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Passive Localization through Light Flicker Fingerprinting

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***Abstract*—In this paper, we show that the flicker waveforms of various CFL and LED lamp models exhibit distinctive waveform patterns due to harmonic distortions of rectifiers and voltage regulators, the key components of modern lamp drivers. We then propose a passive localization technique based on fingerprinting these distortions that occur naturally in indoor environments and thus requires no infrastructure or additional equipment. The novel technique uses principal component analysis (PCA) to extract the most important signal features from the flicker frequency spectra followed by kNN clustering and neural network classifiers to identify a light source based on its flicker signature. The evaluation on 39 flicker patterns collected from 8 residential locations demonstrates that the technique can identify a location within a house with up to 90% accuracy and identify an individual house from a set of houses with an average accuracy of 86.3%.**

***Index Terms*—IoT, localization, machine learning algorithms, wireless sensor network, VLC**

I. INTRODUCTION

The area of indoor localization is well researched with numerous techniques based on WiFi [1], UWB [2], RFID [3], chirp spread spectrum modulation [4] and visible light communication [5]. Most prior work requires instrumenting an environment with reference nodes, which are used by mobile nodes to compute their location through proximity, triangulation, trilateration or RSSI signatures. More recently, infrastructure-less indoor localization made it possible to detect object location by analysing wireless signal strength fluctuations from ambient wireless signals such as WiFi, TV or Radio transmission signal [1]. The technique however relies on the presence of ambient WiFi access points or nearby radio signal emitters, which are not always available in certain environments.

It is well known that indoor LED and compact fluorescent light sources exhibit flicker, which has been mostly seen as nuisance due to interference on visible light communication, video recording [6], detrimental impact on productivity [7] and health concerns [8] [6]. The flicker has been studied mainly within the context of light quality improvement [9] or ergonomics with numerous works on flicker characterisation [10] or minimising distortions [11]. However, investigating this phenomenon in the context of indoor localization has received little attention.

In this paper we measure the flicker profiles from several commercially available LED and fluorescent light sources and show that the flicker waveforms depend on light source type and a bulb model. Compared to traditional incandescent lights, where flicker is caused primarily by 50 Hz/60 Hz AC mains voltage, the flicker in LED and fluorescent sources has a different nature. Both LED and fluorescent sources operate on DC voltage and therefore require a rectifier and voltage regulators, which being a non-linear devices introduces harmonics and distortions into a power signal, resulting in a non-sinusoidal waveform with a distinct shape. This shape depends upon the electrical driver design and its electronic component combination, which may be different for each light bulb type and a bulb model.

Based on this observation we propose a passive localization technique based on fingerprinting artefacts present in the flicker waveform from distinct light sources in indoor environments. Compared to existing techniques, it can work passively without retrofitting the environment with additional equipment such as LED drivers, UWB [2], Bluetooth, Zigbee, RFID [12] or ultrasonic devices [12]. The main goal of the paper is to investigate the feasibility of the concept and report on the performance of the proposed technique. The paper makes the following novel contributions:

- We measure the flicker waveform profiles of commercially available LED and compact fluorescent bulbs and demonstrate that light sources may exhibit distinct flicker characteristics in the frequency and temporal domains.
- We propose a novel passive localization technique based on flicker waveform fingerprinting and experimentally evaluate its performance using real flicker measurement data obtained from multiple residential homes.

The proposed technique first uses principal component analysis [13] to extract the essential features from the light flicker frequency spectrum. The location is then inferred using kNN clustering and an artificial neural network classification methods. Based on extensive measurements and experiments, we show that the proposed technique provides a location accuracy of up to 90% within an indoor environment. The proposed approach does not require any specialised equipment apart from a high-frequency light sensor, which is a tiny low-cost component that can be connected directly to a sensor node or potentially a mobile phone without requiring any additional components.

The rest of the paper is structured as follows: Section II describes the operation of LED and CFL light sources. Section III describes the proposed classification approach. Section IV describes the measurement setup including hardware configuration. Section VI reviews related work on indoor localization, and finally Section VII concludes the paper.

