Image Segmentation Semantic Communication over Internet of Vehicles

Qiang Pan, Haonan Tong, Jie Lv, Tao Luo, Zhilong Zhang, Changchuan Yin, and Jianfeng Li
Beijing Laboratory of Advanced Information Network, Beijing Key Laboratory of Network System Architecture and Convergence, Beijing University of Posts and Telecommunications, Beijing, China 100876.

Emails: {pq569375378, hntong, lvj, tluo, ccyin, lijf}@bupt.edu.cn, zhilong.zhang@outlook.com

Abstract—In this paper, the problem of semantic-based efficient image transmission is studied over the Internet of Vehicles (IoV). In the considered model, a vehicle shares massive amount of visual data perceived by its visual sensors to assist other vehicles in making driving decisions. However, it is hard to maintain a high reliable visual data transmission due to the limited spectrum resources. To tackle this problem, a semantic communication approach is introduced to reduce the transmission data amount while ensuring the semantic-level accuracy. Particularly, an image segmentation semantic communication (ISSC) system is proposed, which can extract the semantic features from the perceived images and transmit the features to the receiving vehicle that reconstructs the image segmentations. The ISSC system consists of an encoder and a decoder at the transmitter and the receiver, respectively. To accurately extract the image semantic features, the ISSC system encoder employs a Swin Transformer based multi-scale semantic feature extractor. Then, to resist the wireless noise and reconstruct the image segmentation, a semantic feature decoder and a reconstructer are designed at the receiver. Simulation results show that the proposed ISSC system can reconstruct the image segmentation accurately with a high compression ratio, and can achieve robust transmission performance against channel noise, especially at the low signal-to-noise ratio (SNR). In terms of mean Intersection over Union (mIoU), the ISSC system can achieve an increase by 75%, compared to the baselines using traditional coding methods.

Index Terms—Image segmentation, semantic communication, Swin Transformer.

I. INTRODUCTION

In the emerging Internet of Vehicles (IoV), there is a massive amount of visual information required to be transmitted among the vehicles to assist driving decisions, which consumes a certain amount of bandwidth resources [1], [2]. However, due to the restricted spectrum resources and the complicated communication conditions in the traffic environment, it is difficult to maintain a reliable connection to transmit large amounts of visual data. To this end, semantic communication [3], [4], with transmitting the data at a semantic level, rather than the symbol level, is becoming a viable solution to solve the above challenges. In current IoV system, vehicles mainly use visual data for locating and obstacle avoidance, it is available for the receiving vehicle to only reconstruct the image segmentation for making driving decisions. According to our research, although semantic communication can reduce the data transmission amount thus reducing the occupied spectrum, the image segmentation semantic communication (ISSC) system has not been well designed.

Existing works [5]–[9] have systematically studied semantic communication. In [5], the authors introduced a preliminary theory of semantic information based on logical probabilistic ranking. The work in [6] presented a model theory based technique for semantic data compression and trustworthy semantic communication with quantitative measurements. Besides, the authors in [7] modeled the communication problem as a Bayesian game to minimize the end-to-end average semantic metric in a dynamic communication scenario. Furthermore, the work in [8] developed a deep learning based semantic communication system for text transmission, which recovered the meaning of sentences, rather than the transmitted bits or symbols. Recently, a semantic communication system for transmitting audio in the Internet of Things (IoT) is proposed, and federated learning is employed to improve the precision of semantic data extraction [9]. However, these aforementioned works did not explore image semantic communication, and image semantic communication is challenging due to the complexity of image structure.

