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Auto-Encoder Learning-Based UAV Communications for Livestock Management

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Abstract: The advancement in computing and telecommunication has broadened the applications of drones beyond military surveillance to other fields, such as agriculture. Livestock farming using unmanned aerial vehicle (UAV) systems requires surveillance and monitoring of animals on relatively large farmland. A reliable communication system between UAVs and the ground control station (GCS) is necessary to achieve this. This paper describes learning-based communication strategies and techniques that enable interaction and data exchange between UAVs and a GCS. We propose a deep auto-encoder UAV design framework for end-to-end communications. Simulation results show that the auto-encoder learns joint transmitter (UAV) and receiver (GCS) mapping functions for various communication strategies, such as QPSK, 8PSK, 16PSK and 16QAM, without prior knowledge.

Keywords: unmanned aerial vehicle; convolutional auto-encoder; livestock farming; deep neural networks

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1. Introduction

Unmanned Aerial Vehicles (UAVs), known as drones, are self-driven aircraft that work without a human pilot on board [1]. Different types of UAVs are employed for various intents [2]. Initially, the military used the technology for anti-aircraft target techniques, intelligence gathering and surveillance of enemy territories [2–5]. Moreover, UAV technology has evolved beyond its initial purpose. It has, in recent years, gained prominence in diverse spheres of human endeavour. The ease of operating drone technology results in the widespread applications of UAVs in diverse fields, thus making it a prosperous technology [6]. Livestock farming is one of the promising applications of UAVs, where UAVs simplify various operations for efficient animal management [7–10]. Over the years, livestock farming has faced environmental, economic, technical and strategic planning due to varying climatic conditions, population growth and intense competition for land and other natural resources [11]. Nevertheless, the use of advanced technologies such as Artificial Intelligence (AI), the Internet of Things (IoT), Machine Learning (ML), cutting-edge sensors, etc., integrated with UAVs has recently resulted in the widespread adoption of drone technology amongst livestock farmers [9]. As an illustration, Figure 1 shows a typical UAV conceptual design framework of a livestock farming management system (LFMS). The system consists of four development stages; the water examination system, Long-Range Wide-Area Network (LoRaWAN)-based network planning, drone mounted with sensors and cameras and drone path planning optimization. The cattle are fitted with transceivers around their necks. This provides a means for sharing information between the drone and the ground station.

The UAVs are controlled either remotely or manually by a pilot at a ground station, guided using a pre-programmed flight procedure. Wireless communication is one of the critical technologies for UAV wireless communication and is classified into a command and control link and a data link [12]. The command and control link provides essential information about the environment, operating conditions and control instructions for a UAV's safe operation. Therefore, it requires high reliability and low latency. Compared to the command and control link, the data link often maintains the target-related information and thus supports higher data rates

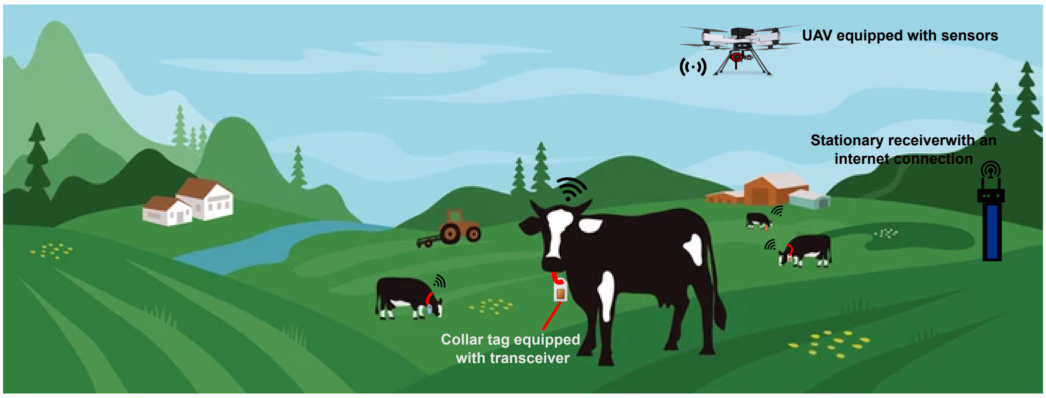

Figure 1. Conceptual framework of UAV-based farm monitoring system [13].

1.1. Motivation

The use of UAVs for livestock location, detection, activity monitoring, anomaly detection and rearing requires onboard sensors operating at radio frequencies (RF) of 2.4 and 5.8 GHz for reliable data transfer between the UAVs and the ground stations [1,4]. However, due to traffic of the target-related UAV data, the tasks become more strenuous and demanding as the resolution of the onboard sensors becomes higher, specifically in the backbone network [14]. Accordingly, this imposes enormous demands on the communication system as well as the challenge of decoding the transmitted data with minimum error probability at the user end. Livestock farming requires extensive farmland, located mainly in rural areas. It is known that many rural areas, even in developed countries, are significantly under-connected with mobile wireless technology. Therefore deploying 5G test beds in rural areas can motivate service providers to improve internet connectivity. Recently, the United Kingdom (UK) launched a project called 5G Rural Integrated Test bed (5GRIT) to create test beds for 5G in rural areas [3]. The project seeks to demonstrate the role 5G networks can play in consolidating farming and tourism sectors using an integrated system of UAVs and AI technologies. Therefore, designing a robust communication system that will provide reliable data transfer between UAVs and the GCS is necessary for UAV-based livestock farming.

1.2. Related Works

Beyond using multirotor UAVs for aerial surveillance, substantial research has been performed on UAVs to ease livestock and agricultural farming [15–17]. Drones have explicitly become helpful in monitoring and enhancing crop and livestock production due to real-time data that help farmers respond more quickly to weed incursion, pest infestation, output projections, livestock health conditions and other issues [18]. UAVs and other related technologies, such as the Internet of things (IoT), have been extensively used for smart agriculture and animal farming [9,19–22].