II. LED and Fluorescent Light Operation

Flicker is an intrinsic problem of the light source and associated electronic components such as drivers or ballasts and can be categorised into visible flicker caused by an alternating 50/60 Hz current and a stroboscopic flicker caused by inherent characteristic of power supply. As shown in Fig. 1, the flicker waveform may have non-sinusoidal form characterised by a maximum, minimum and average value within a single cycle. Although the light sources also exhibit chromatic flickering associated with changing color spectrum [10], this study focuses on visible and stroboscope flickering. The amount of flickering is characterised by percent flicker and flicker index parameters as defined below [10] :

$$Percent\,flicker = 100\%\frac{A-B}{A+B} \tag{1}$$

$$Flicker\,index = 100\%\frac{Area_1}{Area_1+Area_2} \tag{2}$$

Where A, B, $Area_1$ and $Area_2$ are defined in Fig. 1. Many LED bulb manufacturers specify the percent flicker to be less than 30% in the 100-120 Hz frequency range [10]. CFL lamps with magnetic ballasts have relatively high flicker of 37-70% while CFL bulbs with electronic ballast have a flicker of 5%.

In the following subsections we briefly describe the principle of operation of LED, compact fluorescent and incandescent lamps to understand the reason behind the flicker.

A. LED lights

Light-emitting diodes are currently the most energy efficient form of illumination and are steadily gaining adoption in both business and residential spaces. LED light sources operate on DC current with typical operating voltage of 3-3.6 V and produce flicker largely caused by alternating current and inherent properties of power supply. As LED output reacts instantly on changing LED current, their flicker is more noticeable compared to other light sources such as CFL or incandescent lamps.

To understand the reason behind 100 Hz/120 Hz flicker it is helpful to understand the design of a typical LED driver shown in Fig. 2. [14] [15]. Basic offline switching rectifiers comprise a diode bridge, which produces half-waves at double the AC frequency and a buck converter to step down the voltage for an LED lamp. The diode rectifier being inherently a non-linear device, introduces new harmonics, distortions and temporal artefacts to the pure sine waveform. This distortion

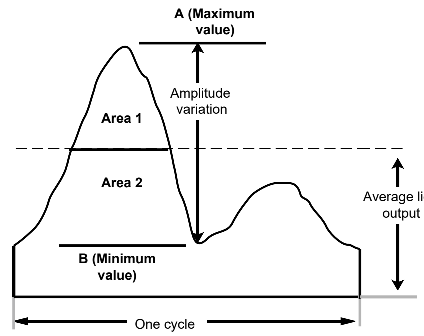

Fig. 1. Flicker waveform may have a non-sinusoidal shape characterised by a minimum, maximum and average values within a single cycle [16].

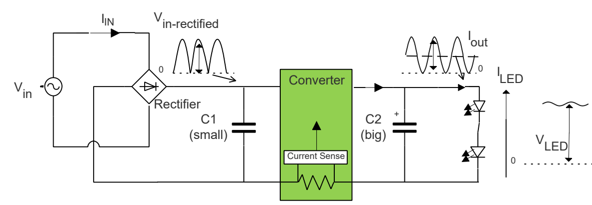

Fig. 2. Basic LED driver contains a rectifier and switching voltage regulator which introduce harmonics and distortions.

is specific to the diode characteristics such as forward voltage and resistance and may differ depending on LED model. In addition, the non-linearity is introduced by duty cycling to control brightness or temperature. The ripple and distortion can be reduced by using capacitors before and after the buck converter, however in practice, they do not eliminate the ripple completely.

B. Compact fluorescent lights

Compact Fluorescent Lights (CFL) rely on fluorescence to produce visible light and consist of a glass tube filled with mercury vapour, which emits ultraviolet light when excited by electric field and causes a phosphor coating to glow. Fluorescent lights are negative differential resistance devices, which means that the more current flows through the device the lower the resistance becomes, which would cause the lamps to destruct if connected to constant voltage source [17]. Therefore, the CFL lights require a ballast to stabilise the current.

The simplest ballast represents a coil in series with the lamp, called a magnetic ballast, introduces flicker at twice the supply frequency. Compact fluorescent lamps use more complex electronic ballasts, which contain a rectifier and a switching voltage regulator and supply current to the lamp at high frequency. This significantly reduces the visible flicker, however, as our experiments show can still be noticeable using high-frequency sampling.

C. Incandescent lamps

Incandescent lamps produce light by heating a wire filament in a bulb filled with inert gas or vacuum and have an efficiency of less than 5% with flickering produced mostly by supply current frequency. Although a new generation of incandescent lamps can theoretically reach up to 40% efficiency, they are mostly limited to lab prototypes [18]. Due to relatively low efficiency, the incandescent bulbs are being phased out or completely banned in some countries. The UK government for example, planned to phase out incandescent bulbs by 2011 The halogen light bulbs, which share the same principle of operation, are planned to be phased out in EU from 2018 [19]. We therefore do not consider incandescent lights in this study.

