	36	10.65	4.15	4	23

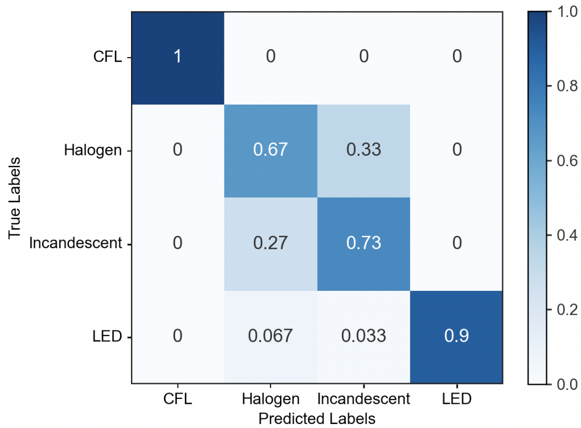


Figure 3: Confusion matrix of bulb-type detection for our kNN model on a held out test dataset. Color-bar and numbers inside the matrix denote prediction accuracy values.

bolster our distinction between energy-inefficient bulbs (i.e. halogen and incandescent) and energy-efficient bulbs (i.e. CFL and LED).

To distinguish between the energy efficiency of certain bulbs, we classify bulb type. To do so, we implement k-Nearest Neighbors (kNN) to detect a bulb's type using the features computed on a BRF as input. kNN is straightforward to implement and is robust to noise in the training data. An observation with N different features or variables is represented as a single data point in an N-dimensional space. The underlying assumption of kNN is that the observations near one another—in this N-dimensional space—have similar characteristics and hence similar outcomes or labels [17]. Since kNN leverages the "closeness" of observations, a new data point in the high-dimensional space is assigned the same label as its k closest neighbors [17]. Assuming that bulbs in the same class—CFL, halogen, incandescent, or LED—have similar characteristics, we train, validate, and test a kNN classifier to detect bulb type.

As described in Section 4.2.3, we compute the following six of the seven features for every BRF – *integral average, angle of inflection, peak location, crest factor, kurtosis* and *skew*. We use these six features as training variables and the corresponding bulb types as labels to train our kNN model. The database was split into train and test sets using a 90/10 split; 90% of our database is used for training, and 10% is held-out for testing. To ensure that the held-out test set represents the entire database, we make sure it contains at least one BRF per unique bulb in the database. Furthermore, we implement a 10-fold cross validation to tune our model's hyperparameter—k—to evaluate prediction errors [18]. In each fold, we randomly divide the train set into an 80/20 split; of the training data set (i.e. 90% of the entire database), 80% of the set is used for training the model and 20% is used for validation. We also use stratified sampling to ensure that, in each fold, the training and validation sets contain a similar data distribution for each bulb type so that the random splitting process did not introduce any bias [19]. For our kNN model, the training and validation accuracy tuple that corresponds to the most optimum hyperparameter—k=4—is (91%, 90.6%).

To test the generalizability of our model, we test it on the held-out test dataset. After retraining our model on the entire dataset with our k=4 hyperparameter, we find that kNN is able to detect the right bulb types with 89% overall accuracy. Furthermore, we analyze the performance of our kNN model on individual bulb types in the held-out dataset. These results are shown in Figure 3. At the bulb-type level, kNN shows prediction accuracy of approximately 90% for LEDs and 100% CFLs. On the other hand, we see a significant difference in performance of our kNN model in predicting halogen and incandescent classes. kNN is able to correctly predict halogen and incandescent bulbs 67% and 73% of the time, respectively. This can be attributed to the observation that halogen and incandescent BRF waveforms are very similar, while the waveforms of CFLs and LEDs are notably more distinct, as shown in Figure 1.

However, while we notice poorer type classification for incandescent and halogen bulbs, we observe that we have achieved our initial goal. In Figure 3, we can see that if we sum up the rows of the true labels for halogen and incandescent bulbs, we achieve an accuracy of 100%. While individual bulb-type classification remains a challenge for halogen and incandescent types, the classification of halogen and incandescent bulbs as "energy inefficient" bulbs is effective. From these results on our supervised learning implementation, we believe we have a good capability to distinguish between energy efficient and energy inefficient bulbs.

