Visible Light Positioning With Diffusing Lamps Using an Extended Kalman Filter

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Abstract—The desire to obtain accurate location-based services has increased with the use of mobile devices. In this study, a visible light based indoor localization method that works with both diffusing and nondiffusing lamps is proposed. The received power from the light emitting diodes (LEDs) is used as sensor input, and an extended Kalman filter (EKF) is used for state estimation. The algorithm relies on knowledge of the expected power distribution in the room. The proposed method is robust to low SNR, nonuniform power distributions, and intermittent measurements. The results show that a tracking error around 1 centimeter can be achieved.

Index Terms—Visible light communication, indoor positioning, extended Kalman filter, indoor motion tracking

I. INTRODUCTION

Global positioning system (GPS) signals are subject to attenuation and losses in indoor environments since the signals cannot penetrate through buildings, walls, and other obstacles. This attenuation makes GPS inaccurate for indoor localization. Research and development in visible light communication (VLC), an alternative wireless communication method using light emitting diodes (LEDs), and the necessity for accurate position based services (PBS) create an opportunity for an alternative solution to the indoor localization and navigation problem. The effort to combine VLC and PBS has become popular in the last decade, yet research on accurate positioning/navigation has not reached a consensus (like GPS) for indoor areas like museums, warehouses, hospitals and industrial facilities. In this paper, an extended Kalman filter (EKF) that uses the received visible light signal strength from either diffusing or nondiffusing lamps as observations is proposed to solve this problem.

The advantages of using VLC instead of radio frequency (RF) based schemes are numerous. VLC does not create and is not susceptible to electromagnetic interference. The competition for bandwidth between communication and navigation purposes creates a problem in RF systems that does not exist in optical systems. The low bandwidth available in RF systems can lead to poor communication service quality and low positioning resolution. In VLC, the already installed illumination sources can be used without causing any electromagnetic interference or any side effects on communication services. VLC systems operate with visible light, which is ubiquitous and not harmful to human health.

Visible light indoor positioning algorithms can be divided into three main approaches: angulation-lateration, scene analysis, and proximity [1]. The transmitter is always the light emitting diode (LED) in VLC systems, and the measurements can be one of the following: received signal strength (RSS), angle of arrival (AOA), or time of arrival (TOA). The measurement type depends on the approach.

In angulation-lateration based methods, geometry is used to solve the distance equations at a reference point [2]. The combination of trilateration and RSS is proposed in [3]; the distance between the transmitter and receiver is calculated using the VLC channel model, and then trilateration is used for finding the position of the user. However, the basic assumption of the relationship between the irradiance angle and the incidence angle may not give accurate results when the transmission angles are not known a priori. In scene analysis methods, the expected RSS is used as reference points (fingerprints), and the RSS at the receiver is matched with these fingerprints; the position is found with respect to these fingerprints [4]. Proximity is the most expensive of these approaches: it takes advantage of a dense grid of lighting fixtures with known positions and unique identities, and then uses RSS measurements for localization [5]. The performance of the extended Kalman filter and the unscented Kalman filter within the context of VLC positioning is discussed in [6]. The transmitter locations and orientations are assumed to be known, and the signals from each luminary are assumed to be measured individually. The handover between luminaries and indoor positioning is investigated. The combination of circular photodetector arrays for measuring AOA is proposed in [7], where the positioning performance is shown to increase as the number of receivers increases.

In this paper, an indoor tracking approach that is a combination of the RSS and an extended Kalman filter (EKF) is proposed based on prior knowledge of the expected power throughout the indoor space. The difference between our work and previous approaches is in the way we define the measurement equation: we use the RSS directly and apply a finite difference method to linearize the RSS measurement model in the EKF, assuming that the expected power distribution in the room is provided to the users prior to tracking. Previous studies assume to know the orientation of the transmitter and receiver to recover the channel model and calculate the derivatives in the EKF. As another contribution of this paper, we analyze the positioning performance for diffusing and nondiffusing light sources, which has not been investigated in published work.
literature. A comparison of the proposed method with the tri-
lateration method is shown for different illumination schemes.
The results show that, as long as a fairly accurate map of
the expected power distribution in the room is available,
our EKF method can be used for accurate localization when
a randomly diffusing lamp is used, while angulation and
lateration approaches would require exact knowledge of the
transmission angles.

Fig. 1 illustrates our positioning method. The power dis-
tribution in the room is collected in an off-line phase, prior
to tracking. The power distribution map could be manually
collected, captured by cameras on the ceiling, or collected
using a learning algorithm – this is the subject of a future
study. The received power levels at the mobile receiver from
the various lamps, used as the only real-time measurements
for the algorithm, and the power distribution in the room are
combined in the online phase using the EKF. The positioning
accuracy depends on the resolution of the power map.