III. Location inference

The proposed localization technique consists of signal filtering, segmentation, feature extraction, dimensionality reduction and classification steps as illustrated in a high-level block diagram on Figure 3. The details of each step are described in the subsections below.

A. Signal Model

We assume that a light flicker is a periodic signal, which we denote

$$x_n = \overline{x} + \frac{1}{N}\sum_{k=1}^{N-1} X_k cos(\frac{2\pi kn}{N} - \phi_k) + \varepsilon \tag{3}$$

Where $\overline{x}$ is a mean value, ϕ_k is phase offset of kth frequency component and ε is i.i.d. zero-mean Gaussian noise. In the presence of non-linear distortions created by lamp rectifier, we assume that each lamp model may have a distinct set of frequency components X_k.

B. Filtering, Segmentation and Normalization

Since mean value $\overline{x}$ mostly depends on ambient brightness, distance, location and orientation of a light sensor relative to the lamp, it does not hold information about the light source itself. To remove this DC component we use a 5^{th} order Butterworth high-pass filter with a pass-band frequency of 10 Hz. The filtered signal was then partitioned into N = 2048[1] sample segments and then normalized to 0..1 range:

$$\hat{x_i} = \frac{x_i - min(x)}{max(x) - min(x)} \tag{4}$$

C. Feature Extraction

The goal of feature extraction is to extract frequency component of a flicker signal, which is accomplished using a discrete Fourier transform.

$$X_k = \sum_{n=0}^{N-1} \hat{x_n} e^{-\frac{i2\pi}{N}kn} \tag{5}$$

A vector of signal amplitudes $|X_k|$ was used as a feature vector. Since Fourier transform results in a large number of possibly correlated variables, a PCA is used to extract the most important frequency components as described below.

[1]Our experiments show that increasing the segment size further does not improve the localization performance.

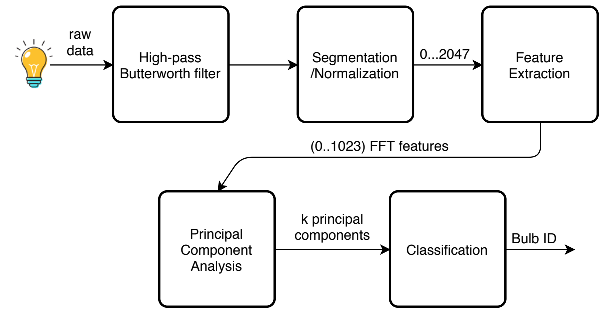

Fig. 3. High-level overview of an approach

D. Principal component analysis

Principal component analysis (PCA) is a statistical technique to reduce data dimensionality by transforming a large number of correlated variables (in our case Fourier coefficients) into a smaller number of principal components, which are linear combinations of original variables. Mathematically, PCA linearly transforms a raw data matrix X of dimension $m \times n$ into matrix Y of dimension $m \times n$ [13]:

$$Y = PX \tag{6}$$

Where n is the number of samples and m is the number of variables in each sample, in our case the number of Fourier coefficients. P is a transformation matrix of dimension $m \times m$ containing eigenvectors of covariance matrix XX^T with rows in order of importance. Y is a transformed $m \times n$ matrix which minimises cross-correlation between its variables. The first $k < m$ rows of matrix Y present compressed features, which are linear combinations of original variables. The reduced dimensionality of a feature vector can make a classifier more stable and robust.

E. Classification

The signal features are fed into either a kNN or neural network classifier to identify a light source. The performance of three classification approaches has been compared:

- kNN: k-nearest neighbour clustering algorithm (k = 15) on raw high-dimensional data.
- PCA-kNN: Feature extraction using principal component analysis and classification using kNN (k = 15).
- PCA-NN: Feature extraction using principal component analysis and classification using neural network. The neural network contained a single layer with (70) neurons for normal and noisy datasets, and two layers with (200, 200) for a full set data.

IV. Measurements

This section describes a hardware setup, resulting datasets and preliminary analysis of the measured data. The purpose of the measurements was to analyse the light flicker fingerprints of 52 LED and CFL light sources.