Along with the development of deep learning, the prior arts have investigated image semantic communication systems [10]–[13]. In [10], the authors proposed an end-to-end joint source-channel coding (JSSC) image system on the structure of autoencoder, which provided a smooth performance degradation with the decrease of signal-to-noise ratio (SNR). Based on JSCC, the work in [11] exploited the channel feedback for image transmission, and provided considerable improvements in terms of the end-to-end image reconstruction quality. Besides, the work in [12] developed a framework for semantic communication with artificial intelligence tasks and built a system for inspecting surface defects of workpieces, which realized a visual semantic communication. Moreover, The authors in [13] extended the semantic communication for image classification tasks to UAV aerial photography and achieved the tradeoff between transmission delay and classification accuracy. However, the works in [10]–[13] were mainly concerned with
how to reconstruct or classify the images accurately but did not propose a system to reconstruct the image segmentation from semantic features at the receiver directly.

In this paper, a novel ISSC system is proposed for the IoV. To our best knowledge, this is the first semantic communication system to reconstruct image segmentation. The main contributions are as follows:

- We propose an ISSC system that enables the sharing of visual data over the IoV. The ISSC system consists of an encoder that extracts the image semantic features at the transmitter and a decoder which reconstructs the image segmentation at the receiver.
- We propose a cascade structure to extract multi-scale semantic features of image based on Swin Transformer at the ISSC encoder. The multi-scale semantic features are first aggregated and then sent to the receiver through a wireless channel. At the ISSC decoder, the received semantic features are decoded to reconstruct image segmentation, which reduces the transmission data and achieves reliable transmission.
- We evaluate the ISSC system performance through simulation experiments. Simulation results demonstrate that the proposed ISSC system can provide robust transmission performance against channel variation, particularly at low SNR, and can reconstruct the image segmentation accurately with a high compression ratio. Compared to the traditional methods, the proposed ISSC system can improve mean Intersection over Union (mIoU) by 75%.

The rest of this paper is structured as follows. In Section II, the system model and problem formulation are presented. We provide a thorough explanation of the proposed ISSC encoder and decoder in Section III. In Section IV, the simulation results are shown and discussed, and Section V concludes the paper.

II. SYSTEM MODEL

We consider a single-link vehicle-to-vehicle image communication scenario where a front vehicle needs to transmit visual data to a rear vehicle that deploy an ISSC system over the IoV, as shown in Fig. 1. Due to the blocking of the front vehicle, the rear vehicle can not see the obstacle. In this scenario, the front vehicle extracts and aggregates the semantic features of the image taken by the camera and sent to the rear vehicle. Image segmentation has the category and location information of objects, so that the rear vehicle can reconstruct the image segmentation to make driving decisions.

The above ISSC system can be simplified as shown in Fig. 2. In the system, the transmitter (front vehicle) sends image semantic features to the receiver (rear vehicle) through a wireless channel. The system consists of two components: (i) the ISSC encoder at the transmitter side, which extracts semantic features from the input image for transmission; (ii) the ISSC decoder at the receiver side, which decodes the received semantic features and utilize them to reconstruct the image segmentation.

A. ISSC Encoder

The ISSC encoder extracts and aggregates the semantic features from the input image $S \in \mathbb{R}^{H \times W \times 3}$ through a multi-scale semantic feature extractor and a semantic feature aggregator, where $H$, $W$, and 3 are the image width, the image height, and the number of channels. The input image is RGB format and every value range is in $[0, 255]$ which needs to be normalized to $[0, 1]$ by the normalization layer. To extract the semantic features from the shallow to the deep, the processed image is put into a multi-scale semantic feature extractor made up of neural networks. Then the semantic feature aggregator fuses the multi-scale semantic features and send them.

We simplify the ISSC encoder parameter as $\alpha$, thus, the relationship between the transmitted semantic features $x$ and the input image $S$ can be given by

$$x = T_\alpha(S),$$

where $T_\alpha(\cdot)$ indicates the function of the ISSC encoder.

