Towards AI-enhanced VLC Systems

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Abstract: We demonstrate that position prediction is feasible in industrial applications with visible light communication (VLC), using artificial intelligence. Accordingly, a long short-term memory neural network is suggested, after experimental demonstrations of the optimized VLC systems.

1. Introduction

Optimization theory is widely used to solve signal processing problems in the physical layer of optical communication systems [1]. Nonetheless, there are practical problems in which artificial intelligence (AI) based on machine learning (ML) can play important roles due to a lack of appropriate system models [2]. Recently, several research groups provided insights into the potential of ML in visible light communication (VLC) systems [3–5]. VLC describes optical wireless communications in which light emitting diodes (LEDs) are implemented for mobile communications. This technology is useful in industrial applications where additional spectrum is needed, and it can be integrated with 5G to offload a significant amount of ultra-reliable and low-latency traffic to the optical domain [6]. The potential of ML algorithms can be exploited in VLC to enhance system performance, to mitigate nonlinear effects, to compensate jitter, to identify modulation format, and to estimate phase deviation, among others [7]. In this paper, we highlight the potential of a long short-term memory (LSTM) neural network in position prediction of VLC systems with optimized parameters in indoor industrial applications. The LSTM-based AI procedure takes into account Pareto fronts obtained after multi-objective optimization in a VLC appropriate numerical model, we thoughtfully denominated Digital Twin (DT) after validation with experimental results.

2. VLC Measurement Setup and Its Virtual Object

Fig. 1(a) depicts the measurement setup used to evaluate the performance of the different VLC scenarios obtained by varying the transmission distances. The standard 5 MHz new radio (NR) analog signals available at the arbitrary function generator (AFG) output were amplified and superimposed onto a bias current (I_{bias}). The output of the Bias-Tee was directly supplied to a commercial LumiLED white LED. After propagation through the line-of-sight (LOS) channels, supported by bi-convex lenses, the VLC signals were detected by a HAMAMATSU photodiode (PD) before analog-to-digital conversion by a mixed domain oscilloscope (MDO) and offline signal processing.

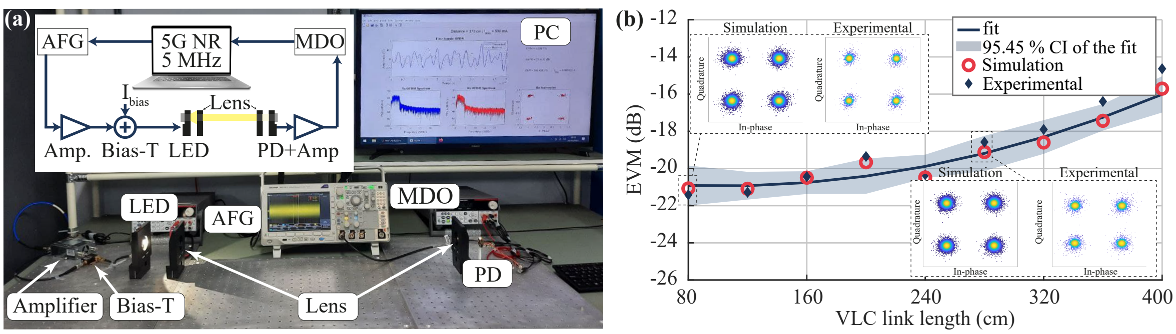

Fig. 1. (a) Measurement setup and (b) performance comparison with its virtual object (DT).

To establish a logical copy (a.k.a., virtual object) of the setup (physical object) we conducted experiments with the VLC scenarios in a linear regime, i.e., disregarding nonlinear effects, by considering the 5G NR signals ($B_W = 5$ MHz) centered at $f_c = 7.5$ MHz with $I_{bias} = 500$ mA and optical modulation index OMI $= (I_{max} - I_{bias})/I_{bias} = 0.267$, for I_{max} the maximum amplitude of the LED current. Moreover, with the error vector magnitude (EVM) measured at each distance, we estimated the system signal-to-noise ratios (SNRs) assuming that

SNR$\approx \frac{1}{\text{EVM}^2}$. Thereafter, we performed simulations with numerical models in which the impact of the transmission distances was included according to the estimated SNRs. Fig.1(b) show performance comparisons between the experimental and the simulation results. As shown in Fig. 1(b), almost all measured EVMs are located in the 95.45 % confidential interval (CI) of the simulation fit curve. This allowed the "timid" Digital Twin denomination.