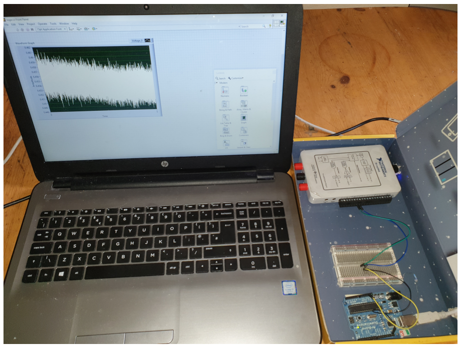

Fig. 4. Hardware setup. Flicker has been measured using Taos TSL257-LF high frequency light sensor and National Instruments MyDAQ data acquisition kit

A. Hardware setup

The light flicker has been measured using Taos TSL257-LF high sensitivity low-noise light-to-voltage optical convertor [20], which contains a photodiode and an amplifier on a single integrated circuit. The light sensor has an output voltage in 0..5 V range directly proportional to light intensity (irradiance) and a latency of less than 100 ns, which makes it suitable for high-frequency sampling and detecting the flicker that would not be noticeable to human eye. The sensor does not require any additional components apart from 5 V source, which was obtained from 5 V output pin of Arduino Duemilanove board, Fig 4. The sampling rate was set to 20 kHz with 100,000 16-bit samples (5 s) for each light source collected using a single continuous measurement. As some light sources, especially CFLs take a relatively long amount of time to warm up, the measurements have been conducted 2-3 minutes after the light was switched on. The data has been collected using National Instruments MyDAQ data acquisition kit [21] connected via USB to a Samsung P510 Core 2 Duo laptop.

B. Lab dataset

This dataset includes light flicker measurements for 13 different lamp models (10 LED and 3 CFL) acquired in a local store in a controlled environment. The measurements have been conducted over 2 hours within a single location. To study the effect of noise, two sets of measurements have been taken for each light source: one measurement was taken in bright conditions and another measurement was taken in the darkest part of the room. These measurements would be referred to normal and noisy data sets in the remainder of the paper. The measurements were conducted while making sure that the sensor output is not saturated, i.e. $V_{sensor} < 5V$. A care has been taken so that a flicker from laptop screen did not pollute the measurements.

C. Residential dataset

This dataset includes profiles of 39 LED and CFL light sources as they occurred in the wild, e.g. in real life indoor locations, such as rooms, halls and desks across 8 different residential locations in Luton, UK. The light sources included ceiling, hall, desk and floor lights. Each light source has been measured when it was the only light source in the location. The measurements have been conducted in the evening after sunset. Most light sources contained a single light bulb only, however, in cases where multiple light bulbs were operated with a single light switch, they were measured as a single light source. As with lab measurements, two sets of measurements have been taken for each light source: one measurement was taken in bright conditions and another measurement was taken in the darkest part of the room, referred to *normal* and *noisy* data in the remainder of the paper. The measurements have been conducted over a 4-week period. The vast majority of houses contained CFL light sources only with only one location containing a mix of CFL and LED lamps as shown in Table I.

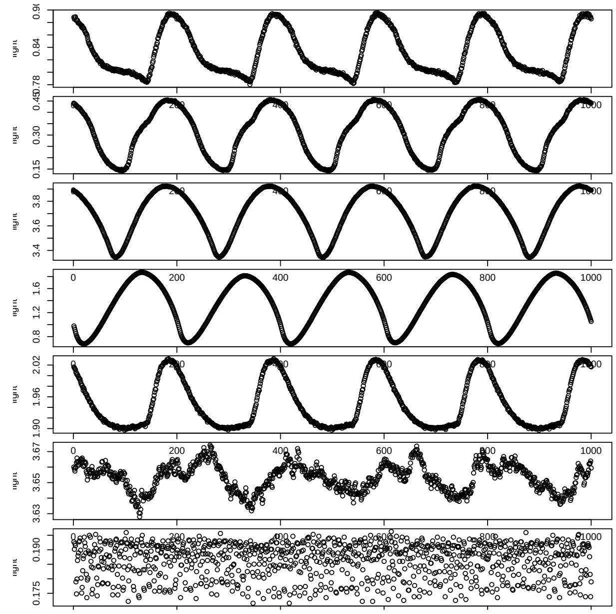

Fig. 5. Flicker waveforms for 5 CFL and 2 LED lights. The waveforms have non-sinusoidal shape that can be visually distinguished, which can be used for localization purposes

D. Example waveforms

Fig 5 demonstrates the variety of waveforms collected from 7 light sources within a single home from a residential dataset. The first 5 waveforms have been produced by CFL ceiling lights, whereas the last two were produced LED ceiling and LED desk light respectively. It is evident that waveforms have varying shapes and frequency characteristics (Fig 6) depending on the light source type and the model. As can be seen, the

TABLE I
LAMP TYPES. RESIDENTIAL DATASET (39 LIGHT SOURCES)

