Semantics-Empowered UAV-assisted Wireless Communication System for Wildfire Detection

Chathuranga M. Wijerathna Basnayaka*†, Dushantha Nalin K. Jayakody* and Marko Beko‡*
‡ Instituto de Telecomunicações, Instituto Superior Técnico, Universidade de Lisboa, 1049-001 Lisbon, PORTUGAL
* COPELABS, Lusófona University, Lisbon 1700-097, PORTUGAL
† Center for Telecommunication Research, School of Engineering, Sri Lanka Technological Campus, Padukka 10500, SRI LANKA
Email: a22201874@alunos.ulht.pt, {dushantha.jayakody, beko.marko}@ulusofona.pt

***Abstract*—With the increasing occurrence of wildfires globally, quick and effective detection methods are vital. This paper proposes an innovative solution for wildfire detection using Unmanned Aerial Vehicle (UAV)-assisted detection systems. On the other hand, semantic communication, a technology designed for efficient data transmission in specialized tasks, plays a crucial role in next-generation wireless communications systems. In this paper, the deep joint source-channel coding (DJSCC) scheme has been used for efficient image transmission as a deep learning-based semantic communication technique for wildfire detection. DJSCC improves source and channel coding for semantic communications, offering advantages such as improved energy efficiency, reduced latency, and improved reliability compared to traditional source and channel code schemes. In this paper, the transmitter-receiver operations of the UAV communication system are modeled as a DJSCC, and they are jointly trained while taking into account the effects of the fading channel. The encoder transforms captured images into compact feature vectors, subsequently transmitting them using a reduced number of channels to minimize latency. Rather than engaging in the reconstruction of the input image in the receiver, the classifier performs a classification task using the received signals at the receiver. Alternatively, if the recovery of an image is required to understand the spread of the wildfire, the decoder reconstructs it by using the received signal at the receiver.**

***Index Terms*—Unmanned Aerial Vehicles (UAV), joint source-channel coding, semantic communication, deep learning, wildfire**

I. Introduction

In recent years, there has been a notable increase in the frequency, size, and severity of wildfires worldwide. This surge has had significant effects on economies, ecosystems, and local communities [1], [2]. For example, approximately 23 million acres of land [3] are lost to wildfires annually around the world and experts predict a further increase in fire risks in the near future. Effective management of wildfires is a considerable challenge, with early detection crucial [4]. However, current methods such as satellite imagery and infrared cameras have limitations, especially in adverse weather conditions such as cloudy conditions.

To prevent wildfires from spreading uncontrollably, using Internet of Things (IoT) networks has emerged as a promising solution [5]. These networks can link various cost-effective self-powered IoT sensors known for their simplicity. Although projections suggest that by the end of 2023, IoT networks could accommodate up to 100,000 IoT devices per square kilometer [6], shortcomings in infrastructure in forested areas and the inherent limitations of IoT devices, including power and computational constraints, make traditional IoT networks unsuitable for efficient data gathering. To overcome this, Unmanned Aerial Vehicles (UAVs) are a viable option [7]. UAVs can handle the demanding data rate and reliability requirements of cellular communication networks. Furthermore, UAVs offer advantages such as flexibility and reduced costs, making them suitable for reaching hazardous and remote disaster-stricken areas [8]. Thus, recent studies propose the use of UAV-added communication networks in managing natural disasters such as wildfires [9]. This paper presents an innovative approach to identifying wildfires using UAVs along with a deep learning-powered semantic communication system. This semantic communication-based approach aims to enable the rapid and accurate identification of wildfires.

In recent years, the field of wireless communication has undergone a significant transformation due to the emergence of semantic communication principles, which are surpassing conventional wireless communication techniques. Unlike traditional methods that prioritize the accurate transmission of separate symbols or bits, semantic communication places its emphasis on effectively conveying the intended meaning and context from the source of information [10]–[12].

As far back as 1949, Weaver [13] introduced the concept of transmitting messages with meaningful intent. He extended Shannon's communication theory by incorporating two additional levels: the semantic level and the effective level. The semantic communication system aims to convey semantic information, while an effective system focuses on an efficient and goal-oriented design. However, the concept of semantic communication or goal-oriented communication did not initially attract significant attention [14], [15]. This was primarily

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due to the pressing need for Shannon's high-rate and reliable communication methods and the limited computational power to develop semantic-aware communication systems [16].

