ECTI Transactions on Computer and Information Technology
Journal homepage: https://ph01.tci-thaijo.org/index.php/ecticit/
Published by the ECTI Association, Thailand, ISSN: 2286-9131

Estimation with Angular Parameters on Channel of Visible Light Communication

Dwi Astharini[1], Muhamad Asvial[2] and Dadang Gunawan[3]

ABSTRACT

Performance of visible light communication (VLC) depends highly on channel conditions, which are sensitive to changes in user position. This paper presents estimation schemes of VLC parameters using a Kalman filter (KF), based on angular parameters of user position. The angular dynamic model is established so that the estimation process is directly in accordance with the Lambertian model of VLC channel. The use of angular model also gave way to use two parameters to describe a three-dimensional position. Estimations based on angular position are formulated, that is the KF estimation of position parameters, and the extended Kalman filter (EKF) where channel gain is estimated and also serves as a state parameter. The performance is observed in simulation and compared to reference models of Cartesian based estimation. The proposed angular model EKF with the channel gain as the state parameter showed comparably higher error than the Cartesian model EKF of 3:2 in comparison but required remarkably less processing time of 1:5 to the referred model.

Article information:

Keywords: Angular Position, Channel Estimation, Kalman Filter, Extended Kalman Filter, Visible Light Communication

Article history:
Received: October 18, 2021
Revised: December 6, 2021
Accepted: March 4, 2022
Published: May 28, 2022
(Online)

DOI: 10.37936/ecti-cit.2022162.245930

1. INTRODUCTION

In recent years, visible light communication (VLC) has gained much attention for development. Various aspects of VLC have been scrutinized to propose schemes for the concerned qualities. As a rule, transmission channel condition i.e. the channel gain is a concern for performance on wireless systems. On VLC, channel condition is a function of distance, the components, and characteristically as an optical system, the angles. In effect, on VLC channel gains are the LED angle of coverage, the equipment position towards LED, and detector or sensor receiving angle, and in indirect effect is the sensor field of View (FOV). With the above in mind, this paper investigates VLC channel estimation, based on angular location.

Estimation of channel condition on VLC has been investigated in previous work. In [1], it is performed using a neural network. Compressive sensing is applied for channel estimation in [2] to support VLC orthogonal transmission. Since the channel is heavily based on position, in [3] user position is determined and predicted based on triangulation of available transmitters.

The view of VLC and its dependence on location made way for the developments of visible light positioning (VLP), which offers high accuracy for indoor positioning in comparepison to conventional methods [4]. Currently VLP is classified in two types, the photodetector (PD) based, and image sensor (IS) based. The PD based VLP uses the Lambertian VLC channel on its system model, such as in [5] where position prediction with Kalman filter is used for adaptive positioning. This is also the case in [6] which investigated the LED power allocation effect on VLP. The IS based, on the other hand, derives the position from projection analysis of image processing. In various references this is applied in synch with odometry [4], [7], [8]. In [4], [8] position is determined using rolling camera shutter and odometry. In [7] the combination is enhanced with LiDAR to achieve a multi-sensor localizer. Without the use of any angle sensor, [9] proposed positioning based on geometric features in image of circular LED projection. While camera images are quite a customary feature in many indoor robots or other equipment, image processing has the basic disadvantage of heavy processing. In this work the proposed positioning is PD based, making use of the Lambertian model.

[1,2,3]The authors are with Electrical Engineering Dept., Universitas Indonesia, Depok, Indonesia, E-mail: dwi.astharini@ui.ac.id, asvial@eng.ui.ac.id and guna@eng.ui.ac.id

Kalman filters (KF) are widely used in broad ranging types of tracking and navigation. Also known to be used on channel estimation, KF has made its way into VLC systems. In [10] KF was used for a hybrid system of VLC and Wi-Fi. User position was modelled with x and y coordinates of indoor area partitioned in grid. The estimators were extended Kalman filter (EKF) and KF with unscented transformation. Also working on multi transmitter models of a VLC system is [5] where the Kalman filter is made adaptive for handover between the access points (AP). In [11], an EKF is applied to the dynamic model based on horizontal coordinates of x, y. While KF has appeared often, all of the works [5], [10], [11] above are using dynamic models with x, y, z Cartesian coordinates. On the work of [12] an unscented Kalman filter (UKF) is applied for dynamic position based on inertial measurement unit (IMU) data. IMU data is also used in [13] on EKF for IS based user positioning. The channel is then derived from estimated position. Another IS based VLP is [14] where high performance positioning is proposed by using the Camshift-Kalman algorithm. The use of images requires rigorous processing but allowes more possibilities for more precise results.

Kalman filters with angular position models are often found in the field of electric machines, but are also used for finding the vehicular or sensor position. The model used in [15] is based on angular position and the speed of the motor to represent location in a two dimensional field. On the other hand, the work in [16] presented a model of vehicle position in relation to GPS. Therefor in some aspects it is adaptable to our scenario of VLC use.

In the works of [10], [11], [13] where EKF is applied to VLC, the channel as a nonlinear estimated parameter appeared solely as the system output. Since EKF is based on higher order Taylor series of both state and output functions, it is less effective when the nonlinearity appears only in the output parts of the model.

