Abstract—The semantic information of the image for intelligent tasks is hidden behind the pixels, and slight changes in the pixels will affect the performance of intelligent tasks. In order to preserve semantic information behind pixels for intelligent tasks during wireless image transmission, we propose a joint source-channel coding method based on semantics of pixels, which can improve the performance of intelligent tasks for images at the receiver by retaining semantic information. Specifically, we first utilize gradients of intelligent task’s perception results with respect to pixels to represent the semantic importance of pixels. Then, we extract the semantic distortion, and train the deep joint source-channel coding network with the goal of minimizing semantic distortion rather than pixel’s distortion. Experiment results demonstrate that the proposed method improves the performance of the intelligent classification task by 1.38% and 66% compared with the SOTA deep joint source-channel coding method and the traditional separately source-channel coding method at the same transmission rate and signal-to-noise ratio.

Index Terms—joint source-channel coding, semantics of pixels, semantic preservation, intelligent task perception results

I. INTRODUCTION

In the past few decades, the wireless mobile communication system represented by 5G has achieved great success. For image data, they employ the separate source-channel coding method (SSCC) under the guidance of Shannon’s separation theorem. As shown in Fig. 1, first, SSCC uses the source coding algorithm (such as JPEG, WebP, BPG) to compress the redundant information, and then the source-independent channel coding method (such as LDPC, Polar, Turbo, etc.) is used to reconstruct in the presence of channel noise. When the source is infinite, SSCC can achieve optimal coding performance. However, in practice, the infinite bits’ assumption of Shannon’s separation theorem cannot be satisfied. In fact, the joint effects of source coding distortion and channel coding error affect the signal quality at the receiver [1], so it is necessary to jointly consider source coding and channel coding. In addition, the rapid development of deep learning technology enables the joint consideration of source coding and channel coding. As shown in the Fig 1, deep learning-based joint source-channel coding (deep JSCC) refers to implement joint source encoding and channel encoding by end-to-end (E2E) semantic communication framework using deep neural networks. Due to the powerful learning ability of deep neural networks, deep JSCC can learn how to remove the redundancy of source information and how to resist the channel noise [1].

At the same time, 6G (sixth generation) puts forward the vision of smart interconnection of everything. On the one hand, the deep integration of communication and artificial intelligence (AI) is required, and research on semantic communication for intelligent tasks [2] has become a trend. On the other hand, efficient coding methods are required. Therefore, deep JSCC considering intelligent tasks has gained extensive attention. For image data, deep JSCC methods can be divided into two categories, one is task-oriented without reconstructing the image. In these works, only the semantic information related to the intelligent task is encoded, and the decoder directly performs the intelligent task [3]–[6]. However, this type of work only can directly perform the intelligent task, and cannot apply to the applications that require image reconstruction. The other is that the receiver completes the image reconstruction. The encoder extracts the global semantic information, and the decoder reconstructs the image according to the received semantic information [7]–[10]. However, existing deep JSCC methods for image reconstruction aim to optimize the visual quality. They only focus on the accurate transmission of pixel-level information, ignoring the semantic information required for downstream AI tasks.

The semantic information refers to that useful for serving the downstream AI task at the receiver [2], which directly affects the perception result and performance of the downstream AI task. There are some works have considered semantic

![Fig. 1: Block diagrams of wireless image transmission schemes. Top: SSCC method. Bottom: deep JSCC method.](image-url)
information preserving during wireless image transmission. Wang et al. [11] used learned perceptual image patch similarity (LPIPS) [12] as loss function to yield images that are visually pleasing to humans. However, they focus on human visual perception without considering downstream AI tasks. Shao et al. [13] leveraged an information bottleneck (IB) framework to formalize a rate-distortion trade off between the informativeness of the encoded feature and the inference performance in a task-oriented manner, i.e., targeting the downstream inference task rather than data reconstruction. Using IB can help to retain semantic information. However, the loss function of IB needs to use label information, so it is suitable for supervision tasks, but not suitable for reconstruction tasks.

