DATA-DRIVEN STATE ESTIMATION FOR LIGHT-EMITTING DIODE UNDERWATER OPTICAL COMMUNICATION

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ABSTRACT

Light-Emitting Diodes (LEDs) based underwater optical wireless communications (UOWCs), a technology with low latency and high data rates, have attracted significant importance for underwater robots. However, maintaining a controlled line of sight link between transmitter and receiver is challenging due to the constant movement of the underlying optical platform caused by the dynamic uncertainties of the LED model and vibration effects. Additionally, the alignment angle required for tracking is not directly measured and has to be estimated. Besides, the light scattering propagates beam pulse in water temporally, resulting in time-varying underwater optical links with interference. We address the state estimation problem by designing an LED communication system that provides the angular position and velocity information to overcome the challenges. In this way, we leverage the power of deep learning-based observer design to explore the LED communication’s state space properly. Simulation results are presented to illustrate the performance of the data-driven LED state estimation.

Keywords Light-emitting diode (LED) · Underwater optical wireless communication (UOWC) · Online estimation · Observer design · Nonlinear systems · Deep learning algorithm · Neural networks.

1 Introduction

Underwater optical wireless communication (UOWC) has rapidly developed nowadays along with the increasing demand for communication such that underwater research scientific, underwater sensors, submarine interconnection, and remote access vehicles. Firstly, a low attenuation window for a blue-green optical beam ensures the stability of the communication link (Schirripa Spagnolo et al., 2020). Light beam with a wavelength around 532nm can pass almost 100 percent of the way through water several meters below the surface (Gkoura et al., 2014). Thus, constructing a high speed and stable underwater communication link tens of meters long is possible (Cossu, 2019). For instance, an LED-based UOWC system for autonomous underwater vehicles (AUVs) network that reaches over 30 meters length has recently been designed by (Tian et al., 2013). Secondly, optical communication is possible to achieve Gb/s or even Tb/s level bandwidth (Wang et al., 2018; Arvanitakis et al., 2020). Thirdly, UOWC saves energy, so it is easy to expand to a large scale. The transmitter only needs a few watts or tens of watts to achieve stable transmission of huge data streams (Son et al., 2018). Hence, the cost to construct an underwater interconnection network or Internet of Things (IoT) is low.

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In the coming 6G era, high speed, low power consumption, and long-distance underwater communication scheme are the key factors enhancing the underwater communication. Traditional acoustic communication generates signals of tens or even hundreds of watts. However, acoustic systems consume massive power and produce severe noise. Additionally, the transmission rate is only up to tens of kbps. On the other hand, radio frequency (RF) communication cannot be used to construct long underwater links due to attenuation over 150 dB/m.

In the future, UOWC will keep contributing on rural connection, deep ocean surveying and data storage. More infrastructures and vehicles will be connected and deployed in underwater environment to build underwater Internet of Things (IoT) to wide-area ocean networks, as illustrated in Fig. 1. A potential application scenario is underwater data center (UDC) as traditional data centers consume huge power and are heavy to move. UDC can cut off nearly all cooling system that reaches a power usage effectiveness (PUE) close to 1.

However, underwater communication environment is relatively complicated because of the inter-symbol interference when the data rate is high, and the constant movement of the underlying optical platform caused by vibration effect, thereby adversely affecting the alignment and transmission quality. Misalignment can introduce severe pointing errors and even interrupt communication. Hence, maintaining an adequate alignment is a key topic in UOWC.

To overcome these issues, performing real-time channel information through an online estimation framework to change the system behavior is an ideal method and can meet the demand. Indeed, data-driven estimation of an underwater dynamical system is an essential problem with several practical applications, specifically in control, diagnosis and monitoring. Hence, estimating the alignment angle between two underwater vehicles is a potential research direction as the alignment angle can be considered as a system state due to the inherent underwater noise and turbulence. On the other hand, the received power of LED has a strong nonlinear relationship with the alignment angle.