Different types of UAVs are applied in pest control, crop irrigation, animal health monitoring, animal rearing and other agriculture-related activities [19]. The joint application that both IoT and UAVs can play in smart-driven agriculture was also discussed in [20]. Maddikunta et al. [9] have explored the architecture, adaption and usage of UAVs for smart agriculture. The authors highlighted the UAV's applications and related technologies to efficiently enhance and optimize diverse agricultural processes using smart Bluetooth-enabled sensors. However, reliable data transfer was the major drawback of this approach due to the short range of the Bluetooth UAV-enabled system. In some scenarios, UAVs could be used as tools for mechanized agriculture to ameliorate disorders in various fields through commercial, scientific, agricultural and livestock enhancement [21]. Specifically, the paper focused on providing details of mechanized agriculture using UAV systems for pesticides and fertilizer application in farms that were obstacle rich. Other issues related to the lack of awareness and special education on precision agriculture in animal farming using UAV technology were also highlighted. Furthermore, Alanezi et al. [22] presented a comprehensive review of the state-of-the-art techniques incorporated with UAVs for livestock. The authors highlighted various pressing issues, challenges and opportunities associated with livestock management.

AI and ML have drawn growing research interests and are ubiquitously emerging in many fields due to their capability to model systems through learning from data [23]. Recently, studies and findings have unveiled the potential benefits of deploying AI and machine learning techniques and UAVs for effective livestock farming [2,3,8,24–26]. Studies have shown the feasibility of using UAV video monitoring to predict the food eating behaviour of rangeland-raised Raramuri Criollo non-nursing beef cows [2]. To address the problem associated with animal counting, a computer vision pipeline that uses DNN architecture for automated Holstein Friesian cattle detection and identification was proposed in [24]. The authors introduced a video processing mechanism to efficiently monitor dynamic cattle footage filmed by UAVs. However, the UAV was manually flown and only captured data within small-sized and relatively spaced herds. Rivas et al. [25] presented the use of artificial intelligence techniques for real-time analysis and cattle monitoring using the information captured by drones. The authors used a camera installed in the drone to take images that were later analysed using Convolutional Neural Networks (CNNs) for cattle identification captured in the images. However, the model could not determine the number of animals in a cluster with utmost precision. Furthermore, a test bed implementation that used deep learning algorithms was designed for precision livestock detection and counting from aerial images captured by drones. In the same vein, the use of UAVs to track the postural position of cattle and sheep was studied in [8] to find the optimal number of UAVs that minimizes the UAV-animal distance using a streaming K-means clustering algorithm. All the targeted herds were fitted with global positioning system (GPS) neckbands to monitor their movements. A dual-stream deep learning (DL) architecture that combined exploration strategies learned from previous experiences with instantaneous sensory inputs was proposed to capture the movement of the cattle [26].

Nonetheless, accurate livestock counting in a multi-path crossing by the same animal is still an open problem. While many works of the literature mainly focus on combining ML algorithms with UAVs for efficient smart farming and livestock management, little or no attention is paid to the part that involves data transfer within the UAV communication network. ML techniques, specifically DL, have been used to solve many physical layer communication problems [27–29]. Therefore, this paper proposes a learning framework for an efficient and reliable communications system for UAV-based livestock management. Our contributions are summarized below:

- We built an auto-encoder for end-to-end wireless communications for UAV-assisted livestock management systems. We showed that learning the entire transmitter (UAV) and receiver (GCS or UAV) implementations for a given communication channel link optimized for a chosen loss function (e.g. minimizing BER) is possible. The basic idea is to describe the transmitter, channel, and receiver as a single deep CNN that can be trained as an auto-encoder. Interestingly, this technique can be used as a model approximator to approximate optimal solutions for systems with unknown channel models and loss functions.
- We simulated the communication links with a different set of communication rates to learn various communication schemes, such as QPSK, 8PSK and 16QAM.

- For a (7, 4) communication rate, the proposed auto-encoder performance matched the optimal Hamming code maximum likelihood decoding scheme.

The remainder of the paper is structured as follows: The system model and problem are presented in Section 2. The proposed methodology is described in Section 3. Section 4 presents the simulation results and discussions. Finally, Section 5 summarizes and concludes the paper.

Notations: We use bold uppercase symbols for matrices, bold lowercase symbols for vectors and lowercase symbols for scalars. Finally, notation $\mathscr{L}(\cdot)$ is reserved for the loss function.

2. System Model and Problem Formulation

Reliable communication among UAVs monitoring livestock is critical for efficient and accurate data transmission for managing large herds. Figure 2 portrays a typical high-speed local architecture network constructed over long-distance WiFi access points to establish communication with UAVs and the ground control stations used for cattle and sheep rearing. The UAVs are equipped with onboard cameras and sensors used for taking images of herds and territorial surveillance. Information about the locations of animals is exchanged between the UAVs and the ground control station (GCS), which could be monitored manually or remotely by a human operator.