From above references, it can be observed that the existing models for VLC channel estimation are based on Cartesian coordinates. Another observation is that in an EKF model, the estimated parameter channel gain is each time regarded only as an output parameter. Motivated by these issues, the contributions of this paper are the following:

- First, we present VLC channel estimation based on angular position in accordance with Lambertian model of a VLC channel.
- Two types of KF estimation are explored to determine the channel condition, the linear KF and the EKF.
- Then for EKF estimation, two models are investigated. On one the channel gain was regarded only as estimated output, and on the other enhanced one the channel gain was modelled also as a dynamic system state.

The angular based model gives the benefit of fewer parameters, since an angle essentially covers two axes, and it is a two-dimensional variable. To the best of our knowledge, this has not been performed in any other published work.

To achieve the aims, first we gave the basic layout of a VLC channel and the role of location in it in the second part of the article. Then a dynamic model is formed for user's position and its changes using an angular parameter. On the third part the models for Kalman filter estimation are then developed based on this dynamic model. On the fourth part a demonstration is done in simulation to observe the performance and a comparison is made. As a comparison, a KF from the existing references is used in which estimation is calculated based on Cartesian coordinates.

2. SYSTEM MODEL

2.1 VLC Channel

VLC channels are described in Lambertian model which can be found among others in [17], [18]. The channel gain is defined in (1).

$$h = \frac{m+1}{2^2} \cos^m \theta . c(\psi) . \cos(\psi) \tag{1}$$

with d and θ as the diagonal distance and the angle position of user equipment (UE) to the LED, respectively, c is UE gains, ψ is reception angle of UE, and $m = -\frac{\ln(2)}{\ln(\cos(\psi_{\frac{1}{2}}))}$ being the Lambertian order as a function of LED coverage ψ. Figure 1 illustrate this lay out for varying positions of a user.

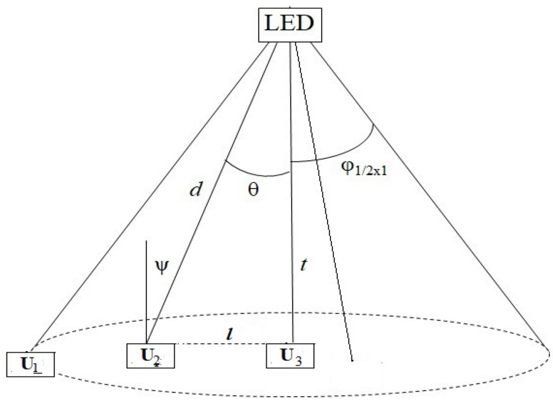

Fig.1: *User position with variety of* θ

The specification of LED is something predetermined in a long run, thus the Lambertian order m is pre-set. In this paper, the value of c on specific user equipment is also assumed static over the period of a transmission session. The reception angle ψ is something that could be developed to be adaptable, but on this occasion will be assumed as fixed for a transmission session. Probable causes of a channel dynamic chage is then the change in position of user equipment, presented in θ and d.

2.2 Dynamic of User Position

A dynamic model of user location must be established. The variables of interest, as observed above, are θ and d, along with their changes. So, the two parameters at any time k can be stated as

$$\theta(k+1) = \theta(k) + u_\theta(k) + w_\theta(k) \tag{2}$$
$$d(k+1) = d(k) + u_d(k) + w_d(k) \tag{3}$$

where $u_\theta(k), u_d(k)$ are the inputs that move the receiver equipment, and $w_\theta(k), w_d(k)$ are the process error for θ and d.

3. KALMAN FILTER FOR CHANNEL ESTIMATION

3.1 Linear Kalman Filter for Position Estimation

From the available models above, the first obvious solution is to perform estimation of position parameters $\theta(k)$ and $d(k)$ during the transmission.

The dynamic model of (2) and (3) is written as a state equation vector

$$x(k+1) = Ax(k) + Bu(k) + w(k) \tag{4}$$

where $x(k)$ is the state vector at a sequence point of k, A and B is the state and input matrix, where

$$x(k) = \begin{bmatrix} \theta(k) \\ d(k) \end{bmatrix}, \quad A = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad B = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix},$$

$$u(k) = \begin{bmatrix} u_\theta(k) \\ u_d(k) \end{bmatrix}, w(k) = \begin{bmatrix} w_\theta(k) \\ w_d(k) \end{bmatrix}.$$

The estimated output is

$$y(k) = Cx(k) + v(k) \tag{5}$$

with $y(k)$ as the output vector at the sequence point of k, C is the output matrix, and $v(k)$ is the measurement error, where

$$y(k) = \begin{bmatrix} \theta(k) \\ d(k) \end{bmatrix}, \quad C = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad v(k) = \begin{bmatrix} v_\theta(k) \\ v_d(k) \end{bmatrix}.$$

The estimation by KF is done according to Algorithm 1, as can be found in numerous references of KF as in [19], [20]. The estimated θ and d are then used to calculate the channel gain according to (1). This estimator is straightforward and linear, and later in simulation showed quite good results. The problem is that this estimator needs measurements of updated θ and d. In previous work, estimation of user position is often done as in [13], where the VLC channel is obtained as derived parameter of the localization by KF, although EKF was used in that work due to nonlinearity within the incorporated IMU data.