Extended Kalman filter (EKF) has widely been used for state estimation of nonlinear models; however, it requires linearizing the nonlinear system dynamics and result in local convergence on the mean estimate. Solanki et al. applied EKF on estimating the angular position and angular velocity of an LED system. However, their model needs much computation and suffers from local convergence; small errors can make the systems unstable. Researchers adopt extended Luenberger observer as well if the system model can be converted into a linear one. Mapping has been introduced to approximate the nonlinear model such as in. However, the mapping is computationally heavy to compute. Inspired by the idea of Luenberger’s observer, researchers developed Kazantzis-Kravaris-Luenberger (KKL) observer. KKL has a good performance on both continuous and discrete-time system. However, people need to find relations between the new linear system and the previous nonlinear system to complete the coordinate transformation. This is not always feasible in implementation.

Recently, researchers proposed to use deep learning (DL) in state estimation to improve the mapping computation easier and computationally more efficient. There have been few reports, but some progress, on using...
DL for state estimation. A deep learning (DL) based extended Luenberger observer to estimate system states has been proposed in (Ramos et al., 2020). This first attempt achieved good accuracy but requires labeled data for supervised learning. In addition to the difficulty of collecting data, this approach generally does not guarantee the whole inter-state mapping. However, this method has been extended to an unsupervised way (Peralez and Nadri, 2021). In this paper, we extended the algorithm proposed in (Peralez and Nadri, 2021) to an LED-based optical wireless communication system to estimate the alignment angle through a deep-learning mapping.

The paper is organized as follows. In Section 2, the LED-based optical communication model is presented, including its state-space and measurement equation. In Section 3, we formulate the deep-learning-based algorithm in which we numerically identify the learned mapping within an online framework. In Section 4, simulation results are provided to illustrate the performance of the data-driven state estimation algorithm to estimate the angular position and angular velocity of the LED system through autonomous, non-autonomous, and closed-loop systems. Finally, concluding remarks are shown in Section 5.

2 LED-based Optical Communication System Model

The LED-based optical link describes a two-way communication that consists of an LED transmitter and a photodiode receiver; each end can rotate by an angle in which it establishes and maintains LOS.

2.1 LED System Dynamics

The detector’s incident power can be determined based on the signal irradiance at the relative detector position. The resulting luminous flux signal model is given as follows (N’Doye et al., 2020).

$$P_d(d, \theta, \phi) = \frac{a \exp \left( -\frac{bd}{d^2} \right) \tilde{I}_\theta}{d^2} g(\phi),$$

where \( \tilde{I}_\theta \) is the angular intensity distribution of the transmitter (Ghassemlooy et al., 2012; Solanki et al., 2018b; N’Doye et al., 2020), \( g(\phi) \) is the dependence of the received LED intensity on the incidence angle \( \phi \) and takes the form of two Gaussian terms with six unknowns (N’Doye et al., 2020).

$$g(\phi) \approx a_1 \exp \left[ -\left( \frac{\phi - b_1}{c_1} \right)^2 \right] + a_2 \exp \left[ -\left( \frac{\phi + b_2}{c_2} \right)^2 \right].$$

Fig. 2 illustrates the variables of interest, which include the transmission distance \( d \), the transmission angle \( \theta \), and the angle of incidence of \( \phi \). All the constants values in this section are nonnegative, and their physical meaning can be found in (N’Doye et al., 2020).

From (1), we formulate the state space representation based on the two variables of interest \( \phi \triangleq x_1 \), and \( \dot{\phi} \triangleq x_2 \) that relate to the angles of the receiver. On the other hand, we note that practically it is not easy to move the distance \( d \) ideally because it needs to move the whole robot. Besides, controlling the angular velocity of \( \dot{\phi} \triangleq x_2 \) is more practical. The robot alignment is performed by stabilizing the angular velocity. Since the distance \( d \) cannot be adjusted easily and
\[ \theta \text{ is fixed, therefore, we define the states as follows} \]

\[ x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} \phi \\ \dot{\phi} \end{bmatrix}. \tag{3} \]

We assume that the dynamic is slow and subject to a Gaussian process. The representation in the discrete-time domain can be written as follows

\[ x_k = \begin{bmatrix} x_{1,k} \\ x_{2,k} \end{bmatrix} = \begin{bmatrix} x_{1,k-1} + T_e x_{2,k-1} + w_{1,k-1} \\ x_{2,k-1} + u_{k-1} + w_{2,k-1} \end{bmatrix}, \tag{4} \]

where \( w_{1,k} \) and \( w_{2,k} \) are the process noises which are assumed to be white independent Gaussian noises. \( T_e \) is the sampling time, \( u_k \) is the control input which acts on the receiver’s angular velocity.