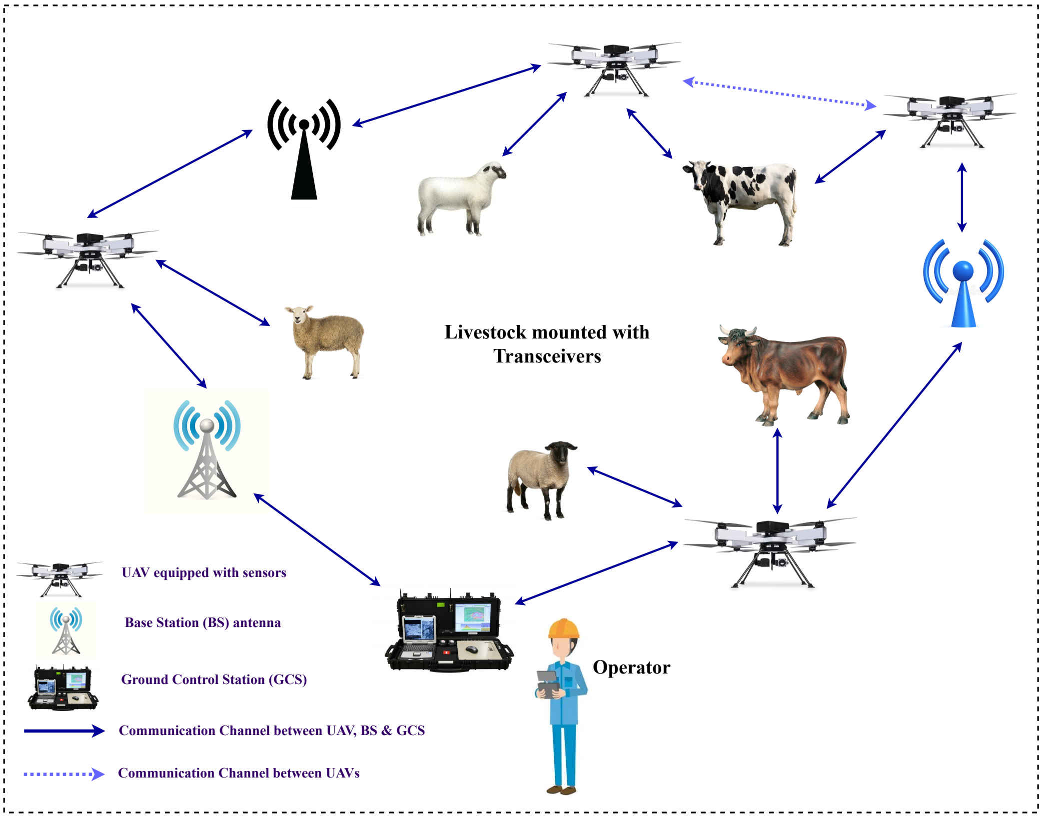

Figure 2. Communications network architecture of UAV-based livestock management system.

Throughout this section, we assume a known perfect channel state information (CSI) between the UAVs and the GCS. The communication links between the UAVs and the GCS can be viewed as a simple communications system consisting of a transmitter, a channel and a receiver. Suppose the UAV wants to send one out of M possible messages $s \in \mathbb{M} = \{1, 2, \cdots, M\}$ to another UAV or GCS through a wireless fading channel. Then the received message is modelled as

$$y = hx + n_0 \tag{1}$$

where x, h and n are the message. The complex baseband message is converted to its equivalent real format using the transformation $f : \mathbb{M} \rightarrow \mathbb{R}^{2n}$ to the message s to generate the transmitted signal $x = f(s) \in \mathbb{R}^{2n}$. It should be noted that the UAV imposes some constraints on the x based on either average energy or average power of the transmitted message as follows [30]

$$\|\mathbf{x}\|_2^2 \leq 2n, \tag{2}$$

$$\mathbb{E}[|x_i|^2] \leq 1. \tag{3}$$

For simplicity, we use Quadrature phase shift keying (QPSK) and 8-phase shift keying (8PSK) modulation schemes because of their abilities to transmit two bits and three per symbol, respectively. As an illustration, for QPSK, the transmitted symbols $s \in \mathbb{M} = \{\frac{1}{\sqrt{2}} \pm j\frac{1}{\sqrt{2}}, -\frac{1}{\sqrt{2}} \pm j\frac{1}{\sqrt{2}}\}$. Compared to ordinary phase shift keying (PSK), QPSK conveys twice as much information using the same bandwidth [31]. The rate at which the message is sent over a communications channel, known as the communication rate, is given by

$$R = \frac{k}{n} \text{ [bit/channel]}, \tag{4}$$

where $k = \log_2(M)$ and M is the number of symbols or modulation index. Intuitively, (4) shows that the communication system transmits one out of $M = 2^k$ messages through n active channels or channel uses. This is usually presented by the notation (n, k) [32].

3. Proposed Methodology

Generally, a simple communications system can be viewed as a particular type of auto-encoder from the deep learning viewpoint [30,33]. An auto-encoder is an unsupervised learning model that learns to squeeze and reconstruct the input. Therefore, it can be considered a dimensionality reduction framework that allows the input reconstruction at the output with minimal error. However, in our case, the auto-encoder is used for end-to-end communication to learn the representations of the messages s that are robust to the channel impairments mapping $\mathbf{x}$ to $\mathbf{y}$, such that the transmitted information can be recovered with a minimal probability of error. Contrary to redundancy removal from the input data for compression, our proposed auto-encoder usually adds redundancy, learning an intermediate representation robust to channel variations for reliable data transfer.

Firstly, the UAV flies above the livestock to capture data (usually real-time images) about the livestock and send it to the GCS for analysis. The reliable data transfer requires that the UAV communication system be divided into a sequence of communication blocks, which are traditionally optimized individually. Such an approach depends on complex mathematical models that are usually intractable. However, the communication blocks are jointly optimized as a single learning block to simplify the process while ensuring reliable data transfer from the UAVs to the GCS. The proposed auto-encoder is shown in Figure 3. Here, the transmitter, which could be a UAV, is the encoder consisting of feedforward convolutional neural network (CNN) layers followed by a normalization layer that guarantees that the physical constraints on $\mathbf{x}$ are met based on (2) or (3). Accordingly, the input s to the encoder is encoded as a one-hot vector $\mathbf{1}s \in \mathbb{R}^M$, having an M-dimensional vector, the s-th element of which is equal to one and zero otherwise. The wireless channel layer is represented by a fading channel obtained from a random normal distribution with zero mean and unit variance and an Additive White Gaussian Noise (AWGN).

Similarly, the receiver (decoder), which could be the GCS, is also implemented as a feedforward CNN. The decoder's final layer uses a softmax activation whose output $\mathbf{p} \in (0,1)^M$ is a probability vector over all possible messages. The estimated message corresponds to the index of the element of $\mathbf{p}$ with the highest probability value. Consequently, the conditional probability density function $\mathbf{p}(\mathbf{y}|\mathbf{x})$ defines the channel, where $\mathbf{y} \in \mathbb{R}^{2n}$ designates the received signal. Once $\mathbf{y}$ is received, the decoder applies the transformation $g : \mathbb{R}^{2n} \rightarrow \mathbb{M}$ to yield the estimate of the transmitted message $\hat{s}$. We train the auto-encoder end-to-end using stochastic gradient descent (SGD) over all possible messages $s \in \mathbb{M}$ using the appropriate categorical cross-entropy loss function to generate the predicted output or reconstructed estimate of the transmitted message. Therefore, the loss function is given by

$$\mathscr{L}(\boldsymbol{\theta}) = -\frac{1}{N}\sum_{i=1}^{N} s_i \log(\hat{s}), \tag{5}$$

where N is the number of samples, $\boldsymbol{\theta}$ is the model parameters (weights of the neural network), s is the original transmitted message, and $\hat{s}$ is the estimated message.