When being transmitted over a wireless channel, the encoded semantic features will suffer channel fading and noise. We consider the condition of a single communication link, where the received semantic features $y$ at the ISSC decoder can be characterized as

$$y = h \cdot x + \rho,$$

where $h$ is the channel fading coefficient, and $\rho \sim \mathcal{N}(0, \sigma^2\mathbf{I})$ is the Gaussian channel noise with variance $\sigma^2$ and $\mathbf{I}$ is the identity matrix.
B. ISSC Decoder

The ISSC decoder is used to decode the received semantic features \( y \) and reconstruct the image segmentation \( \hat{S} \), consists of a semantic feature decoder and a reconstructor. First, the semantic feature decoder needs to reduce the influence of channel noise. Then, the reconstructor needs to get the image segmentation \( \hat{S} \) with the same length and width of the input image. \( \hat{S} \) classifies the pixels in \( S \) into \( N_{cls} \) categories where \( N_{cls} \) is the number of object categories concerned in \( S \) (pedestrians, vehicles, trucks, etc.). We simplify the ISSC decoder parameter as \( \beta \), similar to the ISSC encoder. At this point, the association between the output image segmentation \( \hat{S} \) and the received semantic features \( y \) can be given by

\[
\hat{S} = R_{\beta}(y),
\]

where \( R_{\beta}(\cdot) \) indicates the function of the ISSC decoder.

C. ISSC Objective

The objective of the ISSC system is to reconstruct the image segmentation of the vehicle perceived image at the receiver. Since our system focuses on semantic-level recovery, we use the mIoU metric rather than the bit error rate in traditional communications to evaluate the system performance, which is given by

\[
mIoU = \frac{1}{N_{cls}} \sum_{i=1}^{N_{cls}} \frac{P \cap G}{P \cup G},
\]

where \( P \) is the set of pixel regions predicted by the ISSC decoder for a certain category object, and \( G \) is the actual set of pixel regions for this category object. The higher the mIoU, the better the system performance.

III. ISSC ENCODER AND DECODER DESIGN

In the section, we will introduce the proposed ISSC system architecture, as shown in Fig. 3. Firstly, to efficiently refine visual semantics at various scales, ISSC encoder at the transmitter uses a multi-scale semantic feature extractor and a semantic feature aggregator. At the receiver, the ISSC decoder employs a semantic feature decoder and a reconstructor to perform semantic feature decoding and image segmentation reconstructing, respectively.

A. Multi-scale Semantic Feature Extractor and Semantic Feature Aggregator

The input of the ISSC system is expressed as \( I \in \mathbb{R}^{B\times H\times W\times C} \), denoted a batch of images with \( B \) being the batch size. Before entering the ISSC encoder, the pixel values of the images are normalized to \([0, 1]\) to hasten model convergence and decrease the computing cost. We initially divide every \( H\times W\times C \)-sized image into \( 4 \times 4 \)-sized patches, because the dense prediction task at the receiver benefits from using smaller patches. Following a linear embedding layer, the patch channel can be converted into any number \( C \).

Considering that most of the previous works [10]–[13] on image semantic communication systems are based on convolutional neural networks (CNNs), whose ability to extract semantics is limited by the size of the convolution kernel [14]. As a substitute for CNNs, Swin Transformer [15] has shown strong feature extraction ability and low computational complexity. Therefore, we adopt Swin Transformer in the multi-scale semantic feature extractor to extract image semantic features from shallow to deep layers as shown in Fig. 3. Swin Transformer contains four stages and each has even number of Swin Transformer blocks (STBs). STB utilizes multi-head self-attention (MSA) mechanism to obtain larger receptive fields than CNNs, and the STB architecture can be shown in Fig. 4(a).

Furthermore, to reduce computation overhead, STB divides the input into many independent small regions, called as window partition as shown in Fig. 4(b) left, and computes the self-attention by window based MSA (W-MSA) module separately. Also, to enable the interaction of adjacent pixels in different windows, each regular STB is followed a STB with shifted window based MSA (SW-MSA) module which shifting the windows by \( (\lceil \frac{M}{2} \rceil, \lceil \frac{M}{2} \rceil) \) pixels versus the proceeding STB as illustrated in Figs. 4(a), and 4(b).