	House ID							
Lamp type	1	2	3	4	5	6	7	8
CFL	6	5	5	6	2	5	3	4
LED	0	0	0	0	0	0	0	3
Total	6	5	5	6	2	5	3	7

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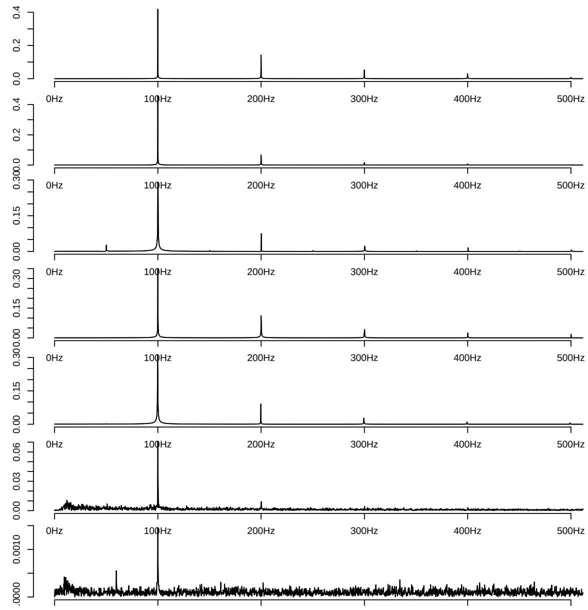

Fig. 6. Fourier transform of flicker waveforms. The light sources exhibit a strong 100 Hz component, double the AC frequency. CFL sources have multiple harmonics at frequencies of x2, x3, x4...of fundamental frequency, whereas LED sources have more high-frequency components

light sources contain a strong 100 Hz component, with CFL lamps showing harmonics at x2, x3, x4... frequency, whereas both LED light sources are characterised by high frequency components.

V. Experimental Results and Discussion

This section reports on the classification accuracy of aforementioned methods to identify a light source. k-fold cross-validation was used to evaluate the classifier performance: a dataset was split randomly into k subsets; each subset was used as a testing set with training performed on the remaining (k-1) subsets. The process was repeated k times, once for each subset, and the average is taken as a classification accuracy. The classification accuracy has been measured separately for normal, noisy and a combined data set. Analysis was conducted in R [22] with $signal$ [23] and $neuralnet$ [24] libraries on Intel i7, 8 MB RAM workstation.

A. Localization accuracy in lab environment

In this experiment, we evaluate the bulb identification accuracy using a lab dataset, which contained light flicker measurements of 13 light bulb models obtained from a local store. The analysis of the dataset using PCA has revealed that 99.8% of total data variance can be represented by just 9 components, with the first two components accounting for 77.9% and 20.9% respectively. This means that the classification can be conducted using 9 features only, which represent a linear combinations of original Fourier frequency components. Moreover, increasing the number of components beyond 9 did not have an impact on the classification accuracy.

Table II shows a classification accuracy for normal, noisy and full datasets using k-fold cross-validation (k = 10). PCA-kNN showed the highest average classification accuracy on normal and noisy datasets, followed by kNN and PCA-NN. The classification accuracy on a full data set is 67.4%, 69.0% and 62.7% for kNN, PCA-kNN and PCA-NN respectively, which represent the average of related columns in Table II. This is lower than expected but nevertheless much higher than random bulb selection (7.7%).

TABLE II
Classification Accuracy

Type	Accuracy, % (normal set)			Accuracy, % (noisy set)			Accuracy, % (full set)		
	kNN	PCA-kNN	PCA-NN	kNN	PCA-kNN	PCA-NN	kNN	PCA-kNN	PCA-NN
CFL	92.0	87.7	96.2	98.0	96.9	99.2	71.9	71.0	80.3
LED	89.3	95.1	84.9	87.8	90.8	84.4	64.2	67.0	49.8
Mixed	90.0	91.7	85.8	90.3	92.5	89.3	66.2	69.0	57.9

B. Localisation accuracy in residential environment

Next, we consider localization accuracy for residential light dataset. We define micro-location as a specific light source such as ceiling light, wall light, desk or a floor light within a room. The classification accuracy for normal and noisy datasets tends to be high with up to 100% for certain locations. The average location accuracy for a full data set is 82.9%, 83.2% and 87% for kNN, PCA-kNN and PCA-NN respectively, Table III. Similarly to previous experiment, the PCA-kNN method has shown the highest accuracy of all three classification methods.