4.3 Novelty Detection

We now consider how to bring our methodology into the real world. For EffiSenseSee to accurately inventory bulbs in the built environment, it must avoid double-counting, asses whether it has extant information of that BRF, and continuously build and updates its database of previously encountered bulbs. As the camera moves through space, it is likely to capture the same bulb multiple times. When EffiSenseSee encounters a bulb for a second time, it would report this as a known bulb, rather than over-counting actual bulbs. Location data (for a non-stationary camera) is not sufficiently precise to distinguish bulbs. Novelty provides an additional dimension. We must build a database of seen bulbs, as well as a capability to identify whether a BRF recorded in the real world is new or extant.

Novelty detection refers to techniques used for identifying observations that are "novel" compared to the main data distribution. Researchers have used novelty detection for multiple purposes, such as personal risk detection using wearable sensors [20], miRNA detection [21], time-series anomaly detection [22], outlier detection in time-series power systems data [23], outlier identification events in power distribution networks [24], novel phase-identification in large X-ray diffraction datasets [25], and structural damage localization through detection of abnormal data points in structural health data [26]. This novelty detection problem belongs to a sub-category of unsupervised outlier detection called one-class classification, where the goal is to identify whether the new observation belongs to the main class or not. A one-class classifier learns the distribution of the training dataset and then labels a new observation as belonging to the distribution or not just like a binary classifier [27].

4.3.1 Single Stage Sum. First, we implement a One-class Support Vector Machine (SVM) algorithm, which is a modification of the supervised binary-classification algorithm and is one of the most popular algorithms for one-class classification problems [28]. One-class SVM learns the distribution of the training set and then labels the test set data points as (1) inliers if they belong to the distribution or (2) outliers if they do not [28].

For novelty detection, we use a different approach to train, validate, and test the model. Test sets contain all the BRFs corresponding to one specific bulb, and the data related to that bulb is not used in the training and validation process at all. Training and validation sets each contain BRF data from the remaining 64 bulbs and are used to tune a single hyperparameter: sensitivity. We train, validate, and test the model 65 times by holding out data of one unique bulb in every iteration for testing, such that the model never gets trained on the held-out dataset.

Performance with this approach is mediocre – the model is only able to label 8 out of 65 bulbs as outliers correctly; the other 57 bulbs were labeled as inliers even though the trained model had never seen their data. Based on our domain knowledge, we suspect that the low performance is a result of BRFs—of different bulbs of the same type—being highly similar. This leads the model to label an unseen bulb's BRF as an inlier incorrectly.

4.3.2 Adding a Random Forests Stage. To address the highly similar nature of BRF signals, we develop a custom technique for one-class classification of time-series data. Our technique is a two-stage classification model, which uses a Random Forests model as stage 1 and then a similarity threshold-based classifier as stage 2. Stage 1 provides us with the three most probable bulbs corresponding to a newly encountered BRF. However, it is probable that the encountered BRF belongs to a bulb never seen before. So, the goal of stage 2 is to compare the newly-encountered BRF more closely with BRFs of the most similar bulbs, which then evaluates similarities and outputs whether the encountered BRF is an inlier or an outlier.

For the stage 2 classifier, we create a database of similarity metrics by computing a centroid BRF for every bulb. Then, we measure twelve different similarity metrics of all the raw BRFs of a bulb with respect to its centroid BRF. Each similarity metric tells us how similar a signal is to its centroid. We pick the twelve time-series similarity metrics discussed, reviewed, and evaluated by Mauceri et al. [29], which were: L1 (Manhattan) distance, L2 (Euclidean) distance, L inf (Chebyshev), dynamic time warping (DTW) [30], Wasserstein or earth mover's distance (WSD) [31], Kullback-Leibler divergence (KLD) [32], cosine similarity [33], edit distance on real sequences (EDR) [34], move split merge metric (MSM) [35], autocorrelation [36], Gaussian kernel-based similarity [37], and Sigmoid kernel-based similarity [28]. Once we measure the twelve similarity metrics per BRF per bulb, we extract the range of each metric for a given bulb (i.e., the minimum and maximum value of each metric for a given bulb). The underlying assumption here is that if a new BRF's similarity metrics fall within their respective ranges—with respect to centroid signal of any specific bulb—then the BRF is highly likely from the same bulb and is thus an inlier.

In practice, the utility of similarity metrics varies based on BRF shape. For each similarity metric, we process its min-max range from the three candidate bulbs. We then count the number of similarity metrics of the encountered BRF that falls within the acceptable ranges of similarity metrics from the three candidate bulbs. If that count value falls below a minimum threshold, then that BRF is then labeled as an outlier; a new is bulb encountered. If the count value is equal to or greater than the minimum threshold for at least one bulb, it means that the encountered BRF is highly similar and is then labeled as an inlier; an existing bulb is encountered.