In addition, some studies in the field of image compression have considered content information [14] and feature information [15]. However, on the one hand, semantic information is not utilized directly, and semantic consistency during transmission cannot be guaranteed. On the other hand, these studies only consider the source coding while ignore the channel coding, which cannot combat channel noise in the actual communication process. In summary, these methods do not jointly consider communication tasks and the semantic information of downstream AI tasks in a stable and universal way. Directly extracting the semantic information behind the pixels can avoid introducing errors due to complex design, and has better scalability. Thus, a semantics of pixels extraction method needs to be proposed for measuring semantic information.

Previous studies have shown that the relationship between the semantic information and the pixel’s information is not strictly linear [16]. In the field of neural network’s interpretability, it can be shown that pixels of the object part are more important than the background part by visualizing the heatmap results [17]. In the field of adversarial attacks, even an attack on a very small number of important pixels can produce completely different perceptual results [18]. All of these indicate that the importance of pixels to the perceptual results is different, that is, the semantic importance is different. That means keeping the accurate transmission of pixel-level information does not guarantee the correct understanding of downstream AI tasks.

Motivated by this, the deep joint source-channel coding based on semantics of pixels (SP-JSCC) method is proposed for wireless image transmission. In this paper, SP-JSCC designs a semantic distortion extractor to preserve semantic information at the receiver by minimizing the semantic distortion. We quantify the semantic importance of pixels through the idea of gradients, which can represent the contribution of pixels to perception results. Then, we design the semantic distortion extractor, which is the core of SP-JSCC and can extract the semantic distortion at the transmitter and the receiver. We use the semantic distortion as the loss function to train the deep joint source-channel codec network in an end-to-end manner, which can retain the semantic information needed by the downstream AI task and so as to improve the task performance of images at the receiver.

**II. SYSTEM MODEL AND PROBLEM DESCRIPTION**

**A. System Model**

Fig. 2 shows an end-to-end communication system for wireless image transmission considering the downstream AI task. An input image \( x \in \mathcal{R}^n \) of dimension \( n \) is to be transmitted, where \( \mathcal{R} \) denotes the set of real numbers, and the transmitter maps the input image \( x \) into a complex-valued symbolic vector \( e \) after the JSCC encoder \( E \), which can be expressed as:

\[
e = E (x, \theta_1) \in \mathcal{C}^n,
\]

where \( s \) denotes the dimension of \( e \), \( \mathcal{C} \) denotes the set of complex numbers, and \( \theta_1 \) denotes the parameters of the JSCC encoder \( E \). The symbol vector \( e \) after encoding is transmitted over a noisy AWGN channel, which can be expressed as:

\[
e' = e + N \in \mathcal{C}^n,
\]

where \( N \in \mathcal{C}^n \) denotes the noise of the channel. The receiver maps \( e' \) to the reconstructed image \( x' \) through the JSCC decoder \( D \), which can be expressed as:

\[
x' = D (e', \theta_2) = D (E (x, \theta_1) + N, \theta_2),
\]

where the reconstructed image \( x' \in \mathcal{R}^n \) is an estimate of the original image \( x \), and \( \theta_2 \) is the parameter of the JSCC decoder \( D \). Then, the reconstructed image \( x' \) is passed through the downstream AI task \( T \), and perception results are obtained, which can be expressed as:

\[
y = T (x'),
\]

where \( y = [y^1, y^2, \ldots, y^C] \), \( y^c (c \in \{1, \ldots, C\}) \) denotes the \( c \)-th perception result and \( C \) is the total number of perception results.

**B. Problem Description**

The existing deep JSCC methods [7–10] use the pixel-level difference between \( x' \) and \( x \) as the loss function to train the joint source-channel codec network, which can be expressed as:

\[
\mathcal{L}_{\text{deep JSCC}} = d (x, x') = \| x - x' \|^2.
\]

\( \mathcal{L}_{\text{deep JSCC}} \) enables \( x' \) to obtain a clear visual quality that is close to the original image \( x \). This approach only maintains the pixel-level consistency during image transmission without considering the perception results of the downstream AI task.

In addition, Wang et al. [11] use learned perceptual image patch similarity (LPIPS) [12] as the distortion part of loss function:

\[
\mathcal{L}_{\text{LPIPS}} = d_{\text{LPIPS}} (x, x').
\]
norm is the normalization using the L2 norm.