TABLE III
Micro-location classification accuracy

Home ID	Accuracy, % (normal set)			Accuracy, % (noisy set)			Accuracy, % (full set)		
	kNN	PCA-kNN	PCA-NN	kNN	PCA-kNN	PCA-NN	kNN	PCA-kNN	PCA-NN
1	83.5	82.2	96.1	98.5	98.5	100	85.3	85.7	94.0
2	77.3	76.7	95.6	69.8	72.1	86.7	57.5	58.8	69.8
3	94.2	93.8	100	96.3	95.9	98.1	90.0	89.6	97.7
4	71.9	70.2	91.4	61.1	58.7	84.3	59.9	60.6	64.1
5	100	100	100	100	100	100	100	100	98.7
6	68.4	66.2	97.3	61.7	61.7	95.6	70.9	71.7	77.4
7	100	100	100	100	100	100	100	100	99.8
8	99.4	97.7	99.9	100	100	100	99.8	99.4	99.2

C. Macro-location inference

As the residential dataset comes from 8 different households, in this experiment we evaluate the ability of the method to correctly recognise a particular household using a sample from a single bulb. To implement this, the flicker waveforms coming from the same household were tagged using the same household ID. As shown in Table IV, the individual house can be identified with an accuracy of up to 86.3%, 93.6% and 67.9% for normal, noisy and full datasets respectively.

Finally, we measured the accuracy of an individual bulb identification across all houses, Table V. The classification accuracy for a full dataset is 24.9%, 23.9% and 41.6% for kNN, PCA-kNN and PCA-NN respectively. This is not sufficient to reliably identify a bulb within an entire dataset, but still significantly higher than a random selection (1 out of 39, or 2.6%).

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TABLE IV
MACRO-LOCATION CLASSIFICATION ACCURACY

Dataset	Accuracy, % (normal set)		
	kNN	PCA-kNN	PCA-NN
Normal set	74.0	73.0	86.3
Noisy set	83.6	86.9	93.6
Full set	73.9	74.0	67.9

TABLE V
MICRO-LOCATION CLASSIFICATION ACROSS ALL HOUSES

Dataset	Accuracy, %		
	kNN	PCA-kNN	PCA-NN
Normal set	71.5	70.6	88.5
Noisy set	74.87	78.5	91.67
Full set	24.9	23.9	41.6

D. Time dependency

As the performance of the approach could be affected by the grid power quality, we conducted an extra set of measurements separated by a 2-hour interval at 9 pm and 11 pm. Typically, the grid power quality in terms of frequency, the total harmonic distortions and other parameters is defined by the relevant regulators. In the EU for example, the power quality is defined by the EN 50160 developed by a working group under European Committee for Electrotechnical Standardisation. Among other parameters, the EN 50160 standard requires that the power frequency is within 50Hz $\pm$ 1Hz for 95% of time and the total harmonic distortion does not exceed 8%. The purpose of these additional measurements was to test the localization technique over a longer time interval.

The measurements have been conducted within one of the residential locations and included 4 separate rooms. As with previous experiments, each set of measurements included 5 seconds of noisy (dark) and 5 seconds of normal (bright) data. A visual inspection of waveforms in Figures 7 and 8 shows that the waveform shapes remain largely stable over time although there have been some minor variations possibly due to noise. We then trained the system on a full set of 9 pm data and validated against a full set of 11 pm and vice versa. Table VI shows the localization accuracy performance. We find that the approach performs well even if the training and testing data are separated by 2-hour interval.

E. Case study

In this section, we evaluate the accuracy of the localization method within one a studio flat by taking additional measurements of 8 light sources including ceiling, kithenette, bathroom, lobby, floor and desk lights. The average classification accuracy was 60.8%, 65.8% and 68.4% for kNN, PCA-kNN and PCA-NN respectively. A confusion matrix in Table VII shows that some light sources such as ceiling and floor A lights are reliably distinguished, whereas others have lower classification rate. Although, the accuracy was not sufficient to be used as a dedicated indoor localization system, we believe that the approach could be used as an opportunistic mechanism to augment the accuracy of existing systems.