5 IMPLEMENTATION

To test on oscilloscope-based BRFs, we use the data collected by Shah et al. [9]. For the camera-based collection, we use the IDS UI-3480LE-M-GL monochrome camera with the Fujinon HF9HA-1B 9mm f/1.4 lens. For details on extracting BRF data with a rolling shutter camera, we refer to the work done by Sheinin et al. [11].

All of our data is processed and analyzed via Python. Each BRF data—from the oscilloscope or camera—is recorded in the form of a CSV file, which we load in Python. To pre-process our data, we use the "scipy" library for the Savitsky-Golay filter. We implement our own moving average filter. We then normalize each BRF and also truncate the data to contain two full cycles, beginning and ending at nadirs. We write and compute our own features outlined in Section 4.2.3. We use the resulting computed features with their associated labels for training, validating, and testing our kNN model. We use the "sklearn" library to run k-fold cross validation and create our model with kNN on Shah et al.'s BRF database.

We also note that we make a couple changes to the model described in Section 4.2.4. We first supersede the "Angle of Inflection" feature—discussed in Section 4.2.3—with the "Rising-Falling Ratio" feature. We make this change because it is easier to compute for both oscilloscope-based and camera-based BRF data, which facilitates better comparison. We also use unprocessed BRFs for all features except "Rising-Falling Ratio" to train this new model. Our method of smoothing BRFs slightly distorts the waveform, and we find that we are able to train our new model with unprocessed, oscilloscope BRFs with the exception of "Rising-Falling Ratio," which requires knowledge of the peak location to determine the rising and falling edges. Lastly, our evaluation model is trained on all the oscilloscope-collected BRFs. As we now have camera-collected BRFs as test data, we use this new data as our test set for evaluation.

All artifacts are available on Github at *https://github.com/alwyen/LightsCameraGrid*.

6 EVALUATION

As quality BRF capture is fundamental, we first evaluate the performance of EffiSenseSee's camera-based data collection. After establishing that the BRFs are of sufficient quality, we then consider the performance of the end-to-end system in both indoor and outdoor contexts. While this work focuses on the detection of inefficient bulbs, we also report EffiSenseSee's accuracy in the more specialized type-classification task. Most confusion is between halogen and incandescent bulbs; CFLs and LEDs are better separated. This

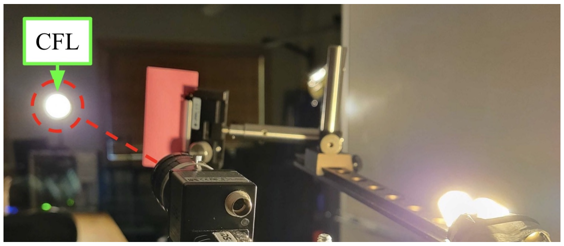


Figure 4: Example indoor setup of imaging a CFL bulb.

suggests that in addition to detecting inefficient bulbs, EffiSenseSee could estimate the penetration rate of replacement technologies.

We then evaluate the performance of our novelty detection methodology to distinguish between previously seen bulbs versus novel, newly encountered bulbs. When classifying bulbs, we ideally only want to count them as efficient or inefficient once in the real world. We find that this becomes more difficult when BRFs have very similar shapes.

6.1 Methodology: ACam-Based BRF Collection

The first question is whether comparatively noisy camera-collected BRFs can be classified by a network trained on oscilloscope-collected data. We use the "ACam" camera with the rolling shutter technique from Sheinin et al.—as described in Section 4.1.2—to collect BRFs.

We begin with indoor data collection. We use the ACam to collect traces of a single halogen, incandescent, CFL, and LED light bulb. Later, we will collect data on a second CFL bulb in our outdoor testing to support our observation that CFL bulb types can be generally classified with EffiSenseSee.

We image each light bulb directly and extract BRFs from selected pixels surrounding the light through a live-capture video stream. The ACam is calibrated to record at a certain fps depending on the grid frequency. This is about 58 fps in our work, which is a small offset from the nominal AC frequency. This allows ACam to act effectively as a sampling mixer, where a different point on the 60 Hz wave is captured every frame. Post-processing then collects pixel intensity over time and reconstructs a normalized BRF for analysis.

It is important to select pixels 'near' the bulb to recover a clean BRF. Using a pixel too close to the brightest area at the center of the bulb will result in clipping, while a pixel too far away will not have sufficient variation in illuminance to extract a BRF. As we are primarily interested in classification, we manually select pixels to extract BRFs via qualitative analysis of our prior BRF knowledge; we leave automation of this task to future work.