Algorithm 1 Kalman filter

Initialization: $A, B, C, Q(k) = E[w(k)w(k)']$,
$R(k) = E[v(k)v(k)^T], P\_init, x\_init$
Input: u
Iterative step:
Measurement update:
$G(k) = P(k|k-1)C'[CP(k|k-1)C' + R]^{-1}$
$x(k|k) = x(k|k-1) + G(k)[y(k) - Cx(k|k-1)]$
$P(k|k) = [I - K(k)C]P(k|k-1)$
Time update:
$x(k+1|k) = Ax(k|k) + Bu(k)$
$P(k+1|k) = AP(k|k)A' + B * Q * B'$
Output:
$y\_est = Cx(k|k)$

With G as the Kalman gain.

3.2 Nonlinear Estimation of Channel Gain

Instead of performing estimation on position parameters of θ and d, the KF can be used directly as an estimator of the channel gain h. As the channel model of (1) is nonlinear, incorporating the channel gain h requires a nonlinear estimator.

A. EKF 1 with h as estimation output

As the system model is a non-linear one, an extended Kalman filter is used for estimation. For the system to be dynamic, the state equation $f(x,u)$ we use is the same state equation as the basic ones shown in (2)-(3). The measured parameter is the channel gain, as a function of θ and d as stated in (1). The output equation is then a non-linear expression of

$$y(k) = h(x(k)) + v(k), \tag{6}$$
$$h(x(k)) = \frac{m+1}{2\pi . d(k)^2} \cos^m(\theta(k)).g \tag{7}$$

with $g = c(\psi).\cos(\psi)$.

This model is similar to the basic model used in the EKF of [10], [11], [13], in which the VLC channel is the estimated and measured value, while the dynamic model is basically user position. The EKF is applied as shown in Algorithm 2, which can be found in references [19].

The nonlinear model is reflected on the Jacobian matrix

$$Jh = \frac{\partial h}{\partial x}, \qquad Jf = \frac{\partial f}{\partial x}.$$

The Jacobian of state and output functions then are

Algorithm 2 Extended Kalman filter

Initialization: $f(x,u), h(x,u), Q(k) = E[w(k)w(k)']$, $R(k) = E[v(k)v(k)^T], P\_init, x\_init$
Input: u
Output: y_est
Iterative step:
Measurement update:
$G(k) = P(k|k-1)Jh'[CP(k|k-1)Jh' + R]^{-1}$
$x(k|k) = x(k|k-1) + G(k)[y(k) - h(k|k-1)]$
$P(k|k) = [I - K(k)Jh]P(k|k-1)$
Time update:
$q(k+1|k) = f(k|k)$
$P(k+1|k) = JfP(k|k)Jf' + B * Q * B'$
Output:
$y\_est = h(k|k)$

$$\frac{\partial f}{\partial x} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \tag{8}$$

$$\frac{\partial h}{\partial x} = \begin{bmatrix} \delta 1 & \delta 2 \end{bmatrix} \tag{9}$$

$$\delta 1 = \frac{m(m+1)g\cos^{m-1}(\theta(k))\sin(\theta(k))}{2\pi d(k)^2}$$

$$\delta 2 = \frac{-2(m+1)g\cos^m(\theta(k))}{2\pi d(k)^3}$$

B. EKF 2 with h as estimation output and state

In this model, the channel gain is incorporated further, not merely as the system output, but also as one of the states in system model, so that

$$q(k+1) = \begin{bmatrix} \theta(k+1) \\ d(k+1) \\ h(k+1) \end{bmatrix} = f(q(k), u(k)) + w(k) \tag{10}$$

$$f_1(q(k), u(k)) = \theta(k) + u_\theta(k) \tag{11}$$

$$f_2(q(k), u(k)) = d(k) + u_d(k) \tag{12}$$

$$f_3(q(k), u(k)) = \frac{m+1}{2\pi . d(k)^2}\cos^m(\theta(k)).g \tag{13}$$

with

$$u(k) = \begin{bmatrix} u_\theta(k) \\ u_d(k) \\ 0 \end{bmatrix}, \qquad w(k) = \begin{bmatrix} w_\theta(k) \\ w_d(k) \end{bmatrix}.$$

The output equation is the non-linear expression of (6)-(7). The Jacobian of state and output functions for this model are

$$\frac{\partial f}{\partial x} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ \delta 1 & \delta 2 & 1 \end{bmatrix}, \tag{14}$$

$$\frac{\partial h}{\partial x} = \begin{bmatrix} \delta 1 & \delta 2 & 1 \end{bmatrix}. \tag{15}$$

The EKF is done according to Algorithm 2 as well, with the differences of the matrices involved within the dynamic model. In contrast to EKF1 is the state equation $f(x,u)$ on EKF2 is defined by (11)-(13).

