# An Artificial Intelligence-based Error Correction for Optical Camera Communication

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***Abstract*—** Optical Camera Communication (OCC) is promising to be the candidate for vehicular wireless communication due to its low cost, unlicensed spectrum and safe for human. Our most recent approach is to add region-of-interest (RoI) signaling functionality for cars via either headlight or taillight using hybrid of a low-rate waveform and high-rate waveform, which is already standardized in IEEE 802.15.7 standard. However, commercialize OCC for vehicular communication still be challenging work. In this paper, we proposed a novel error correction method based on the most trending technology – artificial intelligence (AI) to deal with the various existing issues in the communication channel. The simulation for analyzing the performance of a new method in enhancing the performance of the communication system also be provided

***Keywords—artificial intelligence (AI), error correction, hybrid-spatial-phase-shift-keying (HS-PSK), dimmable-spatial-8-phase-shift-keying (DS8-PSK), optical camera communication (OCC), vehicular wireless communication, IEEE 802.15.7***

## I. Introduction

Hybrid Spatial Phase Shift Keying (HS-PSK) is a typical modulation scheme which had been introduced in IEEE 802.15.7-2018 standard as a hybrid waveform of Optical Camera Communication (OCC) and Vehicle-to-Everything (V2X) communication system [1]. The purpose of the proposed hybrid waveform is to reduce the computational cost which is paid by a receiver (Rx) to detect the light source Tx(s) and demodulating the data [2]. Beside those advantage of the region of interest (RoI) signaling OCC technique, the ability to commercialize in the vehicular communication system still be uncertain and facing many challenges, as mentioned in [3]. One of those big concerns is the stability and reliability of OCC over such complicate and unpredictable channel condition in the V2V system.

Fortunately, recent developments in deep learning technologies provide us a new way to approach and deal with this issue. Instead of deriving a complex mathematical algorithm from a pre-defined system model, deep learning, or AI technologies allow the system to learn and approximate an optimizing model directly from training data. Deep learning has proved itself as an efficient tool to deal with various type of problem, including computer vision [4], speech recognition [5], autonomous vehicles [6], and also communication field [7-9]. Relying on those strength of AI, in this paper, we proposed a novel AI-based error correction (AIEC) to enhance the accuracy of a vehicular communication system in a count on the complex channel condition.

The structure of our paper will be as follow. In section II, we present the architecture of our recent RoI signaling OCC system, which is proposed for V2X scenario. The channel model will be reconstructed with the concern about the blurry phenomenon. In section III, we introduce our novel error correction method based on AI technology, including novel encoding and decoding techniques to deal with such a channel model in the previous section. Section IV will provide our experimental result in proving the robustness of the proposed technique. Finally, Section V is the conclusion of our work.

## II. VEHICULAR OCC SYSTEM

### A. Transmitter architecture

In the transmitter side of our vehicular OCC system, we use the hybrid of a low-rate scheme and a high-rate scheme to modulated the transmitting signal. The main purpose is to simultaneously transfer two data stream using the same transmitter LED array. Figure 1 shows the architecture of a vehicular OCC transmitter, which is proposed by us in [10].

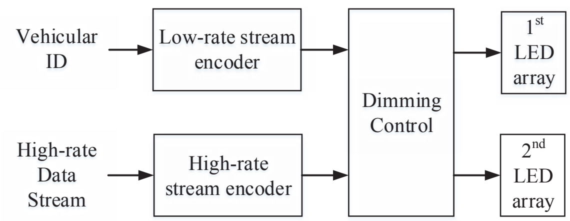



Figure 1. The transmitter architecture in a vehicular OCC system

The low and high-rate data streams can be transmitted using the LED arrays (LED headlights, LED tail lights, etc.) of vehicles. The low-rate stream carries the RoI information (vehicular identity), while the high-rate stream carries the other data support for driving safety purpose (distance, velocity, angle of arrival, etc.). To combine these two streams into the hybrid waveform, the low-rate stream is generated by controlling the dimming level of a high-rate stream, as illustrated in Figure 2.