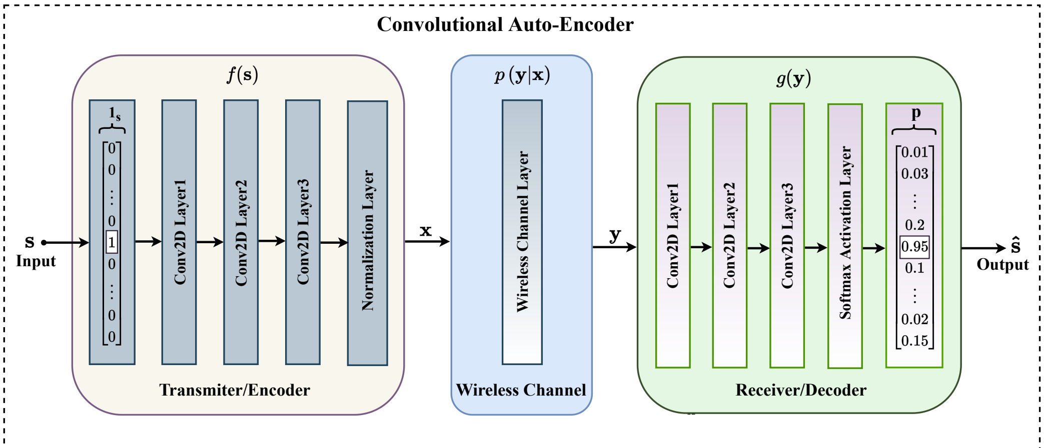

Figure 3. UAV communications system over fading channel depicted as an auto-encoder with an input message s encoded as a one-hot vector.

Accordingly, this end-to-end learning concept is applied to UAV communications, where information about herds (usually images) from the UAVs is sent through a wireless channel to the GCS for effective monitoring. The details of the proposed auto-encoder UAV communications system are shown in Figure 4, and its architectural layout is provided in Table 1.

Table 1. Layout of the proposed UAV-based auto-encoder.

Layer	Output
Input	$(M,\ M,\ 1)$
2D Convolution + ReLU	$(M_{E1},\ M_{E1},\ 2n),\ M_{E1} = \frac{M}{2}$
2D Convolution + ReLU	$(M_{E2},\ M_{E2},\ 2n),\ M_{E2} = \frac{M}{2}$
2D Convolution + ReLU	$(M_{E3},\ M_{E3},\ 2n),\ M_{E3} = \frac{M}{2}$
Flatten	$(M_{E3} \times M_{E3} \times 2n)$
Normalization	$(M_{E3} \times M_{E3} \times 2n)$
Wireless channel + Noise	$(M_{E3} \times M_{E3} \times 2n)$
Fully Connected + ReLU	$(M_{E3} \times M_{E3} \times 2n)$
2D Convolution + ReLU	$(M_{D3},\ M_{D3},\ 2n),\ M_{D3} = \frac{M}{2}$
2D Convolution + ReLU	$(M_{D2},\ M_{D2},\ 2n),\ M_{D2} = \frac{M}{2}$
2D Convolution + ReLU	$(M_{D1},\ M_{D1},\ 2n),\ M_{D1} = \frac{M}{2}$
Fully Connected + softmax	$(M,\ M,\ 1)$

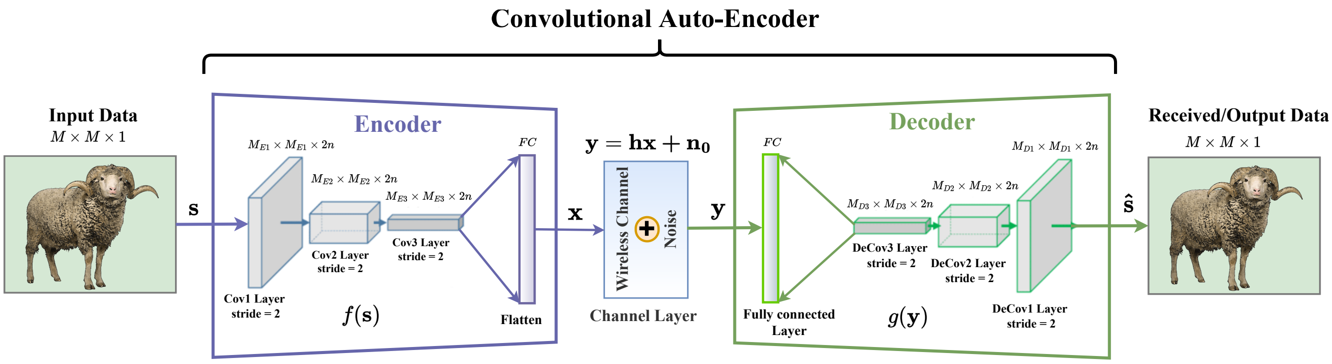

Figure 4. UAV and GCS information communications system over wireless channel presented as an auto-encoder.

Data Generation, Training and Inference

We have generated 50,000 message samples, from which 30,000 are the training samples, and 15,000 samples are used for validation and inference each. The auto-encoder is trained with a fixed signal-to-noise ratio (SNR) or energy per bit to noise power spectral density ($\frac{E_b}{N_0}$) of 7 dB using an Adam optimizer [33] with a learning rate of 0.001. The training was performed with various training batch sizes to determine the appropriate size that gives the best performance. The performance of the trained auto-encoder was tested over different SNR values. We have implemented the auto-encoder model in Keras Tensorflow 2 DL framework and 3.8 Python.

4. Results and Discussions

This section presents the simulation results and discussions based on the performance metric. For performance evaluation, bit-error-rate (BER), $\Pr(\hat{s} \neq s)$ is used as a performance metric for assessing the efficacy of our proposed learning model.