For our indoor testing, we collect between 30-40 waveforms for each bulb type; for our outdoor testing, we collect roughly 80 waveforms for each bulb type. For each waveform, we then extract the features discussed and outlined in Section 4.2.3 and Section 5 and perform kNN classification on the resulting extracted features. We also experiment with both close (i.e. 3 m) and far (i.e. 30 m) distances for data collection. While near-captured BRFs are slightly more consistent than far-captured BRFs for data collection, there is no noticeable degradation in the quality of data that we collect with respect to distance. An example of our indoor setup is shown in Figure 4, and an example of our outdoor setup is shown in Figure 5.

Table 2: Accuracy results of indoor classification for different types of bulbs. The bulb type is bolded in the "Bulb Label" column.

Bulb Label	# Waveforms	Binary Accuracy	Type Accuracy
Phillips **Halogen** 39W	37	100%	16.2%
GE **Incandescent** 40W	30	100%	40%
Sylvania **CFL** 13W	40	100%	95%
Westinghouse **LED** 9W	30	100%	100%

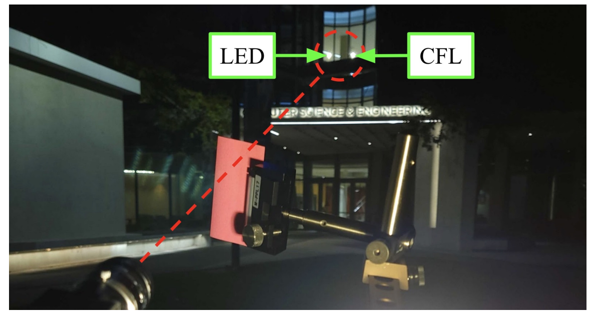


Figure 5: Outdoor setup. The dotted red annotation indicates the light bulbs of interest from the camera's point of view. The LED and CFL bulbs in the image are more than 30 m away from the camera.

6.2 Indoor Results

Results on type-accuracy and binary-accuracy are shown in Table 2. We use "Binary Accuracy" to refer to the binary classification accuracy on energy efficiency (i.e. incandescent and halogen as *inefficient* and CFL and LED as *efficient*) and "Type Accuracy" to refer to the accuracy of bulb-type classification.

We observe that halogen and incandescent bulbs perform well in binary classification but exhibit higher type-classification error. This suggests they are often identified as each other, an observation we explore further in Section 7. Our initial results show that while individual type-classification is still difficult for certain bulb types, we are able to distinguish between energy efficient and energy inefficient light bulbs in an indoor setting.

The type-accuracy for CFL and LED bulbs is higher due to the more unique shapes that their waveforms exhibit. CFL bulbs particularly have a characteristic waveform to CFLs only, making them easier to classify compared to halogen, incandescent, and LED bulbs. On the other hand, LED BRFs can be too unique. This can make it hard to classify new LEDs as their BRFs are not similar to any of the training data. At the same time, these highly unique BRFs present an opportunity to uniquely identify bulbs.

Overall, the transition from analyzing oscilloscope-based data to camera-based data does not pose a significant difference in the quality of our classifier. We thus proceed to data collection and analysis in an outdoor setting to evaluate the performance of our technology in the real world.

6.3 Outdoor Results

We now move from indoor testing with the ACam to outdoor testing and experimentation. We attempt to add variability to our data collection by collecting data over multiple days at different views. We collect BRF data of halogen, incandescent, CFL, and LED bulb

Table 3: Accuracy results of outdoor classification for different types of bulbs.

Bulb Label	# Waveforms	Binary Accuracy	Type Accuracy
Phillips **Halogen** 39W	83	89.1%	13.2%
GE **Incandescent** 40W	80	83.7%	58.7%
Sylvania **CFL** 13W	80	100%	97.5%
Halco **CFL** 13W	80	98.7%	97.5%
Westinghouse **LED** 9W	80	100%	75%

types with the ACam. Specifically, we image light bulbs inside a building as shown in Figure 5.

We show our results in Table 3. We first note that CFL bulbs continue to perform particularly well. In our indoor testing, we test only with the "Sylvania CFL 13W" bulb. For our outdoor testing, we test with a new bulb—"Halco CFL 13W"—to show that the high accuracy for CFL binary- and type-classification is not the result of a specific bulb. We also observe that while the type-accuracy for LEDs is lower from indoor versus outdoor classification, its binary-accuracy is still high.