Semantic info of downstream AI task.

As shown in Fig. 3, we first calculate SP-based weights \(W'\) and use them to weight pixels to obtain the SP-based loss function.

As shown in Fig 4, we first calculate SP-based weights \(W'\). Then use \(W'\) to weight pixels to obtain the SP-based loss function.

First, we pre-train the downstream AI task’s network with parameter \(\theta_0\), and fixed \(\theta_0\) in the following operation. Then, we complete inference with parameters \(\theta_0\) to get perception results \(y\). The gradients of perception results with respect to pixels of image \(x\) is used to quantify the semantic importance, which can be expressed as:

\[
w^c = \frac{\partial c}{\partial x},
\]

where \(y^c\) is \(c\)-th perception result. \(w^c(k \in \{1, 2, \ldots, C\})\) represents the semantic importance to the \(c\)-th perception result \(y^c\). The dimension of \(w^c\) is the same as that of \(x\). To evaluate the comprehensive influence of \(x\) on all perception results \(y\), the average value of \(w^c\) over all perception results is calculated, which can be expressed as:

\[
w = \frac{1}{C} \sum_{c=1}^{C} w^c,
\]

whose dimension is also consistent with \(x\).

However, \(w\) cannot be directly used to design the loss function since it has negative values and its variance is too large. In particular, negative values of \(w\) will cause confusion in loss function, and large variance will cause the missing of some the pixel’s information in loss function. Therefore, we post-process \(w\), and map \(w\) to \(w'\) by:

\[
w' = \text{L2 norm}(\|w\|),
\]

where L2 norm is the normalization using the L2 norm.

Note that since the design of the SP-based distortion extractor, the SP-based weights are specific to the downstream AI task, and therefore SP-JSCC is also task-specific.

### B. SP-based Loss Function

We introduce this section to formulate the SP-based loss function \(\mathcal{L}_{SP-JSCC}\) for wireless image transmission, which can extract the semantic distortion for the downstream AI task.

We use the architecture of JSCC with adaptive rate control [9], which can support multiple rates using a single deep neural network (DNN) model and learn to dynamically control the rate based on the channel condition and image contents. As shown in Fig 4, SP-JSCC encoder \(E\) consists of the source encoder \(E_S\), the channel encoder \(E_C\), and the policy network \(P\). SP-JSCC decoder consists of source decoder
A. Evaluation Metrics

To evaluate the semantic distortion, we use the downstream classification task’s performance at the receiver, including accuracy (ACC) and F1-score, where F1-score is the harmonic mean of precision and recall. To evaluate the distortion of pixels, we use the peak signal-to-noise ratio (PSNR) and the structural similarity index measure (SSIM). To evaluate the transmission rate, we use wireless channel usage per pixel (CPP). Suppose the width and height of an input image are \( W, H \) for RGB (3 channel) pixels respectively. The CPP is defined as \( CPP = \frac{L(g, m) + g_s}{2HW} \), where the function \( L \) represents the length. The range of CPP is \( \left[ \frac{L(g_s)}{2HW}, \frac{L(g_m) + g_s}{2HW} \right] \) depending on the mask \( m \) obtained by the policy network \( P \). The 1/2 factor in CPP is because of complex-valued (quadrature) transmission over the wireless channel.

B. Implementation Details

To serve as the baseline, we use JSCC with adaptive rate control (AR-JSCC) proposed by [9]. We also use BPG as the source coding method and LDPC as the channel encoding mode with regard to SSCC. LDPC codes is (1458, 1944), corresponding to rate 3/4. 16-QAM is used as the modulation method. We evaluate these methods on the CIFAR-10 dataset which consists of 50000 training and 10000 testing images with 32×32 pixels.

For channel, we consider the AWGN wireless channel. It is worth mentioning that we insert the additional SNR-adaptive modules [10] between layers. Thus, we can use a JSCC codec that can adapt to a wide range of SNR conditions. During training, we sample the SNR uniformly between 0 dB and 20 dB. Due to the noise in the AWGN channel, the experiment results have small fluctuations. Therefore, we use the average value of five experiments as the final result.