4. SIMULATION RESULTS

Simulation was done to observe the performance of the three schemes of estimations presented in the previous part. The first used linear KF, estimating the parameters θ and d, and from the result calculated the channel gain h. The second used an EKF with channel gain h as the measured and estimated parameter, with θ and d as state variables for the dynamic model. The third was also based on EKF channel gain h as the measured and estimated parameter, where h is one of the state variables along with θ and d.

The VLC system modelled is an indoor access point as illustrated in Figure 1. The LED transmitter is on the ceiling and is the origin of distance d and angle θ. The PD receivers are assumed to have a certain height from the floor and a considerable vertical distance from the ceiling. Thus, the distance d throughout the time would never be zero. Table 1 shows the parameter set used in the simulation.

Table 1: *Parameter Settings for Simulation.*

Variables		Value
Q	Process error	0.001
R	Measurement error	0.01
θ_0	Initial angle	30°
d_0	Initial distance	2 m
$\psi_{\frac{1}{2}}$	Half angle of LED coverage	85°
g	Total component power	8

Figure 2 shows the performance of KF in estimating θ and d. The bottom graph shows the channel gain h calculated for each resulting θ and d. The right column of Fig 2 shows the error performance. However, channel gain here is calculated outside the estimation process as a byproduct of the position. As h is a derived variable, and not measured, on the right bottom plot there is only one plotting line, showing the error of h_e derived from the estimated θ_e and d_e. As the KF shows good performance in estimating θ and d, the resulting h from calculation also shows a low rate or error.

Figure 3 shows the performance of EKF θ-d in estimating the channel gain h according to the model in 3.2.A. The right column plots shows their error performance. In this model, the concern focuses on the channel gain. The position parameters θ and d are used only for the dynamic movement. The estimated and measured parameter is h, and it is shown on the

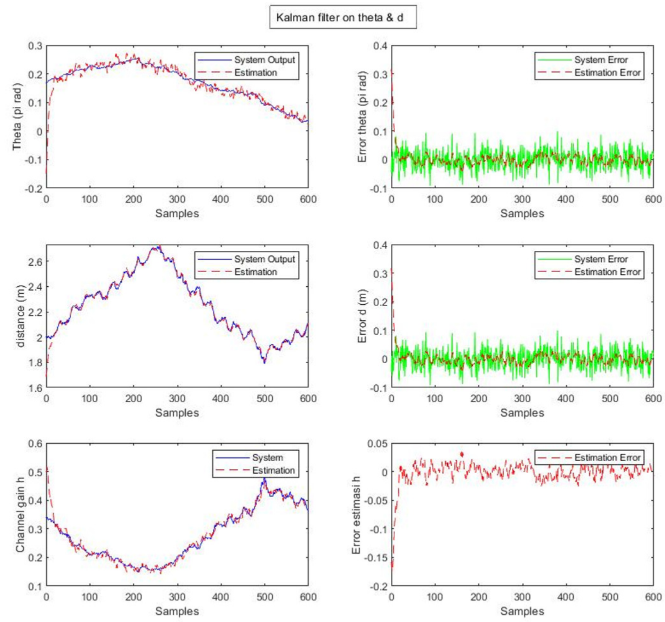

Fig.2: *Performance of estimation scheme 1 KF θ-d, with h posteriori.*

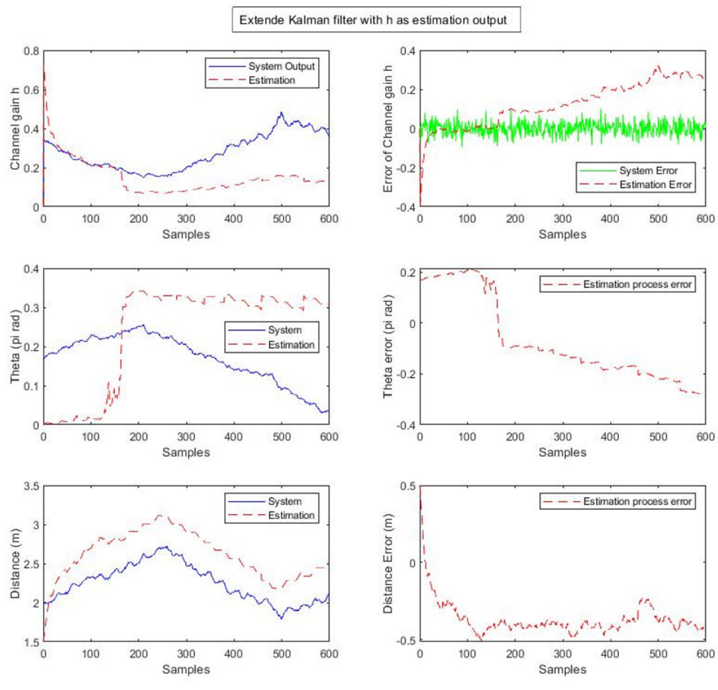

Fig.3: *Performance of estimation scheme 2 EKF θ-d with h as output.*

top graph of Figure 3.