The outdoor accuracy results for halogen and incandescent bulbs are generally worse compared to the indoor accuracy results. Our primary efficiency classification task continues to perform well, yielding almost 90% accuracy for halogen buls. The halogen bulb-type classification particularly suffers with only 13% accuracy. Many of the waveforms are misclassified as incandescent bulbs. In comparison, incandescent bulbs yield close to 80% accuracy for binary-classification and 60% accuracy for type-classification.

6.4 Evaluation of Novelty Detection

We run two sets of experiments to evaluate this method: assessment of the model performance to detect a new bulb (outlier) and assessment of the model's performance to detect a native bulb (inlier). Results of these experiments are shown in Figure 6 and Figure 7. In both the experiments, we evaluate the performance of our classification pipeline at different thresholds (i.e., the minimum number of similarity metrics required to classify a bulb as an outlier or not).

In the first experiment, the stage 1 model is trained on data from all of the bulbs except for one held-out bulb, and then stage 2 is used to classify whether the held-out bulb is an outlier or not. Prediction is considered correct only if the bulb is labeled as an outlier. For a given threshold value, the entire model is run 65 times with every iteration using a different held-out bulb.

In the second experiment, stage 1 is trained on data from raw BRFs of all the 65 bulbs except for one held-out BRF, and stage 2 is made to predict whether the held-out BRF belongs to an existing bulb or not. In this case, a prediction is marked correct only if the bulb is labeled as an inlier. The second experiment is run 65 times for each threshold value with every iteration using a randomly selected BRF of a different bulb.

Figure 6 shows the overall performance of novelty detection. We can see that as the threshold value increases, the model's accuracy of identifying outliers increases, and its performance of identifying inliers decreases. A threshold value of 11 gives the best results with 85% and 71% accuracy in distinguishing a new bulb versus an existing bulb, respectively. We choose higher accuracy for detecting a new bulb because it is more important to identify an unseen bulb

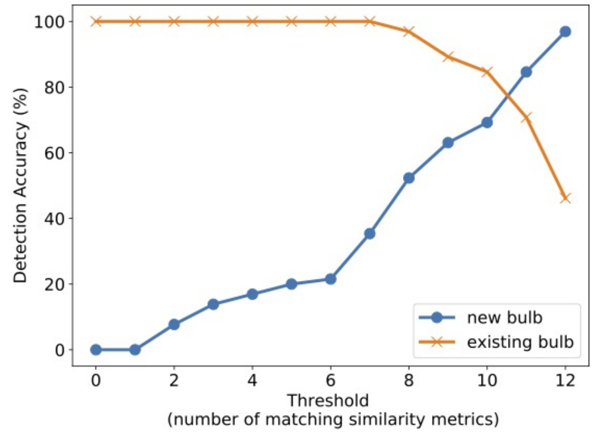


Figure 6: Accuracy of novelty detection based on threshold. This figure shows the changes in accuracy of the novelty detection model in detecting an outlier (new) bulb and a native (existing) bulb as the minimum number of matching similarity metrics (i.e. threshold) increases.

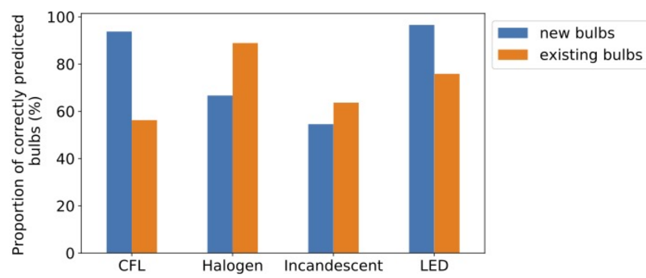


Figure 7: Performance of novelty detection model by bulb type. For CFL and LED bulbs, the novelty detection model performs better in terms of detecting outlier bulbs compared to native bulbs. In the case of halogen and incandescent bulbs, the model is better able to detect native bulbs versus outlier bulbs.

than an already seen bulb; it is worse to miss collecting new data and falsely mislabel BRFs our model has never seen before.

7 DISCUSSION

In this section, we briefly discuss other options for bulb-type classification. We then discuss the challenges with outdoor BRF data collection and analysis with the ACam. Lastly, we discuss the challenges of novelty detection with our oscilloscope-based data and provide future directions for this work.