C. Performance Evaluation and Analysis

Fig 5 compares the original images and the corresponding SP-based weights. The object part in the image is more semantically important than the background part. As shown in Fig 5 SP-based weights give the object part greater weight than the background part, that is, the distribution of SP-based weights pays more attention to the semantic part in the image. This shows the rationality of semantic weights. Therefore, the SP-JSCC approach using the SP-based weights can enable the network focus on semantic consistency during transmission, rather than pixel-level consistency.

Performances are related to transmission rate and channel conditions. The larger the transmission rate, the better the channel conditions, the more favorable the signal transmission, and thus the better performances. We next explore how different performances vary with transmission rate and channel conditions. Fig 6 and Fig 7 gives the variation curve of ACC and F1-score with transmission rate (CPP) and channel conditions (SNR) of different methods, respectively. As shown in Fig 6 and Fig 7 ACC and F1-score are more competitive.

Algorithm 1 SP-JSCC method

Input: An image dataset \( \{x^1, ..., x^n\} \) with \( n \) images.
Parameter: SP-JSCC encoder parameter \( \theta_1 \), SP-JSCC decoder parameter \( \theta_2 \).
Output: SP-JSCC based wireless image transmission system.

1: Pre-train the downstream AI task’s network with parameter \( \theta_0 \), and fixed \( \theta_0 \) in the following operation.
2: Obtain the SP-based weights \( w' \).
3: Initialize the encoder and decoder’s parameters \( \theta_1, \theta_2 \).
4: while not converged do
5:   Image Encoding: \( e \leftarrow E(\theta_1, x) \).
6:   Noise channel: \( e' \leftarrow N + e \).
7:   Image decoding: \( x' \leftarrow D(\theta_2, e') \).
8:   Calculate the semantic loss function \( \mathcal{L}_{\text{SP-JSCC}} \).
9:   Update \( \theta_1 \) and \( \theta_2 \) according to \( \mathcal{L}_{\text{SP-JSCC}} \).
10: end while
11: return The optimal model.
using SP-JSCC. For example, ACC is improved by 1.38% and 66% compared with the AR-JSCC method and SSCC method (BPG+LDPC) at 5 dB, respectively. This is due to the SP-based loss function designed by SP-JSCC, which can retain semantic information that is beneficial to downstream AI tasks, and deserves a competitive ACC. It is worth mentioning that the BPG method cannot recover image under the same transmission rate and channel condition, and its performance is kept at the lowest value. At the same time, ACC and F1-score are close to each other, which is due to the balanced distribution of categories on dataset.

Fig 8 and Fig 9 compares PSNR and SSIM of different methods, respectively, which can illustrate pixel-level consistency. As shown in Fig 8 and Fig 9, PSNR and SSIM are comparable between SP-JSCC and AR-JSCC. This shows SP-JSCC does not compromise the pixel’s information of images. In addition, BPG is poor recovery and low performance under the same transmission rate and channel condition.

The above experimental results show that, on one hand, SP-JSCC considers semantic information of the downstream AI task, which can improve the task performance. On the other hand, SP-JSCC considers the pixel's information of images and has high visual quality. When the image at the receiver...
not only needs to be understood by humans, but also needs to complete downstream AI tasks, SP-JSCC shows obvious superiority.

V. CONCLUSION

To preserve semantic information at the receiver during the wireless image transmission, we propose SP-JSCC method, and give its network design and algorithm. SP-JSCC method quantizes semantic importance of pixels using gradients, and uses semantic distortion to guide the training process. The experimental results show that the SP-based weights focus on the object part of the image, and can effectively represent the semantic importance of pixels. The improvement on the performance of downstream AI tasks is obtained by SP-JSCC, which can illustrate the semantic information needed by the downstream AI task is retained. SP-JSCC can be used for a wide range of AI tasks with no additional inference overhead. However, the disadvantage is that SP-JSCC increases the training overhead. In the future, we will consider other downstream AI tasks, and generalize it to high-resolution images.

REFERENCES

[1] Mingyu Yang, Chenghong Bian, and Hun-Seok Kim. Deep joint source channel coding for wireless image transmission with ofdm. In ICC, pages 1–6. IEEE, 2021.