Figure 5 compares the BER performance of a communications system using uncoded QPSK (4, 4) and a Hamming (7,4) code with the optimal maximum likelihood decoding (MLD) against the BER gained by the auto-encoder (7,4) with different training samples and average fixed energy constraints. It can be seen that the performance of the auto-encoder trained with 25,000 training samples matches the Hamming (7, 4) maximum likelihood decoding scheme. We also observe that the auto-encoder's performance falls as the number of training samples decreases. We ensure that the system operates at a 7/4 communication rate for fair performance evaluation. This result reveals that the auto-encoder has learned the UAV and GCS information mapping (i.e., an encoder and decoder function) that achieves the same performance as the Hamming (7,4) code with MLD without prior knowledge.

Figure 6 compares the BER produced when the input data are modulated with binary phase-shift keying (BPSK), QPSK and 8PSK against the BER achieved by the trained auto-encoder with an average fixed energy constraint based on (2). Generally, the number of encoded bits depends on the number of encoded phases. The BPSK uses two distinct phases shifted by 180^0 compared to QPSK, which utilizes four phases to encode the data. Therefore, the QPSK transmits 2-bit data, twice the data transmitted by BPSK per symbol cycle. In contrast, 8PSK uses eight phases, described by a 3-bit transmitting 3-bit symbols per cycle. Accordingly, while the uncoded QPSK (4, 4) produces a BER lower than the BPSK modulation scheme, the Hamming (7, 4) hard decision decoding scheme outperforms all three modulation schemes. Interestingly, the auto-encoder trained with QPSK and 8PSK-modulated symbols performs better than all the baseline communication schemes. We have observed that the performance gap between the auto-encoders trained with QPSK and 8PSK tends to close between 2 and4 dB SNRs. At these SNRs, the communication rate of the auto-encoder trained with QPSK-modulated symbols decreases; it is thus forced to learn a lower modulation scheme. Beyond the 4 dB SNR, a significant decline in BER is observed, suggesting that the auto-encoder trained with the 8PSK modulation scheme learns to transmit more bits per symbol cycle.

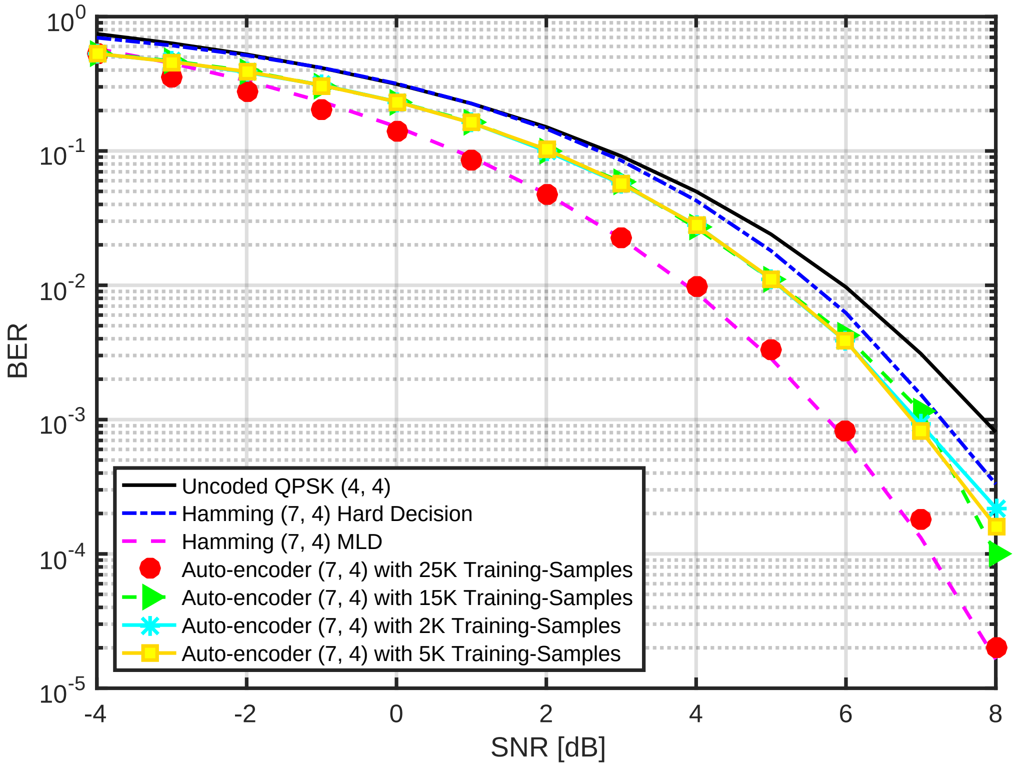

Figure 5. BER vs. SNR for the auto-encoder trained with different amounts of samples against various benchmark communication techniques.