3. Multi-Objective System Optimization and Parameters Forecasting of Predicted Position via LSTM

We implemented a hybrid multi-objective optimization (HMO) procedure based on the multi-objective Grey Wolf optimizer (MOGWO) and the non-sorting genetic algorithm III (NSGA3) to optimize the parameters of the links ranging from 80 to 400 cm. Table 1 shows that the objectives were to minimize transmitted power (P_T) and guard band (B_G) aiming at power and spectral efficiencies respectively, without important performance penalties [see the EVM measurements shown in Fig. 2(c)]. It is worth mentioning that, to maintain performance, reductions in I_{bias} conduct to increases in OMI, as well as in B_G due to intermodulation distortions (IMD) [1]. The polarization current was limited to 2000 mA to limit the impact of the nonlinearities introduced by the LED.

Table 1. Problem formulation. $x_T(n)$ represents the 5G NR signals and d the link distance.

Min. $P_T = \frac{1}{N}\sum_{n=1}^{N}\lvert x_T(n)\rvert^2$ and **Min.** $\frac{B_G}{B_W}$, **s.t.**			
$\lvert 1 - \lvert\frac{EVM(d)}{SNR(d)}\rvert\rvert < 10\%$	$0.1 \leq \text{OMI} \leq 1$	$50 \leq I_{bias} \leq 2000$ mA	$0.1 \leq \frac{B_G}{B_W} \leq 0.5$

Event forecasting is an important issue in the scenario depicted in Fig. 3(a), in which two robots move on a belt in a straight line. Predictions of robots' position can be accomplished to enhance the performance of the VLC LOS links with parameters optimized by the HMO. Here, we suggested the LSTM artificial neural network (ANN) to predict future positions and to forecast the VLC parameters of the positions, taking into account the Pareto fonts provided by the HMO. The interpolation skill of ANNs allowed parameter estimation of link distances that were not optimized and the memorization of past events, that characterizes LSTMs, contributed to the prediction process. Thus, the last (d_{k-1}) and the current (d_k) positions of a robot were the inputs of the LSTM and its outputs were B_G/B_W, I_{bias} and OMI of the predicted position. Considering that our VLC links cover distances between 80 and 400 cm with a step of 10 cm, the column normalized dataset was generated considering all the combination between d_{k-1}, d_k as well as B_G/B_W, I_{bias} and OMI of d_{k+1}, in each step. The training output dataset was extracted from the knee-point of each Pareto front provided by the HMO. For example, if $d_{k-1} = 80$ cm, $d_k = 90$ cm, $d_{k+1} = 100$ cm and $(B_G/B_W, I_{bias}, \text{OMI}) = (a,b,c)$ for $d_{k+1} = 100$ cm, a sample of the dataset can be obtained by the input $(d_{k-1}, d_k) = (80, 90)$ and the output $(B_G/B_W, I_{bias}, \text{OMI}) = (a,b,c)$. It is noteworthy that the robots only move to neighboring distances of the considered steps and they update their current positions via an uplink which is out of the scope of this work. Fig. 3(b) shows the LSTM architecture composed by four hidden layers with 512, 1028, 256 and 64 units, respectively, and by an output layer with 3 units. Hyperbolic tangent and rectified linear unit are the activation functions of the hidden and the output layers, respectively. The LSTM was trained using the Adam optimization algorithm, considering 2048 epochs with a batch size equal to 8 samples.

4. Results and Discussion

The first Pareto front, as well as boxplots with the range of the optimized variables, provided by the HMO at a link of 280 cm are shown in Fig. 2(a). As expected, lower guard bands demand higher transmission powers [1].