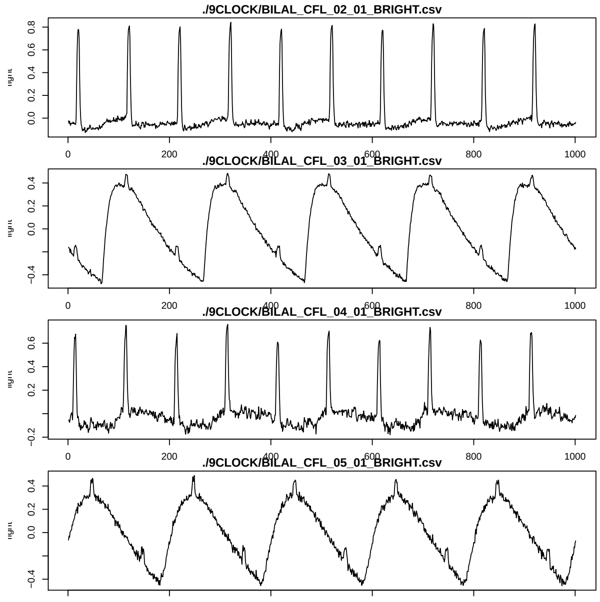

Fig. 7. Light profiles taken at 9pm

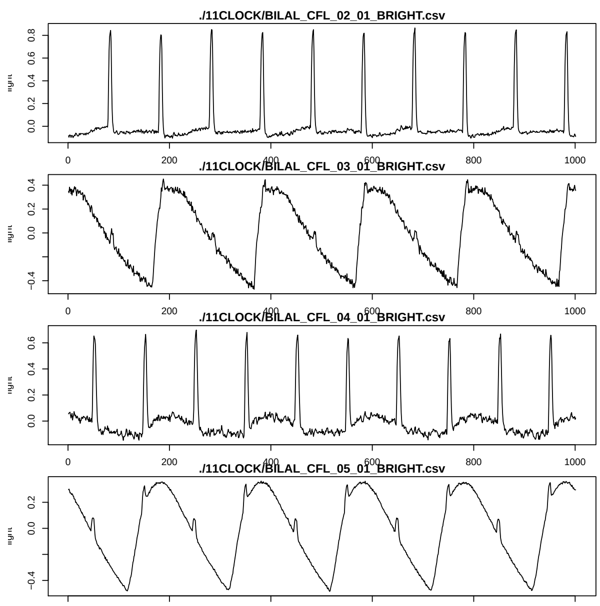

Fig. 8. Light profiles taken at 11pm share visual similarity with those measured at 9pm

The indoor accuracy could potentially be improved by using light sources with unique flicker patterns. Since different households are likely to use a different combinations of light sources, we believe it is possible to increase macro-localization accuracy by mapping those light source combinations to unique locations. For example, if locations 1, 2 and 3 use light sources $\{$A, B, C$\}$, $\{$B, C, D$\}$, and $\{$A, B, D$\}$ respectively, then fingerprinting these light set combinations could be used to more accurately predict the location. The exploration of those ideas is a potential future work.

TABLE VI
TIME DEPENDENCY RESULTS

Dataset	Accuracy, % (full set) KNN	PCA-KNN	PCA-NN
train using 9pm, validate using 11pm	75	75	76.1
train using 11pm, validate using 9pm	75	75	98.6

TABLE VII
LOCALISATION ACCURACY IN A SMALL STUDIO FLAT

actual \ prediction	ceiling A	floor A	floor B	hall	ceiling B	bath	desk	kitchinette
ceiling A	11	0	0	0	0	0	0	0
floor A	0	11	0	0	0	0	0	0
floor B	0	0	7	4	0	0	0	0
hall	0	0	5	6	0	0	0	0
ceiling B	0	0	0	0	11	0	0	0
bath	0	0	0	0	0	0	10	1
desk	0	0	0	0	0	0	9	2
kitchinette	0	0	0	0	0	0	8	3

VI. RELATED WORK

Indoor localization is a well-researched topic with numerous approaches based on RSSI [25], UWB [2], RF-sensing [1], ultrasonic [12], dead-reckoning, signature-based and hybrid technologies [26]. Below we review key existing techniques and their differences from the proposed method.

A. Proximity-based

Proximity based-techniques provide a course grained position, which rely on the fact that direct wireless link can only be established if an object is within a communication range. When using short-range communication technologies, such as active RFID [27] [3], 802.15.4 [26] and Bluetooth Low Energy (BLE), a position can be established with 5-10 meters range. Proximity-based techniques have been used widely in inventory, personnel and wildlife tracking [3] and require instrumenting the space with reference beacons or reader base stations.