On the other hand, current mobile wireless communication systems have significantly improved their data transmission speed, surpassing previous generations by a considerable margin. This progress is bringing the achievable rate of current wireless communication systems closer to the theoretical limits defined by Shannon's theorem, thanks to more efficient channel coding schemes such as Polar codes and Low-Density Parity Check codes [17], [18].

Simultaneously, various new and innovative applications have emerged in wireless communications, such as IoT applications, industrial automation, smart agriculture, environmental and healthcare monitoring, and smart sensor networks [19], [20]. The integration of these applications into wireless communication networks generates an enormous amount of data, potentially reaching zettabyte scales [21]. This surge in data poses a significant challenge for wireless communication networks, as it requires robust methods to maintain strong connectivity despite the limited availability of wireless spectrum resources. Additionally, there is a growing need for low latency and high reliability to support the real-time requirements of mission-critical applications such as wildfire detection and healthcare monitoring. These complex challenges are pushing us to move away from the traditional channel coding schemes that increase the transmission time by increasing the block length and adding a large number of parity bits for error correction. On the other hand, semantic-based communication approaches offer a potential solution by focusing on the meaning within the transmitted information itself. This involves extracting the semantic meanings from the data while filtering out unnecessary information. This process allows for efficient data compression while retaining the essential semantic content. Notably, this approach to communication is particularly resilient, even in challenging conditions where the signal is weak compared to the background noise (low Signal-to-Noise Ratios (SNRs)). This resilience makes it well-suited for applications that demand a high level of reliability.

One effective strategy for developing a semantic communication system is treating it as a joint source-channel coding problem [22], [23]. Joint Source-Channel Coding (JSCC) has posed a challenge in communication and coding theory for a long time. However, recent breakthroughs have shown significant performance improvements over traditional systems that treat source and channel coding separately. This improvement is especially pronounced in scenarios where low latency and low power consumption are critical. These advancements are largely due to the integration of deep learning techniques into the design of JSCC, which has proven to outperform traditional JSCC methods that have been developed over decades of research. In this work, we employ a deep learning-based JSCC known as DeepJSCC (DJSCC) for image transmission [24], [25].

While numerous theoretical studies exist related to DJSCC, its practical implementation has not been extensively explored

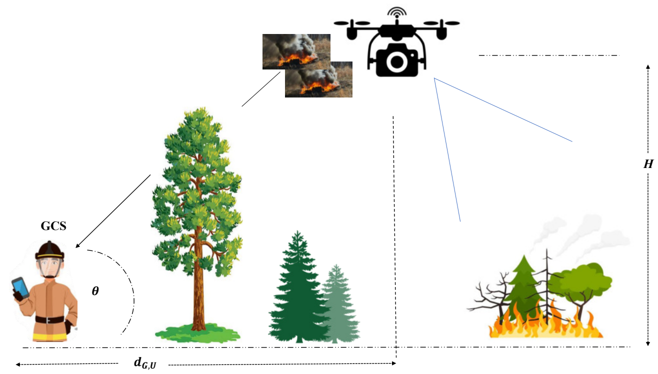

Fig. 1. Communication System model of UAV-assisted Wildfire Detection System.

[26]. This paper focuses on establishing a DJSCC framework for detecting wildfires, comprising an encoder, a decoder, and a classifier. The core objective is to create a seamless end-to-end training system for image classification, specifically tailored for wildfire detection. To emulate real-world conditions in a UAV communication network, this paper models the wireless communication channel as a Rician fading channel. This approach effectively replicates the communication environment present in such networks. Subsequently, the DJSCC framework is implemented to recover images at the Ground Control Station (GCS) in addition to classification since image recovery is a crucial capability, especially in situations where assessing the wildfire's extent is of utmost importance. Additionally, this work determines the optimal altitude of the UAV which achieves the highest levels of classification accuracy and Peak Signal-to-Noise Ratio (PSNR) for image recovery. This capability significantly contributes to a better understanding of wildfire scenarios and facilitates more informed decision-making processes.