## 2.2 Output Measurement Equation

The measurement \( P_{d,k} \) is expressed as

\[ y_k \triangleq P_{d,k} = \bar{C}_p g(x_{1,k}) + w_k, \tag{5} \]

where \( \bar{C}_p = C_p \hat{I}_\theta \exp(-cd_0/d_0^2) \) and \( g(.) \) is defined in \( \text{[2]} \).

We introduce an additional receiver on the same robot with a constant shifted angle of \( \Delta \phi \) to achieve observability, as illustrated in Fig. 3. This shifted angle is added to account for the actual orientation of the receiver. At each movement of the transmitter platform, the states are updated according to the system dynamics. Both \( \phi \) and \( \bar{\phi} = \phi \pm \Delta \phi \) can be controlled to \( 0^\circ \), when \( \phi \) is controlled to \( 0^\circ \) and reads the wirelessly transmitted data, its orientation is being maintained by using \( \bar{\phi} \). The resulting output vector can be written as follows

\[ \begin{bmatrix} y_{1,k} \\ y_{2,k} \end{bmatrix} = \bar{C}_p \begin{bmatrix} g(x_{1,k}) \\ g(x_{1,k} \pm \Delta \phi) \end{bmatrix} + w_k. \tag{6} \]

Given the measurement, the primary goal is to estimate the angular position \( x_{1,k} \) and the angular velocity \( \dot{\phi} \triangleq x_{2,k} \) based on which the control \( u_k \) is designed, to drive \( x_{2,k} \) towards zero, which corresponds to the maximum light intensity’s orientation. In this paper, we rely on the deep learning based-observer design results (Peralez and Nadri, 2021; Bernard and Andrieu, 2019), to online estimate \( x_{1,k} \) and \( x_{2,k} \) from the knowledge of a sequence of the past and current values of the input \( u_k \) and output \( y_k \).

The next section provides the design and algorithm of the deep learning observer-based reference tracking control.
Figure 4: Structure of the deep auto-encoder network model to identify $T$ and $T^{-1}$.

3 Deep learning-based estimation algorithm

We consider the following non-autonomous system

$$\begin{align*}
    x_{k+1} &= f(x_k, u_k) \\
    y_k &= \ell(x_k) \tag{7}
\end{align*}$$

where $x \in \mathbb{R}^n$ is the state, $u \in \mathbb{R}^m$ is the input and $y \in \mathbb{R}^p$ is the output. $f$ and $\ell$ are suitable nonlinear functions.

3.1 Preliminaries

Throughout the paper, we assume that $f$ and $\ell$ satisfy the following assumptions.

**Assumption 1** $f$ is invertible and $f^{-1}$ and $\ell$ are of class $C^1$ and globally Lipschitz.

**Assumption 2** For all $(x_1, x_2) \in \mathcal{X} \subset \mathbb{R}^n$ of system (7) with input $u$, if $x_1 \neq x_2$, then there exists a positive integer $j$ such that $\ell(f^{-j}(x_1)) \neq \ell(f^{-j}(x_2))$.

For brevity, we require system (7) to be reversible in time and thus make Assumption 1. Assumption 2 implies a backward distinguishability hypothesis of the state function (7) to ensure sufficient conditions of the existence, injectivity and uniqueness of a map $T$.