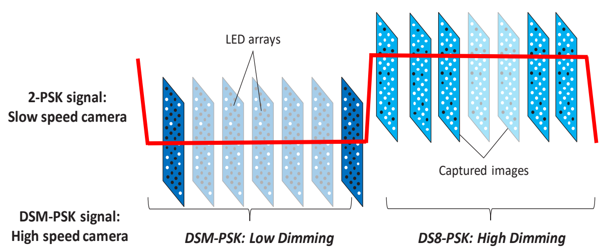



Figure 2. Hybrid waveform using S2-PSK and DS8-PSK modulation scheme

### B. Receiver architecture

In receiving data from the transmitted hybrid waveform, light source identification and demodulation of high-speed data can be time slotted using a single camera. This means that the camera Rx first detects the RoI from the light source identification signal, and then selects the RoI to accelerate the frame rate and achieve high-speed data link. However, the movement between Tx and Rx is considered and the RoI may also move.

The alternative solution is the use of a dual-camera system in which one camera simultaneously detects the RoI for another camera that is demodulating data at high-speed. The low frame-rate (e.g. 30fps) camera shall be used to detect the RoI to reduce cost [4]. This idea is illustrated from the receiver architecture in Figure 3.

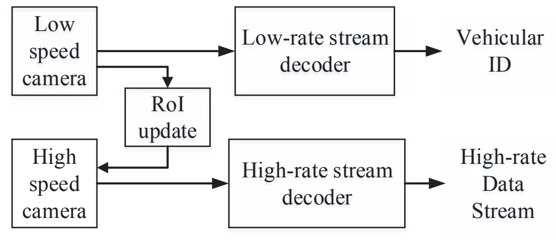



Figure 3. The receiver architecture in vehicular OCC system

### C. Channel model

The channel modeling and coding theory in wireless communication have been studied and developed over many decades. Eventually, nowadays many research works are trying to make the estimation on the channel model from the real world using deep learning technologies [11][12]. However, visible light communication (VLC), as well as OCC still be a premature research area; thus, to apply VLC/OCC in vehicular wireless communication, there still need more intensive research works on the channel model of vehicular OCC system. Figure 4 illustrates our idea of modeling the channel in the V2X communication system.

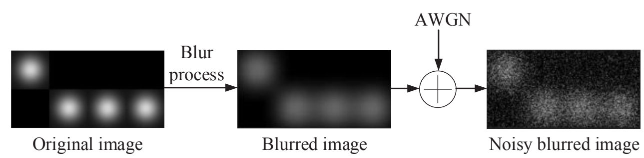



Figure 4. Channel model in vehicular OCC system

The most basic and inevitable factor cause degradation on any communication system is the white Gaussian noise. In the VLC/OCC system, there is various source of white noise such as ambient light radiation from the sun, street light. The unique feature makes OCC is different is the receiver components, which mostly rely on camera and image processing. That fact leads our concern to another issue that can happen in a camera-based communication system: blur phenomenon.

In vehicular OCC system, the source of blur could be varied of, including motion blur, losing focus on the camera, and weather condition such as foggy, rainy or snowy.

## III. AI-BASED ERROR CORRECTION

The existing forward error correction (FEC) technologies are designed to reduce noise when transmitting data at a far distance. However, when we concern about other types of data contamination in vehicular wireless communication including blur phenomenon (motion blur, rainy, foggy, snowy), these technologies are no longer an optimum solution. Propose a new channel coding scheme could be costly since nowadays AI technology can be trained from real-world data to find the approximation of an optimum solution that can perform well in various channel models. In this section, we will demonstrate our proposed AI-based Error Correction (AIEC), which include the novel mapping (encoding) and decoding method.

### *A. AIEC Encoder*

Traditionally, for error correction purpose, the high-rate bitstream will be encoded using channel coding before being mapped into symbols [3]. Our proposed error correction technique is a bit different while it tries to transform each symbol in transmitting data to a new form – a group of new symbols, following pre-defined mapping table. Table 1 provided our example mapping table when the number of symbols in a group is 3.