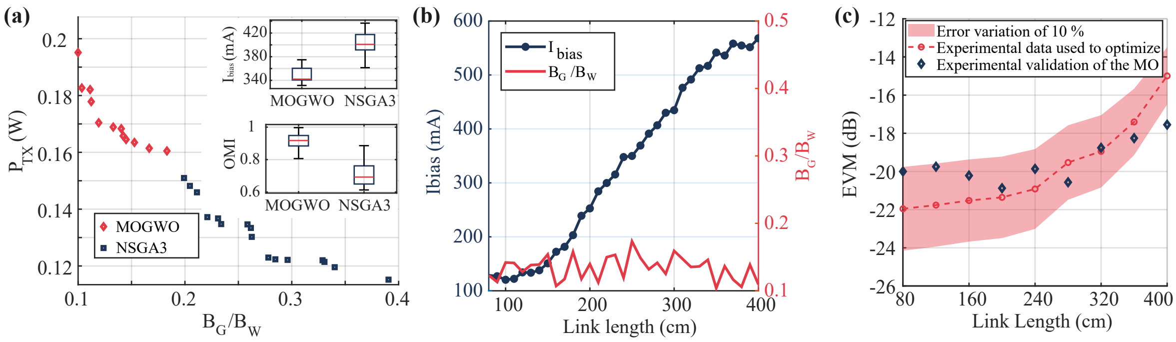

Fig. 2. (a) HMO Pareto front at a link of 280 cm. The insets show boxplots of I_{bias} and OMI. (b) I_{bias} and B_G/B_W versus link distances. (c) Validation of the optimization procedure with experiments.

Fig. 2(b) shows the bias currents provided by the optimization procedure at the knee-points of each Pareto front. The optimized I_{bias} over the increasing transmission distance also increases to overcome the signal attenuation and the noise effects. This power growth benefits the guard band minimization and the relative short variation in the OMI, as illustrated by the B_G/B_W values shown in Fig. 2(b) and the OMI boxplot shown inset Fig. 2(a), respectively. The EVM comparisons shown in Fig. 2(c) demonstrate that, in general, the VLC link performances were maintained after the adoption of the HMO procedure. The performance enhancement registered at 400 cm was guaranteed by the use of a larger OMI determined by the HMO.

As aforementioned, the Pareto fronts returned by the HMO were used in the forecasting described in Section 3. Therefore, the original dataset was divided in 15% for test and 85% for training. Analyzing training losses, the model checkpoint returned an RMSE of 5.10% after training and 7.68% after test. The convergent loss curves for the train and test dataset shown in Fig. 3(c) demonstrate that overfitting did not occur. The success of the proposed LSTM was validated by the RMSE $= 5.10\%$ obtained with the training dataset, as well as by the EVM errors less than 6% shown in Fig. 3(c). These errors were calculated with the system performances obtained with the parameters extracted from the Pareto fronts and the ones returned by the LSTM.

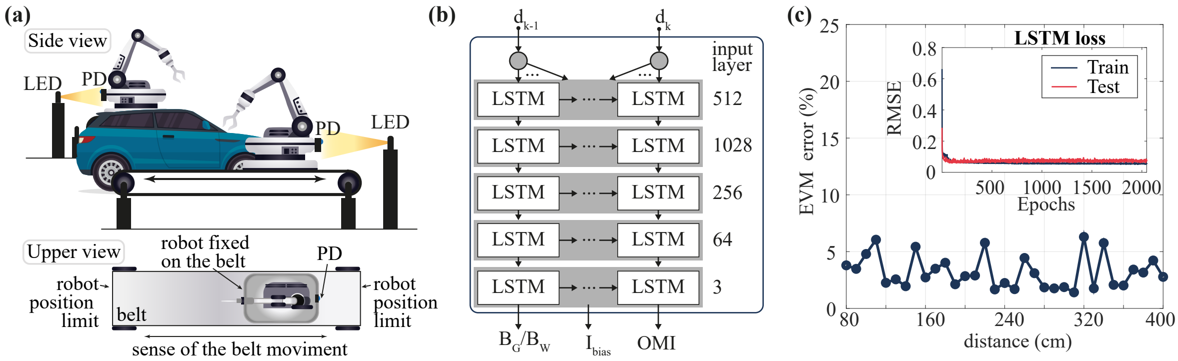

Fig. 3. (a) Industrial scenario with two robots moving on a belt in a straight line. (b) LSTM architecture used to predict positions and the VLC parameters of the positions. (c) EVM error at each link distance and RMSEs obtained with training and test.

5. Conclusion

Artificial intelligence based on LSTM neural network was proposed to forecast position and optimal parameterization of VLC systems in industrial scenarios. Our numerical and experimental results show that multi-objective optimization is mandatory for robust operation in scenarios where transmission power and guard band are minimized aiming at energy and spectral efficiencies, respectively. In low SNR scenarios that represent relative long link distances, we observed that AI can be useful to achieve performance enhancements.

6. Acknowledgements

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