The EKF $\theta - d$ here shows inadequate error performance on estimation of h on the first model with θ and d as state parameters. The estimation error, which is shown in red line of upper right graph, is higher than the measurement error (green line). As revealed in 3.2.A, the system dynamic is modelled on θ and d, while the measurement is done on h, which is a function v. The nonlinearity is due to the parameter h, thus the Jacobian matrix is clearly seen only in $\frac{\partial h}{\partial x}$ while the $\frac{\partial f}{\partial x}$ is a linear matrix. The measured parameter is used for the update process of the Kalman cycle, so in this case the measured h is used to update the state of θ and d. From the simulation results, it is clear that this update process cannot be performed well. The difficulty is especially profound on the variable of angle, and the EKF process seems to have difficulty adjusting θ for the updated h, since the Jacobian matrix is significant only on the output equation. As the h is a function of θ and d, the estimated h_e here also reflects the above difficulties, resulting in high error of estimation values, far be-

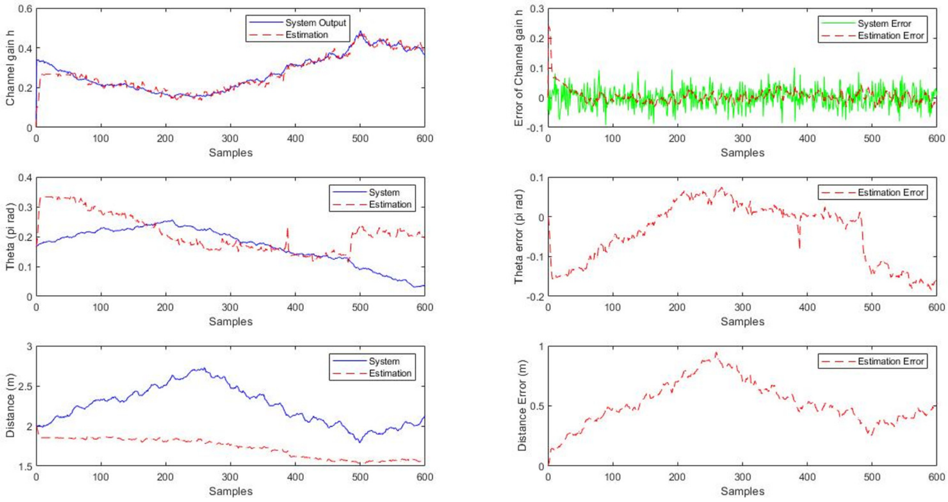

Fig.4: *Performance of scheme 3 EKF θ-d-h with h as states and as output..*

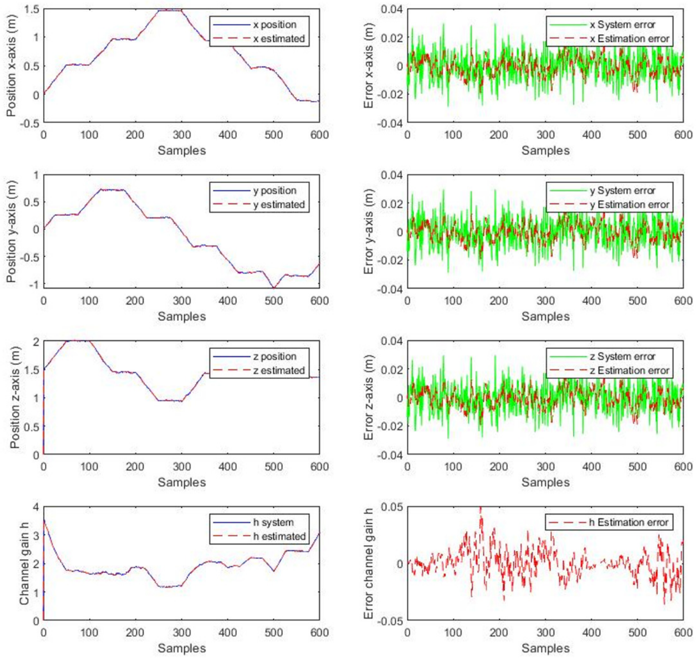

Fig.5: *Performance of estimation scheme 4 KF x-y-z with h posteriori.*

yond the error of measurement, as seen in top right graph of Figure 3. It can be said that EKF $\theta - d$ on this scheme 2 has failed the expectation, since the errors on the estimation process are far higher than the measurement error. The main problem of this model is that the measurement parameter h turned up only as an output parameter of the estimation and h is not used well in the updating process. To overcome the problem in the first EKF scheme, we propose the second model of EKF $\theta - d - h$ as revealed in part 3.2.B as scheme 3. The simulation results are given in Figure 4.

Figure 4 shows the performance of estimation scheme 3 EKF $\theta - d - h$ in estimating h, this time with h, θ, and d as state variables as in model of 3.2.B. The right column of Figure 4 shows the corresponding error performance. As the channel gain h here is incorporated in both state and output equations, the Jacobian matrix shows the nonlinearity both in the state and output equations. This proves to be a better model for angular based EKF, as shown on the top left graph of Figure 4. The update process on variables θ and d for this scheme show problem converging. Nevertheless, the main parameter of estimation is the channel gain, and for this the scheme 3 EKF $\theta - d - h$ has given good performance.

On the top right of Figure 4 the estimation error of channel gain h is small, and substantially lower than its measurement error. Thus, this estimation scheme has fulfilled the expected process objection.