The rest of the paper is organized as follows: Section II
gives a definition of the VLC model. Section III explains the
positioning method and results and conclusions are given in
Sections IV and V, respectively.

II. VISIBLE LIGHT COMMUNICATION MODEL

A. Channel Model

The visible light system consists of a set of LED luminaries
on the ceiling that act as transmitters and a mobile optical re-
ceiver. The visible light from LEDs is known to be incoherent,
so intensity modulation and direct detection are used in VLC
systems. To simplify the analysis, in this study only the line-
of-sight components are taken into account for the channel DC
gain, as in [8] and defined as

$$H_{LOS} = \begin{cases} \frac{A_r (m+1)}{2\pi d^2} \cos^m (\phi) \cos (\psi), & -\Psi_c \geq \psi \geq \Psi_c, \\ 0, & \text{otherwise,} \end{cases}$$

where $A_r$ is the area of the receiver; $m$ is the Lambertian mode
of the transmitted beam, which is related to the semiangle
of the LED, $\Phi_{1/2}$; $\phi$ is the radiation angle for the transmitter;
$\psi$ is the incident angle at the photodetector; and $\Psi_c$ is the
field-of-view of the photodetector. Assuming no delay spread
due to multipath, the received power $P_r$ can be calculated as

$$P_r = H_{LOS} \times P_t,$$

where $P_t$ is the transmitted power from the light source. Each
lamp is encoded with an orthogonal code so that the received
power from each lamp can be determined by correlating with
each code before computing the RSS.

B. Diffuse Model with Light Emitting Diodes

VLP has been proposed for use in large indoor spaces such
as conference halls and museums. Classical architectural light-
ing styles for these environments include chandeliers, which
contain many small moving crystal refracting elements and
cannot be modeled as deterministic. In this paper we address
the ability to perform indoor positioning when chandeliers are
used for VLP lighting.

The angulation-lateration methods rely on the assumption of
known angles between the transmitter and receiver. In reality,
these assumptions may not hold. A diffuser, a chandelier, for
example, makes the light refract through prisms, which results
in a nonuniform power distribution in the room. The output
rays of light through these prisms have random irradiance
angles that make it difficult to use angulation-lateration. In
this paper, we modify the 25-LED lamp proposed in [9] to
imitate the behavior of a diffusing lamp. Each LED has a
random inclination angle; the random angle is used to model
the refraction of light through a prism.

The LED layout configuration of the lamp consists of three
layers, with 1, 8, and 16 LEDs, respectively. Fig. 2 (a) shows
the light rays from a regular 25-LED lamp that has deter-
mministic irradiance angles. Fig. 2 (c) represents the same 25-
LED lamp but now using random irradiance angles (diffused
model), which results in a unique optical power distribution
in the room.

In Fig. 3, the difference between the power contours for
deterministic and random 25-LED lamps is shown. Note that
the radiation pattern emitted by the 25-LED lamp is practically
identical to an equally bright single LED for 60° half angle
emitters. The room is $5 \times 5 \times 3$ m$^3$, with four LED lumini-
aries on the ceiling, positioned at $(x, y, z) = (1.25, 1.25, 3),$
$(1.25, 3.75, 3), (3.75, 1.25, 3)$ and $(3.75, 3.75, 3).$ The trans-
mitted power from each LED is 20 milliwatts, yielding a
total transmitted power of 500 mW per lamp. The random

Fig. 1. Positioning method process by EKF in Visible Light Positioning
(VLP) system

Fig. 2. Lamp structure used: (a) deterministic 25-LED lamp side view and (b)
bottom view; (c) random angle 25-LED lamp model side view
irradiance angles of the diffusing model have a normal distribution with zero mean and standard deviation of 30°. In Fig. 3 (a), (b) and (e), the power distribution in the room floor when the deterministic lamp model is used with different LED semiangles is shown, while Fig. 3 (b), (d) and (e) shows the effect of random transmit angles when the proposed random (diffusing) model is used. The refraction of light through the diffuser results in a nonuniform power distribution in the room.

C. Expected Power Distribution Map

The expected average power map is used as the RSS fingerprints in the Kalman filter. To do this, prior to tracking, the receiving plane (the floor in our case) is divided into equal size sections using a rectangular grid for the power distribution calculation. The received power from each lamp at the each grid point is computed as the average of the expected power over the area of that rectangular portion of the floor. These expected power levels are placed in a matrix $P$ and sent to the user as they enter the room.