7.1 Improving Classification

Our work with indoor and outdoor BRF analysis is done solely through the k-Nearest Neighbor supervised learning algorithm. We experiment with another supervised learning algorithm—Random Forests (RF)—to see how that compares to kNN. We use the same approach outlined in Section 4.2.4 to train and test our RF model. The hyperparameters for this new model are the number of estimators (i.e. trees) and the maximum depth of a tree. We show the

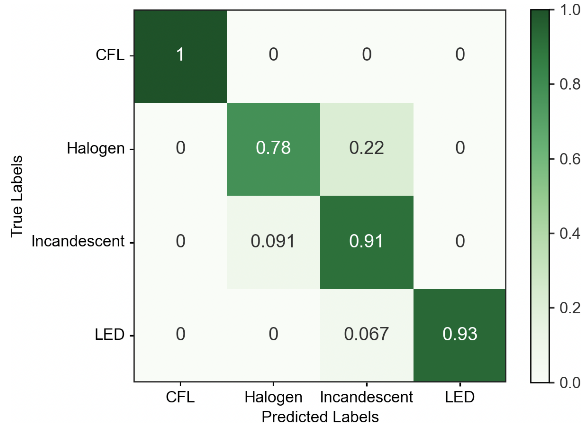


Figure 8: Confusion matrix for bulb-type detection with Random Forests on a held out test dataset. Overall accuracy is slightly better (92% versus 89%) than the kNN model.

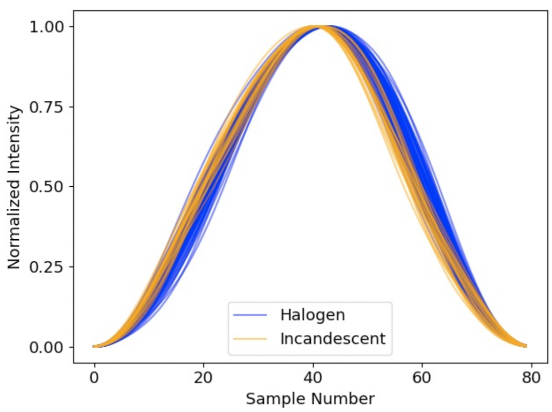


Figure 9: Visual similarity between halogen and incandescent BRFs from the ACam. In this example, the labeled halogen BRFs were misclassified as incandescent BRFs and vice versa.

resulting performance of RF in Figure 8 and find that RF performs slightly better than kNN with an overall accuracy of 92% compared to kNN's 89%. We note that further exploration of other supervised learning algorithms might induce better accuracy performance.

For classifying bulb types, our kNN and RF models work well for CFL and LED bulbs but perform worse with halogen and incandescent bulbs. Our hand-picked features are currently unweighted. Carefully weighted features might better distinguish incandescent from halogen bulbs. Of course, our feature set is not exhaustive either, and the creation and use of additional features could help distinguish between halogen and incandescent bulbs too.

7.2 Challenges with Similar Bulb Types

Our approach to classify inefficient bulbs types works, though there are still many challenges to solve. Energy-inefficient classification stems from bulb-type classification, and we find that halogen, incandescent, and some LED bulbs behave very similarly. This is first shown in Figure 3 and reaffirmed in Figure 8, in which we see that

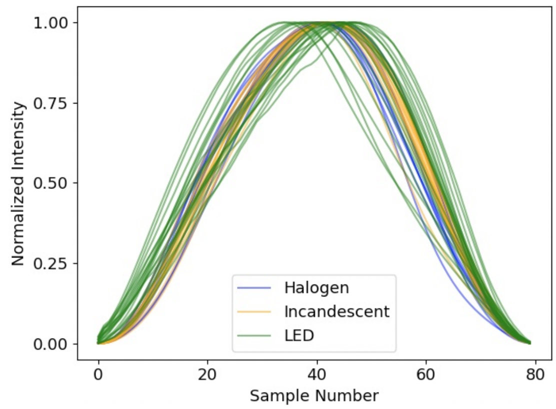


Figure 10: Visual similarity between halogen, incandescent, and LED BRFs. The halogen and incandescent BRFs shown in this figure were collected from the ACam and were mislabelled as LEDs. Each LED BRF is from a unique bulb in Shah et al.'s database and are smoothed and downsampled for visual display.

halogen, incandescent, and LEDs are commonly confused with each other. As shown in Figure 9, halogen and incandescent BRFs look very similar and are hard to distinguish even to the human eye; this can also be seen by the example BRFs of incandescent and halogen bulbs in Figure 1. In Figure 10, this issue is extended to similarity between halogen, incandescent, and LED bulbs.