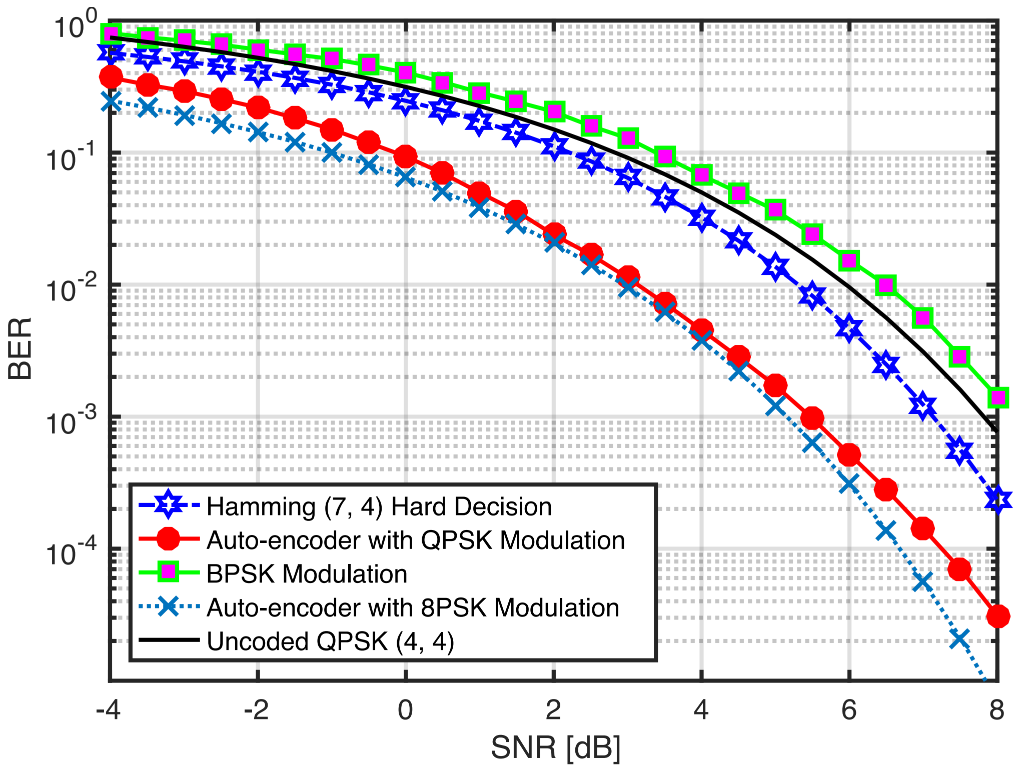

Figure 6. BER vs. SNR for the auto-encoder trained with 25,000 training samples using QPSK and 8PSK modulation schemes against baseline modulation schemes.

Figures 7 and 8 portray the effects of both fixed and varying SNR on the auto-encoder's performance. Figure 7 shows that the BER falls faster when the auto-encoder is trained with a fixed SNR and then saturates at the 25*th* epoch. With this, a relatively small training effort is required for the auto-encoder to learn various communication schemes. However, when the auto-encoder is trained with a varying SNR from -4 to 10 dB, the BER slowly decreases with the training epoch and finally saturates at the 10th epoch, as shown in Figure 8. From these results, we can deduce that an auto-encoder trained with fixed SNR for end-to-end communications converges faster than the one trained with varying SNRs.

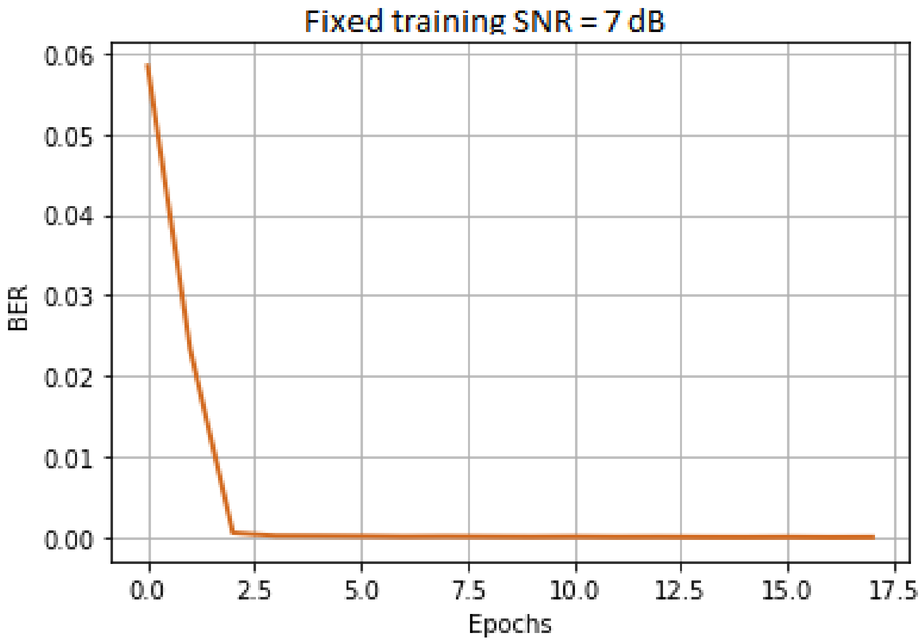

Figure 7. BER vs. the number of epochs of the auto-encoder trained via fixed $SNR =$ dB.

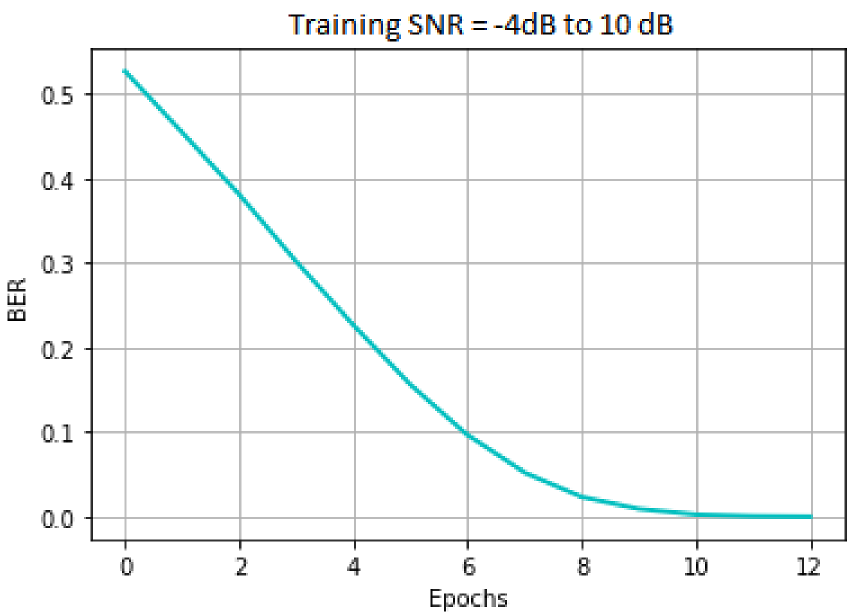

Figure 8. BER vs. the number of epochs of the auto-encoder trained via variable SNR values.

To investigate whether the auto-encoder has learnt some communication schemes without prior knowledge of the channel model, we show the learned constellation representations **x** of all messages for different values of (n, k). Figure 9 depicts a typical $(2, 2)$ system, which assembles rapidly to a classical QPSK constellation rotation. The symbol constellations spread over four possible carrier phases within a unit circle, as in the case of a classical QPSK modulation technique.