Given an input \( Z \in \mathbb{R}^{H\times W\times C} \), STB first partitions \( Z \) into \( \frac{H\times W}{M^2} \) non-overlapping \( M\times M \)-sized windows. Then, STB...
computes the self-attention of pixels separately in each window. For a window feature \( Z' \in \mathbb{R}^{M^2 \times C} \), \( Q \), \( K \), and \( V \) represent query, key, and value, respectively, and can be given by

\[
Q = Z'W_Q, \quad K = Z'W_K, \quad V = Z'W_V ,
\]

where \( W_Q, W_K \) and \( W_V \) are projection matrices shared by different windows. Given \( Q, K, V \in \mathbb{R}^{M^2 \times d} \), with \( d \) being the query/key dimension, the self-attention output matrix of a window can be computed by

\[
\text{Attention}(Q, K, V) = \text{SoftMax}(QK^T / \sqrt{d} + L)V,
\]

where \( L \in \mathbb{R}^{M^2 \times M^2} \) is the learnable relative position bias. In practice, STB uses multiple heads for computing self-attention in parallel, and then concatenates the results as the MSA output.

STB also includes a multi-layer perceptron (MLP) layer, as shown in Fig. 4(c), and two LayerNorm (LN) layers with the residual connection. The whole process of \( Z' \) passes through two successive STBs are computed as

\[
\begin{align*}
\hat{Z}'^{l} &= \text{W-MSA}(\text{LN}((Z')^{l-1})) + (Z')^{l-1}, \\
(Z')^{l} &= \text{MLP}(\text{LN}(\hat{Z}')^{l}) + \hat{Z}'^{l}, \\
\hat{Z}'^{l+1} &= \text{SW-MSA}(\text{LN}((Z')^{l})) + (Z')^{l}, \\
(Z')^{l+1} &= \text{MLP}(\text{LN}((\hat{Z}')^{l+1})) + \hat{Z}'^{l+1},
\end{align*}
\]

where \( l \) is the layer number of STB.

In the multi-scale semantic feature extractor, we get four stages’ features as shown in Fig. 3, which are denoted by \( F_1, F_2, F_3 \), and \( F_4 \). From \( F_1 \) to \( F_4 \), the features become increasingly rich in image semantics.

In the semantic feature aggregator, the ISSC samples \( F_1, F_2, F_3 \), and \( F_4 \) to the size of \( F_3 \) and concatenates them to obtain the features \( F_{sc} \). Then, the features \( F_{sc} \) pass a convolutional layer with \( K \) filters of size 1 and stride 1, the value of \( K \) is used to adjust the ISSC encoder compression ratio.

### B. Semantic Feature Decoder and Reconstructor

At the receiver, the semantic feature decoder consists of three convolutional layers as shown in Fig. 3, which are used to reduce the impact of noise. Each of the convolutional layers has \( K \) filters of size 1 and stride 1.

The reconstructor consists of two convolutional layers, three upsample layers, a softmax activation, and a argmax layer. The first convolutional layer has \( K \) filters of size 1 and stride 1, and the second convolutional layer has \( N_{cls} \) filters of size 1 and stride 1. Three upsample layers interspersed between two convolutional layers gradually make the length and width of the features the same as the input. By passing a softmax activation, we get the features \( P \in \mathbb{R}^{B \times H \times W \times N_{cls}} \), the value of the last dimension is the predicted probability for pixel multi-category classification. Finally, we perform the argmax operation to get the image segmentations \( \hat{I} \in \mathbb{R}^{B \times H \times W \times 1} \) and the value of the last dimension is the category subscript with the maximum predicted probability value.