II. System Model

In Fig. 1, we examine a wildfire detection system utilizing a UAV. The UAV (U) is positioned at an altitude H and equipped with cameras for image capture. The UAV and GCS (G) have coordinates $D_U = (X_U; Y_U; H)$ and $D_G = (X_G; Y_G; 0)$, respectively. The horizontal distance is $d_{U,G} = \sqrt{(X_U - X_G)^2 + (Y_U - Y_G)^2}$. The angle of elevation is $\theta = \arctan\left(\frac{H}{d_{U,G}}\right)$. Communication involves Line-of-Sight (LoS) and Non-Line-of-Sight (NLoS) links between the UAV and GCS.

This study introduces a deep learning-based communication system arrangement consisting of transmitter, channel, and receiver components, as depicted in Fig. 2. The main purpose of the transmitter is to transmit images captured by the camera embedded in the UAV. The transmitter employs the DJSCC technique for wireless image transmission. In contrast to traditional methods that rely on explicit codes for compression and error correction, DJSCC takes a more direct approach by mapping image pixel values onto complex-valued channel input symbols. This eliminates the necessity for distinct coding mechanisms.

These complex-valued channel input symbols are subsequently transmitted through a wireless communication channel connecting the UAV and GCS [24]. The attributes of the channel are modeled using the Rician fading model, which effectively captures signal fading and other fluctuations in the UAV-aided wireless communication system. A key aspect is the joint training of both the transmitter and receiver. This collaborative training strategy enables adaptation to changing channel conditions, ensuring robust image transmission despite the inherently dynamic nature of the channel.

In the considered system, the receiver fulfils both classification and image reconstruction tasks at the GCS utilizing the channel output in accordance with the requirements of GCS. The input image is denoted as $\boldsymbol{I} \in \mathbb{R}^{I_H \times I_W \times I_C}$, where I_H, I_W, and I_C represent the height, width, and number of colour channels, respectively. The total number of pixels in the image is denoted as $k_P = I_H \times I_W \times I_C$. The wireless transmission of the image source is then considered.

The transmitter employs a deep neural network (DNN) as the DJSCC encoder at the UAV, denoted as $f(\cdot, \vartheta)$, where ϑ represents the learnable parameters of the network. Given an input source signal $\boldsymbol{I}$, the output encoded semantic features $\boldsymbol{s}$ produced by $f(\cdot, \vartheta)$ are expressed as $\boldsymbol{s} = f(\boldsymbol{I}, \vartheta)$, where $\boldsymbol{s}$ belongs to the real vector space $\mathbb{R}^{2n_T}$, and n_T is a specific dimensionality. These encoded semantic features $\boldsymbol{s}$ are then reshaped into complex-valued symbols of dimension n_T to form the encoded signal $\hat{\mathrm{s}}$.

After encoding the task-relevant semantic signal s from the transmitted signal $\boldsymbol{I}$, a normalization process is applied to ensure that $\hat{\mathrm{s}}$ adheres to the average power constraint as

$$\frac{1}{n_T}\mathbb{E}\|\hat{\mathrm{s}}\|^2 \leq P. \tag{1}$$

where P denotes the transmission power of the UAV, Subsequently, the encoded signal $\hat{\mathrm{s}}$ is transmitted through the wireless channel. Specifically, we consider a narrow-band or frequency-flat block fading channel, where the channel is assumed to remain constant during the transmission of a single image and may change independently for subsequent images. Thus, the received signal $\boldsymbol{z} \in \mathbb{C}^{n_T}$ is formulated as follows:

$$\boldsymbol{z} = \sqrt{\beta P}\hat{\mathrm{s}} + \boldsymbol{W_n}, \tag{2}$$

Where $\boldsymbol{W_n} \in \mathbb{C}^{n_T}$ represents independent identically distributed (i.i.d.) circularly symmetric complex Gaussian (CSCG) noise with an average noise power of σ^2. In other words, $\boldsymbol{n} \sim \mathcal{CN}(0, \sigma^2 \boldsymbol{I_n})$, where $\boldsymbol{I_n}$ represents the identity matrix. The parameter β signifies the channel gain. In this UAV communication configuration, the channel gain β is considered as the product of the large-scale channel gain and the small-scale channel gain. Both the small- and large-scale channel gains are influenced by both LoS and NLoS channels. Consequently, it is essential to compute the LoS probability between the transmitter and the receiver. The LoS probability between the UAV and GCS can be expressed as in [27],