Table 1. AIEC encoding table with a group of 3 symbols

| **0** | **1** | **2** | **3** | **4** | **5** | **6** | **7** |
|---|---|---|---|---|---|---|---|
| 075 | 476 | 634 | 457 | 542 | 314 | 130 | 124 |
| 750 | 764 | 346 | 574 | 425 | 143 | 301 | 241 |
| 507 | 647 | 463 | 745 | 254 | 431 | 013 | 412 |

Each symbol, or *S_Phase* value, from 0 to 7 (with our concern on applying this error correction coding to DS8-PSK modulation scheme) will be either mapped to 1 out of 3 cases in the column corresponding to that symbol. By using this encoding method, we indirectly increase the Hamming distance between two adjacent symbols in the constellation diagram and somehow spreading the distance equally among symbols. The Hamming distance between two groups in Table 1 could be calculated using the following equation:

$$d = \sum_{i=1}^{3} d_{Hamming}(S_i(A), S_i(B)) \qquad (1)$$

where: $S_i(A)$ : $i^{th}$ symbol of group A

$S_i(B)$ : $i^{th}$ symbol of group B

By using the encoding method in Table 1, we increase the minimum Hamming distance among symbols to 3. This is the main factor make our proposed coding technique be efficient in lowering the symbol error rate significantly.

### *B. AIEC Decoder*

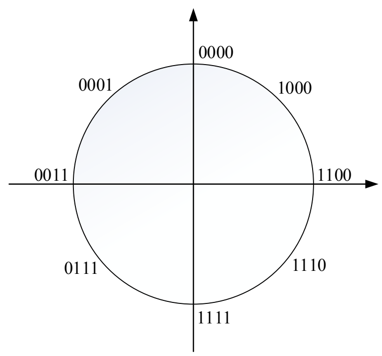
AIEC decoder core principle based on a fully-connect multilayer perceptron neural network. The sample set of parameters (number of hidden layers, number of neurons, an optimizing algorithm, etc.) we used for designing the AIEC decoder is provided in Table 2.

Table 2. A sample of parameters set for designing an AIEC decoder

| | |
|---|---|
| Number of hidden layers | 4 |
| Number of neurons in layers | 12-81-81-8 |
| Optimization algorithm | Adam Optimizer |
| Beta value for regularization | $10^{-4}$ |
| Number of learning epochs | 500 |

The input of AIEC are symbols after demodulating process. These symbols will be gathering to each group of three symbols for error correction purpose. Before these groups of symbols are fed into an Artificial Neural Network, it needs to be passed through a data preprocessing process follow the constellation diagram, as illustrated in Figure 5.

Follow the constellation diagram in Figure 5, the preprocessing step will remap 8 symbols to the appropriate form and make AI understand our definition of Hamming distance among symbols in the previous subsection. This diagram also shows that, in DS8-PSK, the minimum distance among symbols will be 1, and the maximum is 4, as when we concern about the normal Hamming distance defined in [13], for the new 4-bit form.




| **3-bits Input** | **Global Phase Shift Output** | **Symbols encoding (Preprocessing)** |
|---|---|---|
| 000 | 0 | 0000 |
| 001 | 1 | 1000 |
| 010 | 2 | 1100 |
| 011 | 3 | 1110 |
| 100 | 4 | 1111 |
| 101 | 5 | 0111 |
| 110 | 6 | 0011 |
| 111 | 7 | 0001 |

Figure 5. DS8-PSK constellation diagram for data pre-processing for AIEC decoder input

## IV. EXPERIMENTAL RESULTS

To prove the enhancement of our proposed error correction scheme on the communication reliability, we set up the experiment for analyzing the symbol error rate of DS8-PSK receiver side while using our AIEC coding technique, and compare it with the non-FEC Rx. The datasets for SER evaluation is prepared by using LabVIEW, with $10^6$ encoded noisy symbols for each signal to noise ratio (SNR) value. Figure 6 shows our experiment result over additive Gaussian white noise (AWGN) channel.

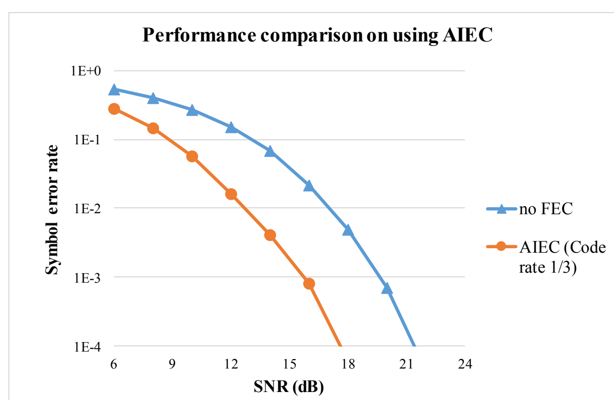



Figure 6. Performance comparison on using AIEC (code rate = 1/3)

From our previous subsection, by using our proposed AIEC encoding table for code rate 1/3 (each symbol is encoded to a 3-symbol group), we have increased the minimum Hamming distance among symbols to 3. This results in the significant decrease of symbol error rate after AIEC decoder.