[2] Zhijin Qin, Xiaoming Tao, Jianhua Lu, and Geoffrey Ye Li. Semantic communications: principles and challenges. arXiv preprint arXiv:2201.01389, 2021.

[3] Mikolaj Jankowski, Deniz Gündüz, and Krystian Mikolajczyk. Wireless image retrieval at the edge. IEEE Journal on Selected Areas in Communications, 39(1):89–100, 2020.

[4] Chuanhong Liu, Caili Guo, Yang Yang, Chunyan Feng, Qizheng Sun, and Jujiu Chen. Intelligent task-oriented semantic communication method in artificial intelligence of things. Journal on Communications, 42(11):97–108, 2021.

[5] Mengyang Wang, Zhicong Zhang, Jiahui Li, Mengyao Ma, and Xiaoping Fan. Deep joint source-channel coding for multi-task network. IEEE Signal Processing Letters, 28:1973–1977, 2021.

[6] Yang Yang, Caili Guo, Fangfang Liu, Chuanhong Liu, Lunan Sun, Qizheng Sun, and Jujiu Chen. Semantic communications with ai tasks. arXiv preprint arXiv:2109.14170, 2021.

[7] Eirina Bourtsoulatze, David Burth Kurka, and Deniz Gündüz. Deep joint source-channel coding for wireless image transmission. IEEE Transactions on Cognitive Communications and Networking, 5(3):567–579, 2019.

[8] David Burth Kurka and Deniz Gündüz. Deep joint source-channel coding of images with feedback. In ICASSP, pages 5235–5239. IEEE, 2020.

[9] Mingyu Yang and Hun-Seok Kim. Deep joint source-channel coding for wireless image transmission with adaptive rate control. In ICASSP, pages 5193–5197. IEEE, 2022.

[10] Jialong Xu, Bo Ai, Wei Chen, Ang Yang, Peng Sun, and Miguel Rodrigues. Wireless image transmission using deep source channel coding with attention modules. IEEE Transactions on Circuits and Systems for Video Technology, 32(4):2315–2328, 2021.

[11] Jun Wang, Sixian Wang, Jincheng Dai, Zhongwei Si, Dekun Zhou, and Kai Niu. Perceptual learned source-channel coding for high-fidelity image semantic transmission. arXiv preprint arXiv:2205.13120, 2022.

[12] Richard Zhang, Phillip Isola, Alexei A Efros, Eli Shechtman, and Oliver Wang. The unreasonable effectiveness of deep features as a perceptual metric. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 586–595, 2018.

[13] Jiwei Shao, Yuyi Mao, and Jun Zhang. Learning task-oriented communication for edge inference: An information bottleneck approach. IEEE Journal on Selected Areas in Communications, 40(1):197–211, 2021.

[14] Mu Li, Wangmeng Zuo, Shuhang Gu, Debin Zhao, and David Zhang. Learning convolutional networks for content-weighted image compression. In CVPR, pages 3214–3223, 2018.

[15] Zhaohui Yang, Yunhe Wang, Chang Xu, Peng Du, Chao Xu, Chunjing Xu, and Qi Tian. Discernible image compression. In ACM MM, pages 1561–1569, 2020.

[16] Cheng Luo, Qinliang Lin, Weicheng Xie, Bizhu Wu, Jinheng Xie, and Linlin Shen. Frequency-driven imperceptible adversarial attack on semantic similarity. In CVPR, pages 15315–15324, 2022.

[17] Ramprasath R Selvaraju, Michael Cogswell, Abhishek Das, Ramakrishna Vedantam, Devi Parikh, and Dhruv Batra. Grad-cam: Visual explanations from deep networks via gradient-based localization. In ICCV, pages 618–626, 2017.

[18] Moustapha Cisse, Yossi Adi, Natalia Neverova, and Joseph Keshet. Houdini: Fooling deep structured prediction models. arXiv preprint arXiv:1707.05373, 2017.

[19] Ian J Goodfellow, Jonathon Shlens, and Christian Szegedy. Explaining and harnessing adversarial examples. arXiv preprint arXiv:1412.6572, 2014.