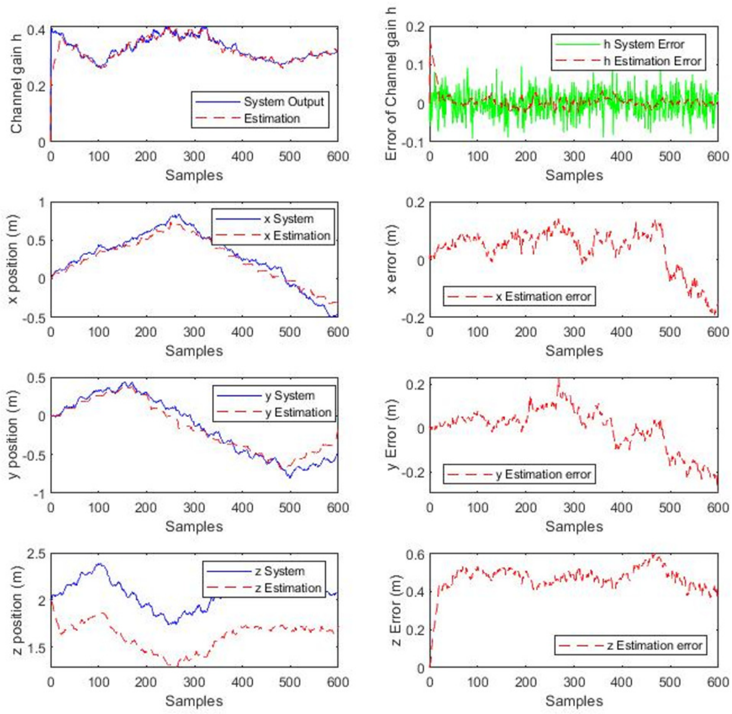

Fig.6: *Performance of scheme 5 EKF x-y-z with h as output.*

For comparison, we draw out the Kalman Filter models from the references, that is with Cartesian coordinates as estimation parameters. Figure 5 shows the $x-y-z$ position estimation using KF $x-y-z$ as in scheme 4. Figure 6 shows scheme 5 of estimation on channel gain h using EKF $x-y-z$, based on the model proposed in [10], [11].

The linear KF $x-y-z$ of scheme 4 in Figure 5 shows very good performance estimating the position in Cartesian coordinates. The channel gain here is calculated outside the estimation process as a byproduct of the position, as was also the case in KF $\theta-d$ of scheme 1 in Figure 2.

The performance of EKF in Figure 6 based on references is not quite satisfactory. The problem is as was revealed in the previous scheme 2 of EKF $\theta-d$ in Figure 3, which is that the measurement parameter h turned up only as an output parameter of the estimation and is not well used in the updating process.

5. RESULTS DISCUSSION AND ANALYSIS

To allow the performance comparison of the five estimation schemes, Table 2 shows the standard deviation error, process time, and vector size, which indicate the resource usage. The standard deviation error in the table is of the estimation process. That is $\sigma(h-h_e)$ without the comparison to the measurement error. Processing time is the average time needed for each estimation cycle, counted only for the estimation process. The vector size is shown for each state and output process of the KF and in the end the number of parameters is summed up to simplify the comparison. For easier comparison, the numbers are also shown asa barchart in Figure 7.

The proposed model is estimation using an angular parameter of the Lambertian VLC channel. In this case, the incident angle θ. In the table, these are scheme numbers 1,2, and 3, corresponding to Figures 2, 3, and 4. The estimation schemes numbered 4-5 which correspond to Figures 5 and 6 are the comparison. Scheme number 5 was obtained from the references [10], [11]. The data of all five schemes was obtained with the same parameters as shown in table 1.

It is seen that scheme 2, requiring the least number of parameters, resulted in high error values. From the point of view of error rate, from the three proposed schemes of estimation using parameters θ and d, the recommended ones are the first model of linear KF for position estimation, and the third and proposed model of EKF, which includes channel gain h as an estimated parameter as well as a state variable. In comparison to the Cartesian based model of schemes 4 and 5, the proposed estimations shows lower performance error rates.

In view of processing time, the proposed EKF has performed very well with average time for each cycle significantly lower than that of the others. This can be achieved because the intended value h is an inherent within the Kalman cycle so that no post-processing is required as in linear KF of schemes 1 and 4. Scheme number 5, although it is also an EKF with h as an estimated parameter, required longer

Table 2: *Comparison of Estimation performance.*

	Estimation scheme	Average cycle time (μs)	Standard deviation error	Estimation Vector size			
				KF State parameter	KF Output parameter	Non KF parameter	Number of parameters
1	KF $\theta - d$	27.71	0.0219	2	2	1	5
2	EKF $\theta - d$	5.91	0.1150	2	1		3
3	EKF $\theta - d - h$	4.92	0.0328	3	1		4
4	KF $x - y - z$	30.71	0.0121	3	3	1	7
5	EKF $x - y - z*$	23.68	0.0204	4	1		5

*[10,11]

time process. This might be due to the higher complexity of the Jacobian matrix $\frac{\partial h}{\partial x}$. As the available parameters are x, y, and z, the matrix $\frac{\partial h}{\partial x}$, must then be derived on these parameters accordingly.