Figure 6 also shows that to achieve the desire SER performance of an OCC system for V2X condition ($10^{-4}$ as our expectation), by using AIEC with code rate = 1/3, it will always guarantee to reduce the SNR value requirement of an AWGN channel by 4dB approximately.

## V. CONCLUSIONS

In this paper, we present our related research works and achievements in vehicular OCC system. From the concern about existing issues and challenges in the vehicular environment, we proposed the novel error correction approaching based on AI and neural network technique. The unique encoding table for a code rate 1/3 also been provided. Finally, to prove the efficiency of our proposed scheme, the experimental setup and results are also provided, with a significant enhancement in the decoding accuracy.

## ACKNOWLEDGMENT

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## REFERENCES

[1] (2016). Kookmin University PHY sub-proposal for ISC using Dimmable Spatial M-PSK (DSM-PSK), accessed on April. 03, 2019. [Online]. Available: https://mentor.ieee.org/802.15/dcn/16/15-16-0015 -02-007a-kookmin-university-phy-sub-proposal-for-isc-using-dimmablespatial-m-psk-dsm-psk.pptx

[2] T. Nguyen, A. Islam, T. Hossan, and Y. M. Jang, "Current Status and Performance Analysis of Optical Camera Communication Technologies for 5G Networks," in IEEE Access, vol. 5, pp. 4574-4594, 2017

[3] T. Nguyen, A. Islam, and Y. M. Jang, ‘‘Region-of-interest signaling vehicular system using optical camera communications,’’ IEEE Photon.J., vol.9, no. 1, Feb. 2017, Art. no. 7900720.

[4] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., 2016, pp. 770–778.

[5] I. Sutskever, O. Vinyals, and Q. V. Le, “Sequence to sequence learning with neural networks,” in Proc. Adv. Neural Inf. Process. Syst., 2014, pp. 3104–3112.

[6] C. Chen, A. Seff, A. Kornhauser, and J. Xiao, “DeepDriving: Learning affordance for direct perception in autonomous driving,” in Proc. IEEE Int. Conf. Comput. Vis., 2015, pp. 2722–2730.

[7] S. Cammerer, T. Gruber, J. Hoydis, and S. ten Brink, “Scaling deep learning-based decoding of polar codes via partitioning,” arXiv:1702. 06901. [Online]. Available: http://arxiv.org/abs/1702.06901

[8] S. Dörner, S. Cammerer, J. Hoydis and S. t. Brink, "Deep Learning Based Communication Over the Air," in IEEE Journal of Selected Topics in Signal Processing, vol. 12, no. 1, pp. 132-143, Feb. 2018.

[9] F. Liang, C. Shen and F. Wu, "An Iterative BP-CNN Architecture for Channel Decoding," in IEEE Journal of Selected Topics in Signal Processing, vol. 12, no. 1, pp. 144-159, Feb. 2018.

[10] M. D. Thieu, T. L. Pham, T. Nguyen, and Y. M. Jang, “Optical-RoI-Signaling for Vehicular Communication”, unpublished.

[11] Y. Yang, F. Gao, X. Ma, and S. Zhang, "Deep Learning-Based Channel Estimation for Doubly Selective Fading Channels," in IEEE Access, vol. 7, pp. 36579-36589, 2019.

[12] H. Ye, G. Y. Li and B. Juang, "Power of Deep Learning for Channel Estimation and Signal Detection in OFDM Systems," in IEEE Wireless Communications Letters, vol. 7, no. 1, pp. 114-117, Feb. 2018.

[13] Warren, Jr., Henry S. (2013) [2002], Hacker's Delight (2 ed.). Addison Wesley - Pearson Education, Inc. pp. 81–96.