$$P_{\mathrm{LoS}}(\theta) = \frac{1}{1 + A\exp\left(-B(\theta - A)\right)}, \tag{3}$$

where A and B are parameters characterizing the S-curve and are environment-dependent. The large-scale channel gain α for the channel between the UAV and GCS is determined as follows [28]:

$$\begin{aligned} -10\log\alpha = 20\log\left(H\csc\theta\right) + 20\log\left(\frac{4\pi f_c}{c}\right) \\ + \eta_{NLOS} + \frac{\eta_{LOS} - \eta_{NLOS}}{1 + A\exp\left(-B(\theta - A)\right)}. \end{aligned} \tag{4}$$

where f_c and c are the carrier frequency (Hz) and the speed of light (m/s), respectively. η_{NLOS} and η_{NLOS} represent the expectations of additional environmental-dependent excess path loss for the LoS and NLoS components, respectively. Assuming that the UAV and GCS remain static during the transmission of a block and ignoring the Doppler effect, we employ the Rician fading model to investigate the small-scale channel characteristics and multi-path propagation in this system. The probability distribution of the small-scale channel gain (g) follows a non-central chi-square distribution, and the probability density function for the small-scale channel gain can be expressed as:

$$f_{g(z)} = \frac{(K+1)e^{-K}}{\bar{g}} e^{\frac{-(K+1)z}{\bar{g}}} I_0\left(2\sqrt{\frac{K(K+1)z}{\bar{g}}}\right), \tag{5}$$

where $z \geq 0$, $\bar{g} = 1$, $I_0(\cdot)$ is the zero-order modified Bessel function of the first kind, and K is the Rician factor, which can be expressed as follows [29]:

$$K = \frac{P_{\mathrm{LoS}}(\theta)}{1 - P_{\mathrm{LoS}}(\theta)} = \frac{1}{A\exp(-B(\theta - A))}. \tag{6}$$

Then, the channel gain, and average SNR at the receiver can be calculated as $\beta = \alpha g$, $\bar{\gamma}_{SNR} = \frac{\alpha P}{\sigma^2}$ respectively. The receiver then facilitates image recovery and execution of classification tasks, thereby enabling the detection of wildfire occurrence. In the receiver, the real and imaginary components of $\boldsymbol{z}$ are amalgamated (reshaped) to form $\hat{\boldsymbol{z}} \in \mathbb{R}^{2b}$ for subsequent processing. Following this, the receiver undertakes data recovery and classification tasks based on $\hat{\boldsymbol{z}}$.

From one perspective, the receiver performs the classification task directly within the feature space. This involves entering the derived features $\hat{\boldsymbol{z}}$ into a pragmatic function $M(\hat{\boldsymbol{z}})$ to obtain the classification result denoted as $L = M(\hat{\boldsymbol{z}})$. In this system, a DNN serves as the pragmatic function for classification. On the other hand, the decoder at the GCS in the receiver maps received $\hat{\boldsymbol{z}}$ to the estimated reconstruction of the original transmitted image, denoted as $\hat{\boldsymbol{I}} \in \mathbb{R}^{k_p}$. The decoder at the GCS performs image reconstruction using the function $\hat{\boldsymbol{I}} = q(\bar{\boldsymbol{z}}, \gamma)$, where the decoding DNN is represented as $q(\cdot, \gamma)$ and is parameterized by γ. Our goal is to extract and transmit task-relevant semantic information $\hat{\mathrm{s}}$ of the original image $\boldsymbol{I}$ to minimize the communication overhead (in terms of the