With the diffusing lamp model, the irradiance angles are not only random but could also be time varying. We assume that the room conditions change slowly. The random movement of the crystals (prisms) causes changes in the power distribution map. In our algorithm, the power map in the room is found by averaging power distributions that are captured at pre-defined time intervals. The best power map update frequency depends on the air flow in the room and the interference of light with moving people.

D. Signal to Noise Ratio Analysis

The signal to noise ratio (SNR) analysis is important for a reliable sensor system. The main noise sources in a visible light communication (VLC) system are shot and thermal noise [10]. Shot noise depends on the background light and the transmitted power from the light sources while thermal noise results from the receiver electronics.

In [3], a typical indoor illumination level of 400 lumen results in an SNR= 50 dB for a bandwidth of 640 KHz for indirect sunlight exposure. We assume there are other uncertainties that act like noise, including errors in the power estimation shadowing of the line-of-sight between the transmitter and the receiver, other objects in the room, uneven dimming of the lamps, and the inclination angle of the mobile device. These effects may degrade the SNR, and therefore, thermal and shot noises are not enough to model the uncertainties in the system. We add a third noise term that we call “uncertainty” noise to account for the factors mentioned above. Hence, SNR on the whole system is accounted for and given as

$$ SNR = \frac{R^{2} P_{2}^{2}}{\sigma_{\text{shot}}^{2} + \sigma_{\text{thermal}}^{2} + \sigma_{\text{uncertainty}}^{2}}. $$

where $R$ is the receiver responsivity.

When the optical power is low, the “uncertainty” noise is dominant in the system because there are estimation errors in the power map collection step. For high optical power, the estimation error is small, therefore thermal and shot noise dominate.

III. POSITIONING/TRACKING METHOD

The positioning/tracking method based on the EKF presented in this paper is an alternative to previous indoor positioning approaches. Prior to tracking, the received power on the room floor is calculated as described in section II-C, and then this data is sent to the mobile device. The next step is state estimation using an extended Kalman filter (EKF) using the received power levels from each lamp as the measurements. Previous Kalman filter based algorithms for VLP assume that they have a priori information about the irradiance and inclination angles to recover the position from the received power [6].

The discrete time extended Kalman filter is a well-known tool in state estimation problems. Given a discrete time state space system, the dynamical system evolves according to

$$ x_{k} = f(x_{k-1}) + q_{k-1}, $$

$$ y_{k} = h(x_{k}) + r_{k}, $$

where $x_{k} \in \mathbb{R}^{n}$ is the state vector, $y_{k} \in \mathbb{R}^{m}$ is the measurement vector, the process noise is $q_{k} \sim N(0, Q_{k})$ (a zero mean, Gaussian distributed noise with covariance $Q_{k}$), and $r_{k} \sim N(0, R_{k})$ is the measurement noise with covariance $R_{k}$. $f(\cdot)$ is the dynamic model function and $h(\cdot)$ is the measurement model function. Previous studies on human motion...
modeling show that a piecewise-constant white acceleration model is an accurate representation of mobile user motion [11].

The purpose of our algorithm is to estimate the position of the mobile user. The state is \( \mathbf{x} = [x, y, \dot{x}, \dot{y}]^T \), where the Cartesian coordinates are aligned with the walls of the room and denoted as \( x \) and \( y \); \( \dot{x} \), \( \dot{y} \) represent velocity components. Known reference points are used for finding the initial states in the room such as doors, windows, or lighting fixtures. The choice of initial error covariance matrix is the error introduced from the initialization.

The VLC channel gain equation given in Section II-A is a nonlinear function [8], and as a result, the measurement vector \( \mathbf{y} \), which is a vector of received power strengths from the luminaries, is a nonlinear function of the state. The EKF relies on the linearization of nonlinear functions, yet the derivative of the channel equation is difficult to evaluate without exact emitted angle information. The EKF requires an evaluation of the Jacobian \( H(\cdot) \) of \( h(\cdot) \). In this paper, we approximate this using a finite difference method for linearization. The physical area of the room is divided into \( N \times J \) squares. Then the average power received in the square \((i, j)\) is denoted as \( P_{(i,j)} \), where \( i = 1, \ldots, N \) and \( j = 1, \ldots, J \) are the indices in the \( x \) and \( y \) directions. The grid shown in Fig. 4 represents the power distribution map or matrix \( \mathbf{P} = [P_{(i,j)}] \). In the figure, the predicted position from the previous iteration of the EKF is denoted by the symbol \( \star \). We take the power at this location in the grid as the predicted power, \( \hat{P}(\hat{x}) \), used in the EKF update equation. Then we approximate the Jacobian needed for the Kalman gain as

\[
H(\mathbf{x}) \approx \begin{bmatrix}
\frac{P_{(i+1,j)} - P_{(i-1,j)}}{\Delta x} & P_{(i,j+1)} - P_{(i,j-1)}
\end{bmatrix}
\]

(6)

where \( i \) and \( j \) are the indices of the power of the predicted state vector and \( \Delta x \) is the granularity of the power map.