B. Trilateration-based

In trilateration-based techniques, a mobile object measures a distance to three or more reference points with known locations and then applies a simple geometric transformation to compute its position. The distance is estimated using received signal strength information (RSSI), UWB, ultrasonic or time-difference of arrival method (TDOA). The RSSI-based methods are popular since the signal strength information is provided by virtually all transceivers but rely on certain assumptions on radio-propagation model and its parameters within an indoor environment. RSSI values are also relatively noisy due to interference and multi-path fading, which results in low position accuracy. UWB transceivers estimate range with centimetre-level accuracy, however, require specialised and more expensive hardware [2]. Time-difference of arrival method estimates distance by measuring the time difference between arrival of an RF and ultrasonic signal, which requires the mobile node to have additional equipment to support both RF and ultrasonic communication. All trilateration methods rely on existing infrastructure or reference nodes with known positions.

C. RF Signature-based

RF signature-based methods operate by simply mapping each object location to a tuple $(RSSI_1, RSSI_2...RSSI_n)$ in a training phase, where $RSSI_n$ is the signal strength between an object and each reference point [26]. In normal operation, the object position is established by measuring signal strength to each reference point and comparing the resulting RF signature with the database constructed during the training phase. The RF signature-based methods do not make any assumptions on a radio propagation model but still rely on an ambient infrastructure of reference nodes. RF signature-based methods are sensitive to changes in the radio environment and require retraining after each major change, which can be time and labour intensive process.

D. RF sensing-based

RF-sensing is relatively new and detects human presence by monitoring its impact on ambient wireless network links. It is based on the fact that the human body consist of 65% of water, which attenuates, reflects and scatters radio waves in 2.4 GHz frequency band [6] and can cause signal strength fluctuations in surrounding wireless links that can be detected by traditional radio signal receiver. Since these fluctuations are dependent on the object position relative to each wireless link, the exact position or activity can be detected through statistical analysis and machine learning techniques [1]. The technique is non-invasive and provides situational awareness about the environment non-invasively without any co-operation from the person.

Although RF-sensing does not require any dedicated equipment and relies on ambient wireless links from already existing Wi-Fi infrastructure, it does require some additional equipment to monitor and analyse ambient RF signals. Secondly, the technique relies on a training phase to recognise a position, which can be very labour and time consuming process. Finally, the technique is known to be very sensitive to even minor changes in the environment, such as change in furniture position and requires recalibrating the system after a major change. In contrast, passive light flicker fingerprinting requires a length training phase or any specialised equipment apart from a mobile device with a low-cost high-frequency light sensor.

E. VLC-based

VLC is a recent optical communication technology that transmits data by modulating the visible light emitted by Light Emitted Diodes (LEDs). The position is established through a proximity to a certain reference node or by measuring the angle of arrival for most accurate localization. The advantage of VLC-based localization techniques is a wide-spread availability of LED lights within indoor environments. However, the VLC based localization methods require a specialised LED driver on light sources to incorporate positioning information and support LED light sources only. In contrast, the proposed method works with all a wide range of unmodified light sources including compact fluorescent lights and standard LEDs. [28] have recently proposed a similar method that exploits flicker fingerprints for infrastructure-less indoor localization. The work however uses a very high frequency sampling, on the order of 1 MHz and convolutional neural network classifier (CNN) as classification method. In our work, we show that it is possible to obtain a reasonable localization accuracy using a relatively low frequency signal and use a principal component analysis for classification. We also show that is possible to use the method to identify a macro-location, such as a household, and demonstrate a temporal stability of the proposed method over normal and noisy datasets.

VII. Conclusions and Future Work

Indoor localization is an essential ingredient for indoor navigation systems [12], healthcare [29], context sensitive and assisted living applications. In this study, we propose and evaluate a novel method for passive localization based on fingerprinting light flicker patterns. The method requires neither additional infrastructure such as reference beacons nor modification of existing light sources. As no flicker dataset seems to be publicly available, we have built our own dataset containing light flicker profiles of 39 light sources collected from 8 households as well as an additional 13 commercially available CFL and LED bulbs.

The evaluation has shown that an indoor location such as a room or a desk, can be identified with up to 90% accuracy. A flicker waveform can also help in identifying a global location, i.e. a particular household with up to 86.3% accuracy. The experiments indicate that the location information can be obtained opportunistically, depending on the presence of unique patterns in the environment. This could potentially be used in context-aware applications to provide an additional information about the user location or a context. Having said this, we do not envision the proposed technique as direct replacement of dedicated infrastructure-based localization techniques.

While this study focused on visible stroboscopic flickering, some light sources are known to exhibit chromatic flickering associated with changing color spectrum [10], which is an interesting topic for future work. Furthermore, some indoor locations are often illuminated with multiple light sources simultaneously resulting in an arbitrary superposition of multiple light waveforms, which may have an impact on the accuracy. The authors leave investigation of such scenarios as a potential future work.

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