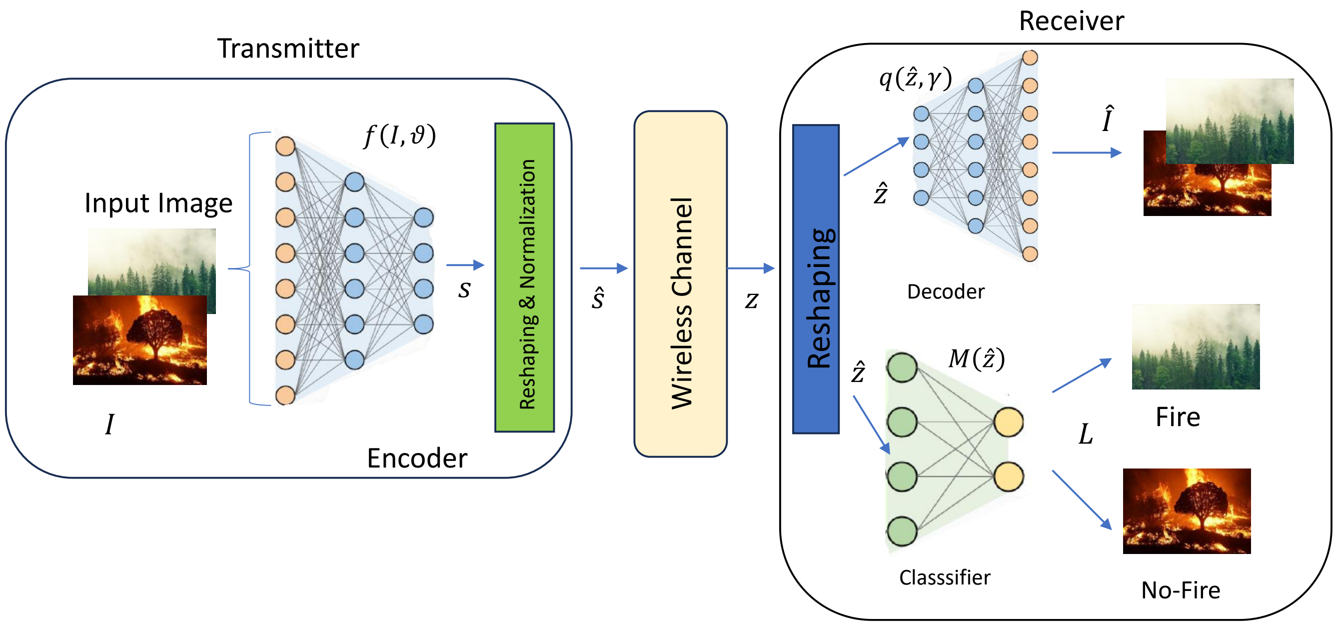

Fig. 2. The proposed DJSCC-based communication system for image recovery and classification for wildfire detection

number of symbols n_T to be transmitted) while guaranteeing the performance of image recovery and classification tasks to detect wildfires. Specifically, the performance of the image recovery task is evaluated using PSNR and the performance of the image classification task is evaluated using classification accuracy. The PSNR is a quantitative measure to evaluate the similarity between two images. For an original image $\boldsymbol{I}$ and its corresponding reconstructed or processed image $\hat{\boldsymbol{I}}$, the PSNR is calculated using the following equation:

$$\mathrm{PSNR}(\boldsymbol{I},\hat{\boldsymbol{I}}) = 10 \cdot \log_{10}\left(\frac{\mathrm{MAX}^2}{\frac{1}{k_P}\|\boldsymbol{I}-\hat{\boldsymbol{I}}\|^2}\right), \qquad (7)$$

where MAX represents the maximum possible value of the image pixels.

III. SIMULATION RESULTS

In this section, simulation results are presented to validate the functionality of the system model in terms of image recovery and classification for the detection of wildfires. Specifically, experiments are conducted using the wildfire detection image dataset [30]. This dataset comprises colorful images with dimensions of 250 × 250 × 3 pixels, depicting various real-world wildfire scenarios, as well as non-fire scenarios in forest environments. The DNN architecture for the encoder at the UAV comprises an input layer for images, followed by four convolutional layers with the Generalized Divisive Normalization (GDN) activation function. The decoder at the GCS in this system comprises four layers, utilizing inverse convolutional operations and GDN activations to reconstruct images. During training, the model is optimized with the Adam optimizer, aiming to minimize the Mean Squared Error (MSE) between the reconstructed image and the original input. The classifier has dense layers for feature processing and binary classification. The classifier is trained using the Adam optimizer and sparse categorical cross-entropy loss. Unless otherwise specified, the simulation parameters are configured as follows: $d_{G,U} = 1500\,\mathrm{m}$, $f_c = 900\,\mathrm{MHz}$, $c = 3 \times 10^8\,\mathrm{m\,s^{-1}}$, $\eta_{\mathrm{LOS}} = 0.1\,\mathrm{dB}$, $\eta_{\mathrm{NLOS}} = 21\,\mathrm{dB}$, $\mathrm{P} = 30\,\mathrm{dB\,mW}$, $n_T/k_P = 1/6$, and $\sigma^2 = -100\,\mathrm{dB\,mW}$ [29].