**Lemma 1** (Peralez and Nadri, 2021) Suppose that assumptions 1 and 2 hold and for any constant input $\bar{u}$, there exists a map $T: \mathcal{X} \to \mathbb{R}^q$ for almost any controllable pair $(A, B)$ of dimension $q = p(n + 1)$ with $A$ Hurwitz that ensures

$$T(f(x, \bar{u})) = AT(x) + B\ell(x), \quad \forall x \in \mathcal{X}, \tag{8}$$

and a pseudo-inverse $T^{-1}$ such that the following system

$$\begin{align*}
    z_{k+1} &= Az_k + By_k \\
    \hat{x}_k &= T^{-1}(z_k) \tag{9}
\end{align*}$$

is an observer for (7) for a constant input $\bar{u}$. Then, the unique solution of (8) is given as follows

$$T(x) = \sum_{j=0}^{+\infty} A^j B \ell(f^{-j}(x, \bar{u})). \tag{10}$$

**Lemma 2** (Peralez and Nadri, 2021) Let assumptions 1 and 2 hold for a constant input $\bar{u}$. Assume that $A$ can be obtained such that $T$ and $T^{-1}$ in lemma 1 satisfy

$$|\Omega(z_1, u) - \Omega(z_2, u)| \leq \lambda_u |z_1 - z_2|,$$

where $|\cdot|$ is the Euclidean norm and

$$\Omega(z_k, u_k) = T\left(f(T^{-1}(z_k), u_k)\right) - T\left(f(T^{-1}(z_k), \bar{u})\right).$$
Then, for all \( u \in \mathcal{U} \) such that \( \rho(A + \lambda_u I) < 1 \), the following system

\[
\begin{align*}
    z_{k+1} &= Az_k + By_k + \Omega(z_k, u_k) \\
    \hat{x}_k &= T^{-1}(z_k)
\end{align*}
\]  

(11)

is an observer for \( T \).

Remark 1  An analytic expression of \( T \) (i.e., the existence and injectivity of \( T \)) of this class of linear LED non-autonomous dynamics with exponential output \( (4)-(6) \) can be proven by relying on the resolution of a time-varying PDE that provides solutions of which transform the dynamics \( (4)-(6) \) into linear asymptotically stable ones (see, for instance \( \text{Bernard and Andrieu} 2019 \)). However, it is essential to mention that an explicit close form expression of \( T^{-1} \) is usually challenging to obtain, and it is not always straightforward to determine the function \( T \) derived from \( (10) \).

Our next objective is to numerically identify the injective mapping \( T \) and its left inverse \( T^{-1} \).

3.2 Online Estimation of \( T \) and \( T^{-1} \)

A deep auto-encoder network is used to identify the mapping of \( T \) that satisfies \( (8) \) along with \( T^{-1} \) for non-autonomous system, as shown in Fig. 4. Hence, two loss functions are computed during the training phase \( \text{Peralez and Nadri} 2021 \). The first loss function minimizes the trajectory dynamic to identify a latent space \( \hat{T} \) as follows

\[
    \mathcal{L}_{\text{dyn}} = \| T(x_{k+1}) - AT(x_k) + B\ell(x_k) + \hat{\Omega}(x_k, u_k) \|,
\]

(12)

where

\[
    \hat{\Omega}(x_k, u_k) = \sum( f(x_k, u_k)) - ( f(x_k, \bar{u})).
\]

The second loss function uses a reconstruction loss of the auto-encoder to learn \( T^{-1} \) such that \( \hat{x} \) is recovered. The reconstruction cost is given by

\[
    \mathcal{L}_{\text{recon}} = \| x_k - T^{-1}(T(x_k)) \|,
\]

(13)

where \( \| \cdot \| \) is the mean squared-error.

The LED-based optical model \( (4)-(6) \) is trained by minimizing the two loss functions \( (12) \) and \( (13) \) on the dataset \( D = \{ x_k, x_{k+1}, \bar{u} \} \) where \( x_k \) and \( x_{k+1} \) are generated from a uniform random distribution on \( \mathcal{X} \) and from the LED model dynamic \( (4)-(6) \), respectively. For some constant value \( \bar{u} \) of the input, we first learn the mapping \( T \) and \( T^{-1} \), then we apply a small enough input during evaluation which can be seen as a disturbance. Algorithm 1 summarizes the steps of the deep learning based-observer design.