While the error rate of schemes 3 and 5 are not very different, that is about 3:2; their time comparison is quite substantial. For scheme 3 the average time for each cycle about 1:5, or twenty percent of that of scheme 5, thus reducing 80% of the required processing time. From this we can deduce that the use of angular parameters in channel estimation can reduce the processing time considerably.

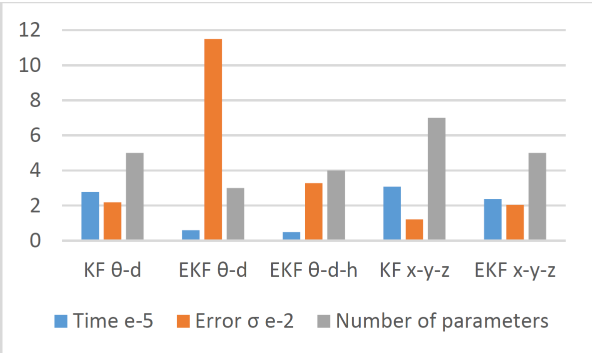

Fig.7: *Comparison of estimation performance.*

The linear KF is a straightforward linear estimation of movement with good performance, well suited for robotic devices in which the movements can be well determined. For receiving equipment with more obscure movement such as handheld devices, channel condition is more likely to be the available parameter of measurement, thus the EKF is more suitable. In this case, the EKF to be used is that of the third estimation scheme, where channel gain h is an estimated parameter and a state variable for the dynamic model.

6. CONCLUSION

The channel condition in VLC is sensitive to relative position between the photodetector receiver and the LED transmitter where small movement on user equipment could result in alteration of the channel gain. This paper has presented Kalman filter estimation for VLC channel gain based on angular parameters according to the Lambertian model. The angular model proposed is based on two variables for three-dimensional movements. It is also developed in concern of the channel model. The two state variables are directly determining factors in changes of the channel condition. Three schemes of KF were explored. First was the KF estimation of position parameters. Next was the EKF of channel gain with position parameters as state parameters. The third was the EKF of channel gain which includes the channel gain as the state parameter. The proposed EKF with angular parameter of Lambertian VLC succeeded in reducing the processing time by 80% from the previous model with Cartesian coordinates. Linear KF is a straightforward linear estimation of movement and showed good performance with a standard deviation of estimation error of 0.0219. For system with channel gain as a measured variable, the proposed EKF was the third model, which included the channel gain as the state parameter. This EKF 2 managed to give a considerably lower rate of error than the other measured ones that is with standard deviation of estimation error of 0.0328. Further investigation based on this angular parameter of the Lambertian VLC model could be carried out on other nonlinear estimations like unscented KF and a particle filter, for suitability in different conditions.

ACKNOWLEDGEMENT

This work was supported by Universitas Indonesia Tadok Grant no. NKB-0157/UN2.R3.1/HKP.05.00/2019.

References

[1] A. Yesilkaya, O. Karatalay, A. S. Ogrenci, and E. Panayirci, “Channel estimation for visible light communications using neural networks,” in *Proceedings of the International Joint Conference on Neural Networks*, Oct. 2016, vol. 2016-October, pp. 320–325, doi: 10.1109/IJCNN.2016.7727215.

[2] M. T. Niaz, F. Imdad, W. Ejaz, and H. S. Kim, “Compressed sensing-based channel estimation for ACO-OFDM visible light communications

in 5G systems," *EURASIP J. Wirel. Commun. Netw.*, vol. 2016, no. 1, p. 268, 2016.

[3] M. Al-Nassrawi, H. Le-Minh, Z. Ghassemlooy, T. T. Son, and M. Zhang, "Indoor positioning using single transmitter for visible light communications system," in *2017 1st South American Colloquium on Visible Light Communications, SACVLC 2017*, Jan. 2018, vol. 2018-January, pp. 1–6, doi: 10.1109/SACVLC.2017.8267608.

[4] Z. Yan, W. Guan, S. Wen, L. Huang, and H. Song, "Multirobot Cooperative Localization Based on Visible Light Positioning and Odometer," *IEEE Trans. Instrum. Meas.*, vol. 70, 2021, doi: 10.1109/TIM.2021.3086887.

[5] Y. S. Eroglu, F. Erden, and I. Guvenc, "Adaptive Kalman Tracking for Indoor Visible Light Positioning," in *Proceedings - IEEE Military Communications Conference MILCOM*, Nov. 2019, vol. 2019-November, doi: 10.1109/MILCOM47813.2019.9021016.

[6] M. F. Keskin, A. D. Sezer, and S. Gezici, "Optimal and robust power allocation for visible light positioning systems under illumination constraints," *IEEE Trans. Commun.*, vol. 67, no. 1, pp. 527–542, Jan. 2019, doi: 10.1109/TCOMM.2018.2866849.

[7] W. Guan et al., "Robot Localization and Navigation using Visible Light Positioning and SLAM Fusion," *J. Light. Technol.*, Nov. 2021, doi: 10.1109/JLT.2021.3113358.