Fig. 3 illustrates the average SNR plotted against the altitude of the UAV for different transmission power levels and distances. The results indicate that the optimal altitude for maximum average SNR is approximately $400\,\mathrm{m}$. At lower altitudes, the average SNR remains low due to the weak LoS signal. As altitude increases towards the optimal value, the average SNR experiences rapid growth due to a stronger LoS component that outweighs the impact of path loss. However, beyond optimal altitude, path loss dominates other factors, resulting in a decrease in the average SNR. In addition, decreasing distance and increasing transmission power increase the average SNR level significantly as illustrated in the graph.

Fig. 4 depicts the classification task of the DJSCC across varying average SNR levels. As depicted in the figure, the DJSCC framework was initially trained for two scenarios: $\bar{\gamma}_{\mathrm{SNR}} = 10\,\mathrm{dB}$ and $\bar{\gamma}_{\mathrm{SNR}} = 20\,\mathrm{dB}$. These trained DJSCC frameworks were subsequently applied directly to different channel conditions. The purpose of this simulation was to evaluate the DJSCC's performance across various average SNR levels, offering insights into its behavior before integrating it into the UAV communication model and simulating it under UAV channel conditions. The results clearly demonstrate

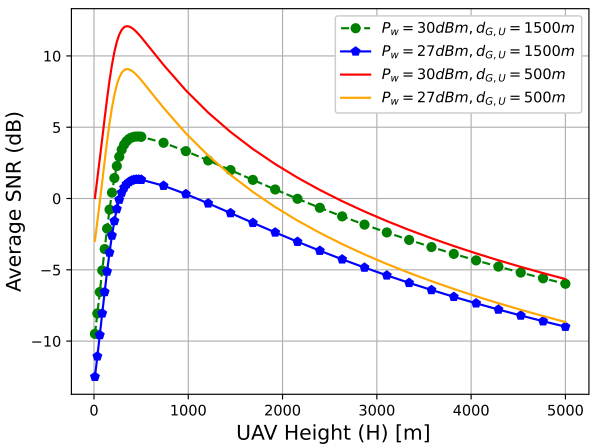

Fig. 3. Average SNR as a function of UAV Height.

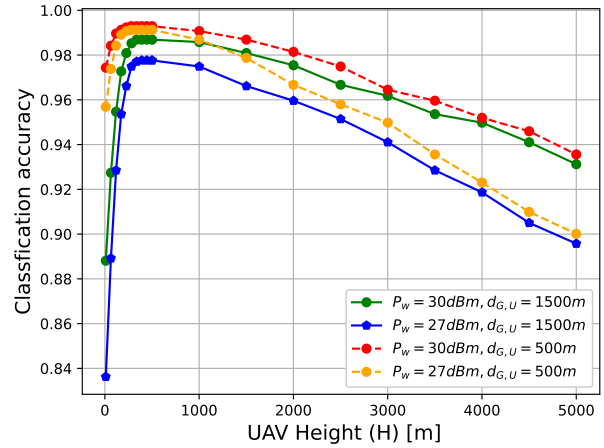

Fig. 5. Classification accuracy as a function of UAV height.

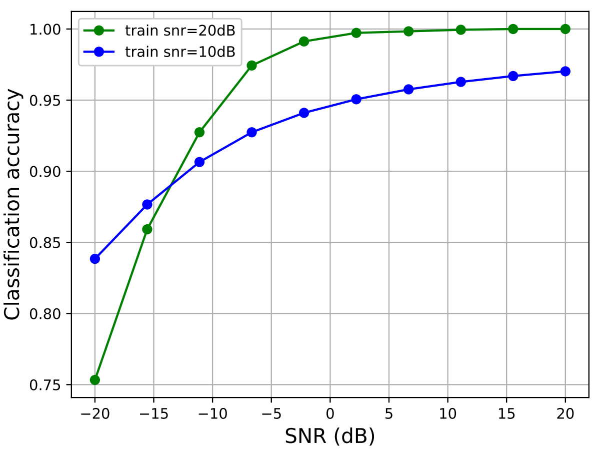

Fig. 4. Classification accuracy as a function of average SNR for different training SNR levels.

that higher average SNR levels during training lead to better performance at high SNR levels. However, frameworks trained at lower SNR levels maintain a high accuracy rate for very low SNR levels when compared to their high SNR-trained counterparts. This phenomenon arises from the fact that a high average SNR during training causes DJSCC to prioritize the signal, which is advantageous for strong signals but may struggle with weaker ones. In contrast, training at a lower SNR makes DJSCC more sensitive to weak signals, enabling it to detect them even in the presence of noise.