**Algorithm 1: Online estimation of \( T \) and \( T^{-1} \)**

*Data: Choose \( A \) and \( B \) and \( T \) randomly*

1. while \( k \leq \text{max}_\text{iter} \) do
2.     Compute \( z_k = T(x_k) \)
3.     while \( i \leq \text{dimension of } z \) do
4.         \( b_i = \frac{1}{D(z_i, u)} \)
5.     end
6.     \( T(x) \leftarrow \text{diag(} [b_1, b_2, \ldots] \text{)} \cdot T(x) \)
7.     minimize \( \mathcal{L}_{\text{dyn}} = \| T(x_{k+1}) - AT(x_k) + B\ell(x_k) + \hat{\Omega}(x_k, u_k) \| \)
8.     end
9. while \( k \leq \text{max}_\text{iter} \) do
10.     minimize \( \mathcal{L}_{\text{recon}} = \| x_k - T^{-1}(T(x_k)) \| \)
11. end

Remark 2  Note that the white Gaussian process noises can be embedded in the additive input signal. Hence, the learned mappings \( T \) and \( T^{-1} \) hold for a small excitation signal as the contraction property \( (11) \) remains still satisfied.
TABLE I: RMSE: state and output errors performance estimation.

| Controllers | RMSE | G1 | \(\hat{G}_1\) [rad] | G2 | \(\hat{G}_2\) [rad/s] | H1 | \(\hat{H}_1\) [rad/s] | H2 | \(\hat{H}_2\) [rad/s] | \(\Delta H\) [rad/s] |
|-------------|------|----|---------------------|----|---------------------|----|---------------------|----|---------------------|---------------------|
| Open-loop   | 0.10 | 0.01 | 0.20               | 0.01 | 0.30               | 0.01 | 0.40               | 0.01 | 0.50               | 0.01               |
| Closed-loop | 0.05 | 0.01 | 0.15               | 0.01 | 0.25               | 0.01 | 0.35               | 0.01 | 0.45               | 0.01               |

Figure 5: Open-loop case with \(u = 0\): true states \(x_1\) and \(x_2\) and their estimated states \(\hat{x}_1\) and \(\hat{x}_2\), respectively.

Figure 6: Non-autonomous case with \(u = 0.1 \cos (5t \times 0.01)\): true states \(x_1\) and \(x_2\) and their estimated states \(\hat{x}_1\) and \(\hat{x}_2\), respectively.

Figure 7: Non-autonomous case with \(u = 0.1 \cos (5t \times 0.01) + 0.2 \sin (5t \times 0.01)\): true states \(x_1\) and \(x_2\) and their estimated states \(\hat{x}_1\) and \(\hat{x}_2\), respectively.
Figure 8: Closed-loop setting with $u = -0.001 \dot{x}_2$: true states $x_1$ and $x_2$ and their estimated states $\hat{x}_1$ and $\hat{x}_2$, respectively.

Table 1: RMSE: state and output errors performance estimation.

| Controllers          | RMSE            | $x_1 - \hat{x}_1$ [rad] | $x_2 - \hat{x}_2$ [rad/s] | $y_1 - \hat{y}_1$ [W] | $y_2 - \hat{y}_2$ [W] |
|----------------------|-----------------|-----------------------|--------------------------|-----------------------|-----------------------|
| Open-loop (OL)       | $u = 0$         | $5.2 \times 10^{-3}$  | $19.2 \times 10^{-3}$    | $8.8 \times 10^{-3}$  | $13.6 \times 10^{-3}$ |
| Input function IF$^1$| $u = 0.1 \cos (5t \times 0.01)$ | $7.2 \times 10^{-3}$  | $51.8 \times 10^{-3}$    | $11.6 \times 10^{-3}$ | $19.3 \times 10^{-3}$ |
| Input function IF$^2$| $u = 0.1 \cos (5t \times 0.01) + 0.2 \sin (5t \times 0.01)$ | $5.7 \times 10^{-3}$  | $50.3 \times 10^{-3}$    | $1.73 \times 10^{-3}$ | $2.5 \times 10^{-3}$  |
| Closed-loop (CL)     | $u = -0.001 \dot{x}_2$ | $6.3 \times 10^{-3}$  | $22 \times 10^{-3}$      | $8.4 \times 10^{-3}$  | $16.7 \times 10^{-3}$ |