[8] H. Song et al., "Single LED positioning scheme based on angle sensors in robotics," *Appl. Opt.*, vol. 60, no. 21, pp. 6275–6287, Jul. 2021, doi: 10.1364/AO.425744.

[9] R. Zhang, W. De Zhong, Q. Kemao, and S. Zhang, "A Single LED Positioning System Based on Circle Projection," *IEEE Photonics J.*, vol. 9, no. 4, Aug. 2017, doi: 10.1109/JPHOT.2017.2722474.

[10] M. Rahaim, G. B. Prince, and T. D. C. Little, "State estimation and motion tracking for spatially diverse VLC networks," in *2012 IEEE Globecom Workshops*, 2012, pp. 1249–1253, doi: 10.1109/GLOCOMW.2012.6477760.

[11] N. T. Nguyen, N. H. Nguyen, V. H. Nguyen, K. Sripimanwat, and A. Suebsomran, "Improvement of the VLC localization method using the Extended Kalman Filter," in *IEEE Region 10 Annual International Conference, Proceedings/TENCON*, Jan. 2015, vol. 2015-January, doi: 10.1109/TENCON.2014.7022416.

[12] Q. Zou et al., "A VLC and IMU integration indoor positioning algorithm with weighted unscented Kalman filter," in *2017 3rd IEEE International Conference on Computer and Communications*, ICCC 2017, Mar. 2018, vol. 2018-January, pp. 887–891, doi: 10.1109/CompComm.2017.8322671.

[13] Q. Liang and M. Liu, "A Tightly Coupled VLC-Inertial Localization System by EKF," *IEEE Robot. Autom. Lett.*, vol. 5, no. 2, pp. 3129–3136, Apr. 2020, doi: 10.1109/LRA.2020.2975730.

[14] W. Guan, Z. Liu, S. Wen, H. Xie, and X. Zhang, "Visible Light Dynamic Positioning Method Using Improved Camshift-Kalman Algorithm," *IEEE Photonics J.*, vol. 11, no. 6, Dec. 2019, doi: 10.1109/JPHOT.2019.2944080.

[15] D. Watzenig and G. Steiner, "Offset compensation for capacitive angular position sensors by evaluating the Kalman filter innovation sequence," in *Proceedings of the IEEE International Conference on Industrial Technology*, 2004, vol. 3, pp. 1457–1462, doi: 10.1109/icit.2004.1490778.

[16] S. Baek, C. Liu, P. Watta, and Y. L. Murphey, "Accurate vehicle position estimation using a Kalman filter and neural network-based approach," in *2017 IEEE Symposium Series on Computational Intelligence, SSCI 2017 - Proceedings*, Feb. 2018, vol. 2018-January, pp. 1–8, doi: 10.1109/SSCI.2017.8285360.

[17] H. Marshoud, P. C. Sofotasios, S. Muhaidat, G. K. Karagiannidis, and B. S. Sharif, "On the Performance of Visible Light Communication Systems With Non-Orthogonal Multiple Access," *IEEE Trans. Wirel. Commun.*, vol. 16, no. 10, pp. 6350–6364, 2017, doi: 10.1109/TWC.2017.2722441.

[18] L. Yin, X. Wu, and H. Haas, "On the performance of non-orthogonal multiple access in visible light communication," in *2015 IEEE 26th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*, 2015, pp. 1354–1359, doi: 10.1109/PIMRC.2015.7343509.

[19] R. G. Brown and P. Y. C. Hwang, *Introduction to Random Signals and Applied Kalman Filtering*, 4th ed., no. 4. Wiley, 2012.

[20] A. Nadzilah, D. M. Gandana, J. Muliadi, and Y. Daryanto, "Application of Kalman filter to track ship Maneuver," Oct. 2017, doi: 10.1109/CITSM.2017.8089287.

Dwi Astharini received the bachelor degree in electrical engineering (S.T) from Institut Teknologi Bandung, Indonesia, in 1997 and the M.Sc. degree in electrical engineering from Universitaet Karlsruhe, Germany, in 2001. Currently she is pursuing the Ph.D. degree in electrical engineering at Universitas Indonesia, Depok. She is also a lecturer with the Department of Electrical Engineering Universitas Al Azhar Indonesia. Her research interest include software defined telecommunication and visible light communication.

Muhamad Asvial received the bachelor's degree in electrical engineering from Universitas Indonesia, in 1992, the master's degree in telecommunications engineering from Keio University, in 1998, and the Ph.D. degree from the University of Surrey, U.K., in 2003. He is currently a Professor in wireless telecommunications with Universitas Indonesia, where he is also a Lecturer with the Department of Electrical Engineering. His research interests include satellite communications and mobile wireless technology.

Dadang Gunawan received the bachelor's degree in electrical engineering from the University of Indonesia in 1983, the master's degree from Keio University, Japan, in 1989, and the Ph.D. degree from the University of Tasmania, Australia, in 1995. He is currently a Professor with the Department of Electrical Engineering, Universitas Indonesia. He has published hundreds of academic papers in international journals and proceedings, as a first author or a co-author. His interests are in wireless and signal processing technology.