7.3 Camera-based Collection Challenges

There are some limitations with the current camera technology and setup. The first is that BRF data collection with the ACam is still highly manual. In practice, this limits the number of BRF waveforms that can be collected with the ACam. Recall, we cannot simply select the brightest pixels of an imaged bulb due to oversaturation. This is the reason why we record BRFs from neighboring pixels surrounding the light. While there are computer vision techniques (i.e blob detection) that can help us automate this process, choosing the right pixel at blob edges is a harder engineering problem. We also mention that there are various real-world situations for data collection that we have not yet considered, such as imaging lights with lampshades or imaging multiple lights stacked behind one another. While we believe that the ACam will function in a variety of different scenarios, we have yet to explore many of the situations situations that we might encounter data collection at scale.

In addition, because BRFs are recovered from many frames, they are highly sensitive to small vibrations. In an outdoor setting, there are a few environmental factors (i.e. wind) that can shake the camera enough to disrupt BRF capture. Eventually, we envision EffiSenseSee operating on mobile platforms, which will require pixel-tracking to recover BRFs from bulbs moving through the scene.

7.4 Metadata to Augment Novelty Detection

Our novelty detection methodology is not consistent across bulb types and particularly struggles with halogen and incandescent BRFs. It performs better, however, as the database of prevously seens bulbs gets smaller. We plan to incorporate additional *in situ* metadata to assist with the novelty detection task (e.g. using GPS data to only include bulbs within 20 m).

7.5 Future System Discussion

In Section 1, we posed two questions: where are the inefficient bulbs that remain, and how much are they actually used? EffiSenseSee brings us one step closer to answer the first question; the second question still remains unanswered. To target this second question, we discuss a variety of future trajectories. We briefly mentioned mobile platforms; this allows us to observe and record a larger variety of bulbs that a static platform would offer. However, a mobile solution inherently eschews longitudinal measure.

We then consider stationary deployment. While this enables long, temporal readings, it is impossible to observe the majority of lights in comparison to a mobile deployment. However, stationary deployment is currently the best solution to on-time measurement. Perhaps hybrid stationary-mobile deployment will be adequate, though this vision is unclear. In either deployment scenario, we imagine scaling up with (1) multiple camera modules roaming through an area via person or vehicle or (2) multiple camera modules statically viewing an area over many vantage points.

There are also privacy concerns from imaging various places and landmarks. Fortunately, the ACam uses very short exposure and is naturally privacy-preserving; only point sources of light are visible [11]. This holds true video-based data acquisition, in which the low exposure prevents identification of nearby surroundings. As such, we believe that there should be few privacy concerns; information obtained other than the lights themselves are obscured.

8 CONCLUSION

We present EffiSenseSee, which provides a methodology to automatically identify inefficient light bulbs in the built environment through predictive labeling with supervised learning. We further show how to autonomously classify bulbs as halogen, incandescent, CFL, or LED. We find that classifying CFL and LED bulb types are easier due to their characteristic light behavior; classifying and distinguishing between halogen and incandescent bulb types remains a challenge because of their highly similar light responses. While imperfect in an outdoor setting, we show the ability to classify energy-efficient (i.e. CFL, LED) and energy-inefficient (i.e. halogen, incandescent) light bulbs; this is achieved with camera-collected data of light bulbs and the supervised learning algorithm, k-Nearest Neighbor. Our work provides one step towards cataloging light bulbs in the real world with camera-based sensing.

ACKNOWLEDGEMENTS

This material is based upon work supported by the National Science Foundation Graduate Research Fellowship Program under Grant No. DGE-2038238. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation. This work was also supported in part of the Rockefeller Foundation 2018 POW 004. We thank the reviewers and our anonymous shepherd for their time and thoughtful feedback. We particularly thank Mark Sheinin for support with the ACam technology as this new work would not be possible without it.