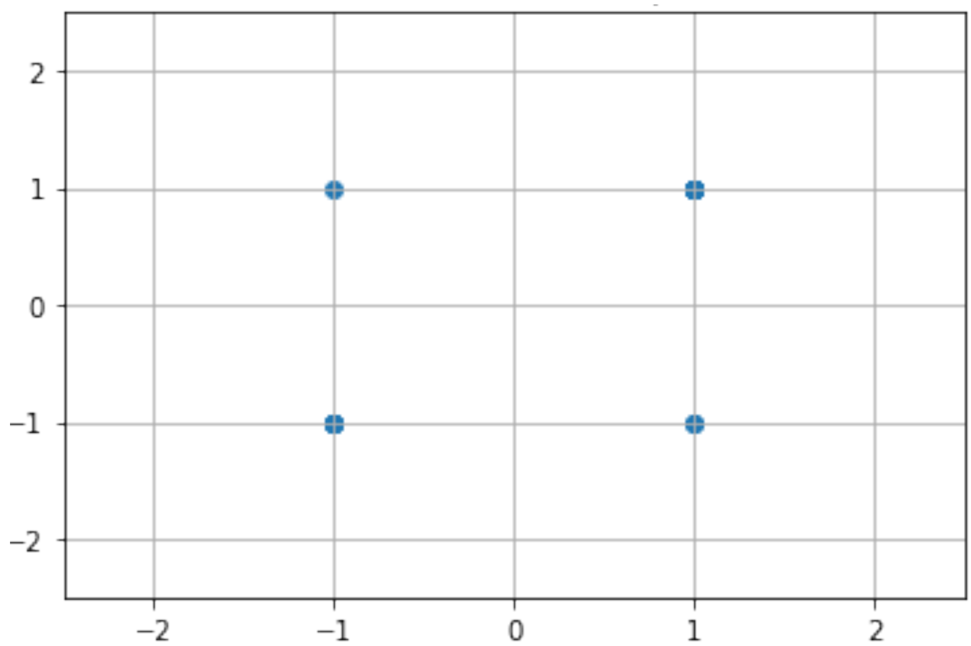

Figure 9. Learned constellation produced by auto-encoders using a (2, 2) communication rate with an average energy constraint.

Correspondingly, Figure 10 illustrates a $(4, 2)$ communication system that produces a rotated 16PSK constellation. Interestingly, with a fixed, average energy constraint, the resulting constellation produced by the learned auto-encoder is similar to the one constructed by the classical 16PSK. The effect of the choice of normalization function for a transmit message under some constraints is noticeable from Figure 11 for the same settings but with an average power normalization rather than an average fixed energy constraint. This produces an intriguing hybrid pentagonal/hexagonal grid structure similar to the performance from a distorted 16QAM constellation with a symbol near the origin surrounded by five equally spaced nearest neighbours. Therefore, this shows that an auto-encoder trained with the average energy constraint produces a much more regular and well-defined communication scheme that matches a particular classical communication technique.

To find whether the proposed auto-encoder is doing well during the learning phase, we compare the training loss against the validation loss in Figure 12. It can be observed that both the training loss and validation loss converge at the eighth iteration. This further demonstrates that the auto-encoder is doing well in learning various communication strategies for efficient data transfer between the UAVs and the GCS.

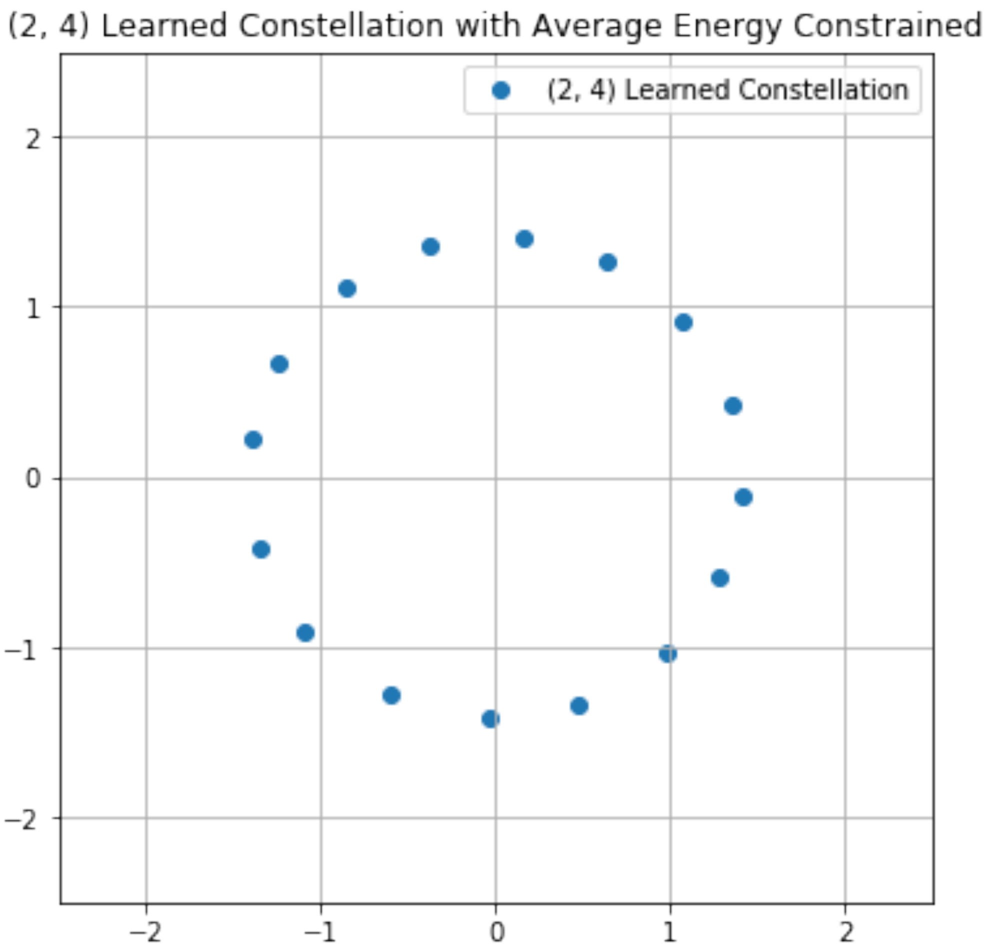

Figure 10. BER vs. SNR for the auto-encoder test with different amounts of test samples against various benchmark communication techniques.