Fig. 5 presents the relationship between UAV altitude and classification accuracy. Initially, the DJSCC is trained with $\bar{\gamma}_{\text{SNR}} = 20\,\text{dB}$ and $K = 0.5$. The DJSCC's performance is contingent on the SNR level; consequently, at low UAV altitudes, classification accuracy is reduced due to weak LoS channels. However, as depicted in Fig. 5, the classification accuracy increases towards its optimal point. This trend aligns with the observation in Fig. 3, where the average SNR value increases towards its optimum due to strong LoS conditions. Subsequently, similar to the average variation in SNR, the classification accuracy also decreases. This decline can be attributed to the increased influence of path loss, which is more prominent under strong LoS channel conditions.

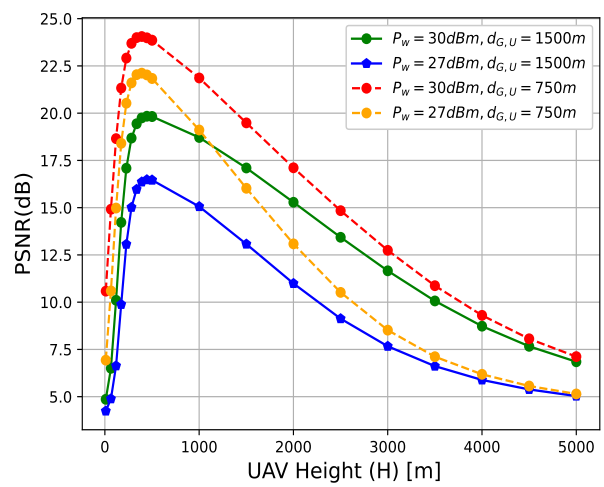

Fig. 6. PSNR as a function of UAV height.

Fig. 6 presents the relationship between UAV altitude and PSNR for image recovery. In this scenario as well, the DJSCC is trained with $\bar{\gamma}_{\text{SNR}} = 20\,\text{dB}$. Subsequently, the trained DJSCC is used for image transmission. The transmitted image is reconstructed using a received signal, and then the PSNR is measured. In Fig. 6, the PSNR is measured for different UAV altitudes, simulating changes in the channel as well. The performance of the DJSCC depends on the SNR level. Thus, at lower UAV altitudes, the PSNR is low due to low average SNR levels caused by weaker LoS channels. However, the PSNR increases dramatically as it approaches its optimal point. This trend aligns with the observation in Fig. 3, where the average SNR value increases towards its optimum due to stronger LoS conditions. Similarly, as the average SNR varies, the PSNR also experiences a sharp decrease after reaching its optimal point. Notably, the reduction in PSNR is more significant compared to the reduction in classification accuracy. This is due to image reconstruction demands a higher SNR compared to classification.

IV. Conclusion

This paper presents an innovative solution for wildfire detection utilizing UAV-assisted systems and a deep learning-based semantic communication approach. The DJSCC scheme is employed for streamlining the image transmission, and with a jointly trained encoder-classifier/decoder framework, it accomplishes the data transmission and classification.

This study thoroughly assessed the performance of the proposed system, with a particular focus on crucial metrics like classification accuracy and image PSNR. Our evaluation involved varying UAV flying altitudes, power levels, and transmitter-receiver distances to gauge the system's performance. The Kaggle wildfire detection image dataset was used to train the encoder and decoder, leveraging its diverse image collection.

Future studies may involve latency issues and compare them with conventional communication systems that utilize typical channels and source coding techniques. Such explorations could provide crucial understanding into the efficiency and benefits of the suggested semantic-aware UAV-supported wildfire detection system.

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