The performance metric used to evaluate the algorithm is the root mean square error (RMSE) between the estimated and the true positions. Both light dimming and the uncertainties mentioned in Section II-D are modeled as different SNR levels.

The size of the room is \( 5 \times 5 \times 3 \) m\(^3\) and \( \Delta x \) is set to 1 cm for the first results. The velocities of the mobile user are 0.1 m/sec in the \( x \) direction and 0.3 m/sec in the \( y \) direction. The position of the luminaries and the transmitted power are the same as in Section II-B. The receiver is assumed to be moving on the room floor.

The success of the EKF depends on the dynamic model and the process noise level chosen \( Q_k \). The effect of the variance of the process noise on the positioning error is shown in Fig. 5. We assume that the mobile user is following an S-shaped trajectory. The same process noise levels in the EKF are tested for different SNR levels, and the process noise that yields the minimum RMSE is chosen for the remainder of the simulations.

Figs. 6 and 7 show the tracking results for the 25-LED lamp model for the S-shaped target trajectory and a constant velocity trajectory respectively. In the simulations, the process noise is kept the same, but the peak SNR is different. The results show that the tracking results do not deviate from the true trajectory significantly until the SNR falls below 25 dB.

In Figs. 8 and 9, tracking results when the diffuse model is used are shown for the two trajectories used in Figs. 6 and 7. Under the same peak SNR as the deterministic 25-LED lamp model, the results show that the tracking errors are worse than in Figs. 6 and 7; this is due to the random diffusion angles. The positioning error for the constant velocity target is higher than for the S-shaped motion; the straight motion is subject to lower average SNR because it is more often further from the LEDs.

In Fig. 10, a comparison of the proposed method and the trilateration method proposed in [3] is shown. The EKF
method performs better under low SNRs. The performance of the deterministic 25-LED lamp with EKF and the trilateration method can be compared, but a fair comparison for the diffusing lamp cannot be done because the random inclination angles of the LEDs are unknown. The irradiance and incidence angles are required for the trilateration method. We also compare the performance of a single LED lamp with the 25-LED lamp. The results show that when the LED semiangle is large, the tracking performance is close, because the power map of the 25-LED lamp and single LED lamp are similar.

Fig. 11 shows a comparison of the trilateration and EKF methods when the grid area is 1 dm² instead of 1 cm² used in the results above. We observe that the positioning performance is similar when the 25-LED and the diffusing lamps are compared. The positioning accuracy is limited by the quantization error, yielding almost identical results for the diffusing lamp model and the 25-LED lamp. As the grid size increases, the number of power samples decreases, and the accuracy of the Jacobian of \( h(\cdot) \) reduces. When the SNR is high, trilateration performs better because it does not depend on the motion model and is not affected by the quantization error on the power map. The same conclusion holds true for the tracking performance for a single LED lamp and a 25-LED lamp.

In Fig. 12, we compare the performance of the EKF using a 25-LED lamp versus using an extreme diffusing lamp. The extreme diffusing lamp model is still random but slightly different than the 25-LED diffusing lamp model. In the extreme case there are many tiny prisms that make the light refract. The results shows that as we increase the number of diffused
light rays, the positioning error decreases.

V. CONCLUSION

In this paper, an estimate of the received power distribution in the room from visible light LEDs was used in an extended Kalman filter to solve the indoor positioning problem. The results showed that in the best case scenario where the mobile user was moving in a straight path and the SNR is 65 dB, the RMSE was under 1 centimeter for the 25-LED lamp and 39 centimeters for the diffusing lamp model. In the worst case scenario where the target motion was nonlinear and the SNR was 15 dB, the RMSE was around 10 centimeters for the diffusing lamp model. The results showed that the proposed method performs well under different scenarios and noise levels. We concluded that indoor tracking could be achieved by combining the received optical power and a Kalman filter. When the signal was generated from a diffusing lamp, the EKF approach could still pin-point the user location unlike previous methods that failed in this case.

REFERENCES