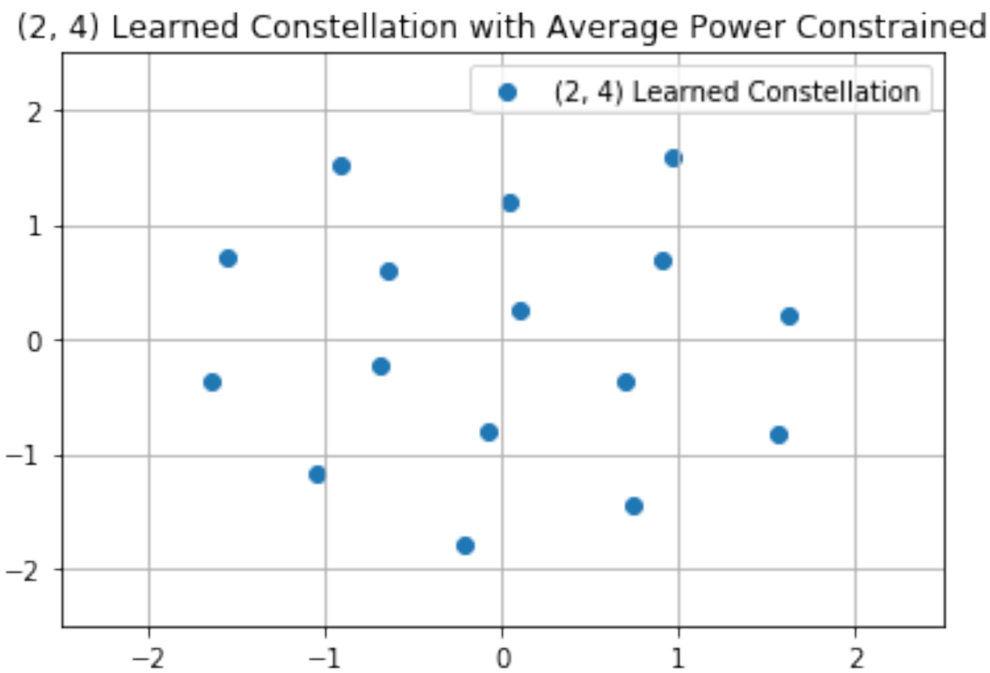

Figure 11. BER vs. SNR for the auto-encoder test with different amounts of test samples against various benchmark communication techniques.

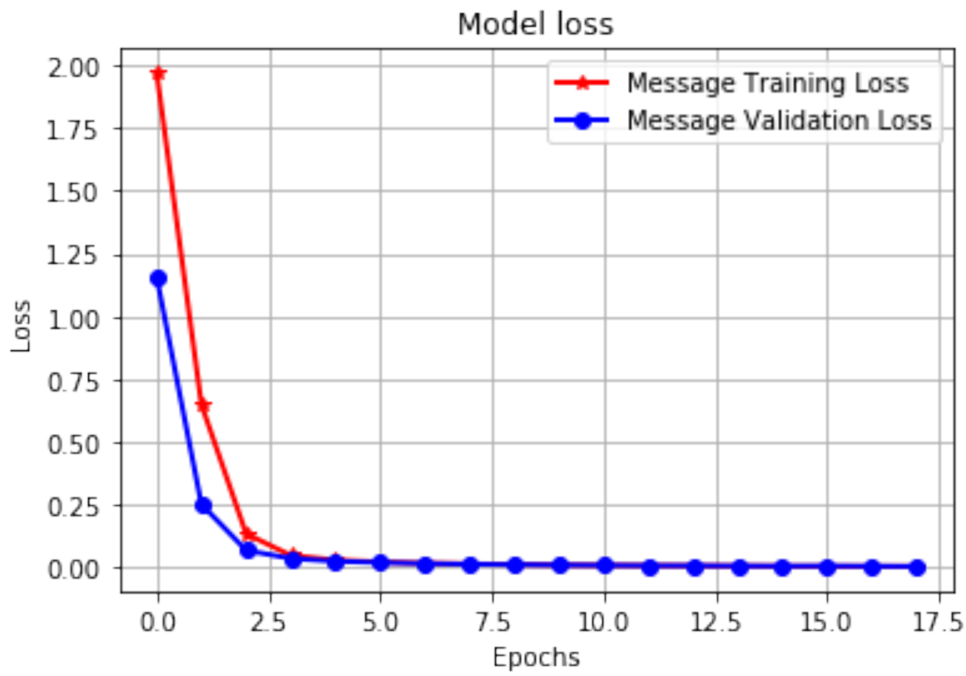

Figure 12. BER vs. SNR for the auto-encoder test with different amounts of test samples against various benchmark communication techniques.

5. Conclusions

This paper presents a communications system as an end-to-end optimization scheme using an auto-encoder to jointly learn UAV (transmitter) and GCS (receiver) signal processing implementations without prior knowledge. The auto-encoder was trained with fixed and varying SNR values and an input message modulated with different modulation schemes, such as BPSK, QPSK and 8PSK, and various communication rates. We have seen from the results that the proposed learning-based communication framework can learn standard and distorted classical modulation techniques when trained with average and average power constraints, respectively. Comparisons with conventional baselines in various scenarios unveil a competitive BER performance against traditional communication techniques. From the results, we find that the proposed learning approach demonstrates its efficacy in terms of reliability in learning optimal communication schemes in a challenging environment or situations where the optimal strategies are not known. This could be used to design UAV communication links for reliable data transfer and efficient smart livestock farming. Future work should consider various channel types and communication rates for a more practical UAV communication system for different baseline schemes. An extension to a multiantenna UAV system with particular attention to beamforming, secrecy, channel interference and energy efficiency is appealing.

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