4 Simulation Results

In this section, we present numerical simulation results that illustrate the performance of the proposed online estimation methodology. The simulations are carried out by using Python. We employ synthetic data generated from the LED-based optical model (4)-(6). We apply the proposed deep learning observer algorithm to minimize the two-loss functions (12) and (13) on the training data set. We consider three scenarios for the new inputs: the first deals with the open-loop case, the second considers the non-autonomous case with two different external inputs, and the last is built from the closed-loop setting. We first identify the learning mapping $T$ and $T^{-1}$ in open-loop setting (i.e. $\bar{u} = 0$). Then, we predict the LED states using the learned model with new inputs and initial conditions. Finally, we compare the prediction results with the reference solution, which is derived by solving the exact LED system (4)-(6) with the same new inputs. We conduct the deep neural network training using Adam optimizer through dense neural networks with the open-source Pytorch library. The LED model is trained with $2 \times 10^5$ data trajectories randomly sampled with a uniform distribution on the domain $X = [-0.5, 0.5] \times [-0.5, 0.5]$. We consider the eigenvalues for the observer, corresponding to $A = \text{diag}[1 - T, 1 - 2T, 1 - 4T, 1 - 6T, 1 - 8T, 1 - 10T]$ and matrix $B$ is given by $B = \text{ones}(6, 2)$ in our discrete framework. The measurement power is corrupted with zero mean Gaussian noise of 0.001 variance and the shifted angle $\Delta \phi = 6^\circ$. The deep learning algorithm uses activation function $\text{tanh}(\cdot)$ and consists of one hidden layer for both networks with 500 nodes. Overall, the hyperparameters of the DL algorithm are chosen to ensure a good compromise between the estimation performance and minimum loss function.

4.1 LED States Estimation

4.1.1 Open-loop simulations

We firstly perform open-loop simulation results to illustrate the importance of estimating the mapping $T$ and $T^{-1}$ in the unforced LED model. Fig.5 shows the open-loop simulation results. $u = 0$ and the root-mean-square error (RMSE) is shown in Table 1. It can be seen that the observer exhibits good performance with the reference solution. Hence, the results illustrate the ability of the proposed method to identify the mapping $T$ and $T^{-1}$.
Figure 9: Output prediction results along with their reference solutions when $u = 0.1 \cos (5t \times 0.01)$: effect of the power signal strength to the distance between the receiver and the transmitter.

Figure 10: Output prediction results along with their reference solutions when $u = 0.1 \cos (5t \times 0.01) + 0.2 \sin (5t \times 0.01)$: effect of the power signal strength to the distance between the receiver and the transmitter.

4.1.2 Non-autonomous simulations

For comparison purposes, we perform simulation results for two non-autonomous cases IF$^{1}$ and IF$^{2}$ with $u = 0.1 \cos (5t \times 0.01)$ and $u = 0.1 \cos (5t \times 0.01) + 0.2 \sin (5t \times 0.01)$ along with the reference solution, as illustrated in Figs. 9 and 10 respectively. Table I shows the corresponding RMSE for both input functions IF$^{1}$ and IF$^{2}$. Hence, we observe good agreement of the angular position and velocity with the reference solution for relatively small enough input signal. From Table I it is worth noting that the RMSE increases slightly for both external inputs compared to the open-loop case, however the overall results exhibit good performances. Hence, one can conclude that the learned mappings can be used to estimate and predict system behavior for adequate external inputs.

4.1.3 Closed-loop simulations

For further performance analysis, we perform a closed-loop test based on the estimated angular velocity. We set the angular reference position to 0.2 rad and the angular velocity to zero. Fig. 8 illustrates the estimated angular position and velocity states of the LED and the output power prediction results under a closed-loop controller along their reference solutions. Table I also provides the corresponding RMSE. We observe good performance with the true states.
sensitivity analysis results under open loop control. Fig. 9 and Fig. 10 proved the the observer has good stability performance. Furthermore, Fig. 10: Sensitivity Analysis Result of $D = 0.1 \cos(5C \times 0.01)$.