REFERENCES

[1] Annual energy outlook 2022. Technical report, U.S. Energy Information Administration (EIA), 2022.
[2] D&R International, Ltd. Building energy data book. Technical report, U.S. Department of Energy, 2011.
[3] Commercial building stock assessment 4 (2019) final report. Technical report, Northwest Energy Efficiency Alliance, May 2020.
[4] NMR Group, Inc. Ma19r15-e 2019 residential lighting on-sites (massachusetts residential lighting on-site study). Technical report, December 2020.
[5] Residential stock building assessment (rbsa) ii combined database. Technical report, Northwest Energy Efficiency Alliance, 2017.
[6] Amanda Gonzalez, et al. What we know and don't know about embodied energy and greenhouse gases for electronics, appliances, and light bulbs. In *ACEEE Summer Study on Energy Efficiency in Buildings*, 2012.
[7] Scott Dimetrosky, et al. Chapter 21: Residential lighting evaluation protocol. Technical report, National Renewable Energy Laboratory (NREL), 2015.
[8] Mark Sheinin, et al. Computational imaging on the electric grid. In *CVPR*, 2017.
[9] Zeal Shah, et al. GridInSight: Monitoring electricity using visible lights. In *BuildSys*, 2019.
[10] Carolyn Hronis. Table hc5.1 lighting in u.s. homes, by housing unit type, 2020. https://www.eia.gov/consumption/residential/data/2020/hc/pdf/HC%205.1.pdf.
[11] Mark Sheinin et al. Rolling shutter imaging on the electric grid. In *ICCP*, 2018.
[12] Ye-Sheng Kuo, et al. Luxapose: Indoor positioning with mobile phones and visible light. MobiCom '14, 2014.
[13] Shilin Zhu and Xinyu Zhang. Enabling high-precision visible light localization in today's buildings. MobiSys '17.
[14] Chi Zhang and Xinyu Zhang. Litell: Robust indoor localization using unmodified light fixtures. MobiCom '16.
[15] Lucas Zanco Ladeira, et al. Spectrometry for light bulb classification. In *2021 55th Annual Conference on Information Sciences and Systems (CISS)*, 2021.
[16] Fengxi Song, et al. Feature selection using principal component analysis. In *ICSEM*, volume 1, 2010.
[17] Prakash Nadkarni. Chapter 10 - core technologies: Data mining and "big data". In Prakash Nadkarni, editor, *Clinical Research Computing*. 2016.
[18] Jerome Friedman, et al. *The elements of statistical learning*, volume 1. 2001.
[19] Yunming Ye, et al. Stratified sampling for feature subspace selection in random forests for high dimensional data. *Pattern Recognition*, 46(3), 2013.
[20] Luis A. Trejo et al. Towards an efficient one-class classifier for mobile devices and wearable sensors on the context of personal risk detection. *Sensors*, 18(9), 2018.
[21] Malik Yousef, et al. Feature selection has a large impact on one-class classification accuracy for micrornas in plants. *Advances in Bioinformatics*, 2016, 2016.
[22] J. Ma and S. Perkins. Time-series novelty detection using one-class support vector machines. In *IJCNN*, volume 3, 2003.
[23] Yuxun Zhou, et al. Non-parametric outliers detection in multiple time series a case study: Power grid data analysis. In *AAAI*, 2018.
[24] Yuxun Zhou, et al. Nonparametric event detection in multiple time series for power distribution networks. *IEEE TIE*, 66(2), 2019.
[25] L. Banko, et al. Deep learning for visualization and novelty detection in large x-ray diffraction datasets. *npj Comput Mater 7*, 2021.
[26] Young-Jin Cha and Zilong Wang. Unsupervised novelty detection–based structural damage localization using a density peaks-based fast clustering algorithm. *Structural Health Monitoring*, 17(2), 2018.
[27] Paolo Oliveri. Class-modelling in food analytical chemistry: Development, sampling, optimisation and validation issues – a tutorial. *Analytica Chimica Acta*, 2017.
[28] Bernhard Schölkopf, et al. Estimating the support of a high-dimensional distribution. *Neural Comput.*, 13(7), July 2001.
[29] Stefano Mauceri, et al. Dissimilarity-based representations for one-class classification on time series. *Pattern Recognition*, 100, 2020.
[30] Meinard Müller. Dynamic time warping. *Information retrieval for music and motion*, 2007.
[31] Michael Muskulus et al. Wasserstein distances in the analysis of time series and dynamical systems. *Physica D: Nonlinear Phenomena*, 240(1), 2011.
[32] Yoshihide Kakizawa, et al. Discrimination and clustering for multivariate time series. *Journal of the American Statistical Association*, 93(441), 1998.
[33] Yonggui Dong, et al. A cosine similarity-based negative selection algorithm for time series novelty detection. *Mechanical Systems and Signal Processing*, 2006.
[34] Lei Chen, et al. Robust and fast similarity search for moving object trajectories. In *SIGMOD*, 2005.
[35] Alexandra Stefan, et al. Move-split-merge metric for time series. *TKDE*, 2012.
[36] Pedro Galeano and Daniel Peña. Multivariate analysis in vector time series. 2001.
[37] Bernhard Schölkopf, et al. Support vector method for novelty detection. In *NIPS*, volume 12, 1999.