We have conducted simulations in the loop with the inputs signal and the closed-loop controller to examine the system into a stable linear system. We then designed an observer to estimate the angular position and angular velocity of the LED state variables and control inputs and confirms that the receiver signal strength continuously decreases with the link distances over the performance of the optical communication link when the distance between the receiver and the transmitter increases. Figure 11: Output prediction results along with their reference solutions when $u = −0.001\dot{x}_2$: effect of the power signal strength to the distance between the receiver and the transmitter.

| Controller | Distance $d$ | $x_1 - \hat{x}_1$ [rad] | $x_2 - \hat{x}_2$ [rad/s] | $y_1 - \hat{y}_1$ [W] | $y_2 - \hat{y}_2$ [W] |
|------------|-------------|-------------------------|-------------------------|---------------------|---------------------|
| $u = 0.1 \cos(5t \times 0.01)$ | $d = 0.085$ | $7.4 \times 10^{-3}$ | $51.7 \times 10^{-3}$ | $11.6 \times 10^{-3}$ | $19.3 \times 10^{-3}$ |
|            | $d = 0.1$   | $6.9 \times 10^{-3}$ | $45.6 \times 10^{-3}$ | $7.8 \times 10^{-3}$ | $13.4 \times 10^{-3}$ |
|            | $d = 0.2$   | $5.7 \times 10^{-3}$ | $50.3 \times 10^{-3}$ | $1.73 \times 10^{-3}$ | $2.54 \times 10^{-3}$ |
| $u = 0.1 \cos(5t \times 0.01) + 0.2 \sin(5t \times 0.01)$ | $d = 0.085$ | $6.64 \times 10^{-3}$ | $40.1 \times 10^{-3}$ | $13.0 \times 10^{-3}$ | $15.6 \times 10^{-3}$ |
|            | $d = 0.1$   | $5.7 \times 10^{-3}$ | $31.5 \times 10^{-3}$ | $6.8 \times 10^{-3}$ | $10.9 \times 10^{-3}$ |
|            | $d = 0.2$   | $7.3 \times 10^{-3}$ | $24.7 \times 10^{-3}$ | $2.2 \times 10^{-3}$ | $3.1 \times 10^{-3}$ |
| $u = −0.001\dot{x}_2$ | $d = 0.085$ | $6.3 \times 10^{-3}$ | $22.0 \times 10^{-3}$ | $8.4 \times 10^{-3}$ | $16.7 \times 10^{-3}$ |
|            | $d = 0.1$   | $4.9 \times 10^{-3}$ | $43.3 \times 10^{-3}$ | $5.1 \times 10^{-3}$ | $9.5 \times 10^{-3}$ |
|            | $d = 0.2$   | $5.4 \times 10^{-3}$ | $30.9 \times 10^{-3}$ | $1.6 \times 10^{-3}$ | $2.5 \times 10^{-3}$ |

4.2 Sensitivity Analysis

We have conducted simulations in the loop with the inputs signal and the closed-loop controller to examine the performance of the optical communication link when the distance between the receiver and the transmitter increases. As illustrated in Figs. 9-10 and 11, we observe that the signal strength significantly decreases in both excitation input and closed-loop signals when the distance between the transmitter and the receiver increases. Furthermore, Table 2 shows the RMSE of the state estimation and output power prediction errors performance with different link distances and control inputs and confirms that the receiver signal strength continuously decreases with the link distances over the prediction time.

5 Conclusion

In this paper, we have leveraged the power of deep learning-based observer design to estimate the LED state variables and analyze the output power prediction under measurement noise on the underwater optical communication channel. Indeed, we presented a numerical method for constructing the mapping, which drives the LED discrete-time nonlinear system into a stable linear system. We then designed an observer to estimate the angular position and angular velocity of the LED system. Using the learned mapping for constant input setting (for instance, open-loop setting) and measurement
noises, we have shown that the proposed deep learning framework can identify the LED states for small enough inputs signal, including a closed-loop control.

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