The goal of the reconstructor is to categorize the image pixels correctly, therefore, we utilize the cross entropy of multi-category classification for each pixel as the loss function, which can be given by

\[
\mathcal{L}_{CE} = \sum_{i=1}^{N_{cls}} (y_i \log(p_i)),
\]

where \( p_i \) is the probability that the pixel is classified as category \( i \) and \( y_i \) is the classification indicator with value 0 or 1. For a batch of images, the loss function of the whole ISSC system can be given by

\[
\mathcal{L}_{ISSC} = \frac{-\sum_{n=1}^{B} \sum_{m=1}^{H \times W} \mathcal{L}_{CE}}{B \times H \times W}.
\]
TABLE I
SIMULATION PARAMETERS

| Module                      | Layer Name               | Parameter | Values       |
|-----------------------------|--------------------------|-----------|--------------|
| Multi-scale Semantic Feature Extractor | 4×Swin Transformer Stage | depths    | 2, 2, 18, 24 |
|                            |                          | embedding dimension | 96          |
|                            |                          | window size   | 7           |
|                            |                          | patch size    | 4           |
|                            |                          | MLP ratio     | 4           |
|                            |                          | activation    | GELU        |
| Semantic Feature Aggregator | 4×Down/UpSample         | sampling rate | 1/4, 1/2, 1, 2 |
|                            | Convolutional Layer      | kernel size   | 1×1         |
|                            |                          | stride        | 1           |
|                            |                          | number        | K           |
| AWGN                        | AWGN                     | SNR_{\text{train}} (dB) | 1-20        |
| Semantic Feature Decoder    | 3×Convolutional Layer    | sampling rate | 1, 2, 4     |
|                            |                          | kernel size   | 1×1         |
|                            |                          | stride        | 1           |
|                            |                          | number        | K, K, K     |
| Reconstructor               | 2×Convolutional Layer    | kernel size   | 1×1         |
|                            |                          | stride        | 1           |
|                            |                          | number        | K, N, ncls  |

Fig. 5. Image segmentation visual comparison between the traditional method and the ISSC system under an AWGN channel at $r = 3$. Varying randomly between 1 and 20 dB and Adam algorithm is employed to optimize the model. Additionally, we use an online hard sample mining technique that only trains pixels with confidence below 0.7 and keeps training at least 100,000 pixels. TABLE I lists the simulation parameters.

For the purpose of comparison, we implement the traditional modular wireless transmission mode, which adopts JPEG and PNG for source coding, 2/3-rate Low-Density Parity-Check Codes (LDPC) for channel coding, and 4-QAM, 16-QAM, and 64-QAM for modulation. At the receiver, we employ the DeepLabv3+ and the OCRnet to get the received image segmentations. For a fair comparison, we set the compression ratio $r = 3$ for both ISSC system and traditional methods.

Fig. 5 shows the image segmentation comparison of the traditional method using 16-QAM modulation and the ISSC system under an AWGN channel with 22 dB SNR. In this case, ISSC system only transmits 1/3 less data than the traditional method using 2/3 rate LDPC. From Fig. 5, we see that the traditional method has a better segmentation at details than ISSC system. This is because that the traditional method can completely reconstruct the low compression ratio coded image under high SNR. We can also see that the segmentation result of the ISSC system for the vital objects (vehicle, human, road, etc.) are closed to those of the traditional method, which demonstrates the advantage of the proposed ISSC system.

In Fig. 6, we display the mIoU comparison with different SNR values. We can observe that, as the channel SNR increases, the mIoU of both the ISSC system and the traditional methods increase due to the gentler noise. We can also see that the mIoU of the ISSC system is more robust with the steadier mIoU, in contrast to the traditional methods sharply drop when the channel quality deteriorates. The reason for the steep line of the traditional methods is that, JPEG encodes the image into flag and data bits, which would be transmitted incorrectly at low SNR. And the wrong flag bits will severely impact the image reconstruction and damage the image segmentation. This phenomenon is known as “cliff effect” [10]. From Fig. 6 we see that, “cliff effect” is avoided by ISSC system with transmitting semantic features. This is because the ISSC system can effectively extract image semantic features, thus achieving more robust transmission against channel variation. Fig. 7 shows the visual display of the “cliff effect” in a traditional method that uses JPEG and 16-QAM under the AWGN channel with 18 dB, 19 dB, 20 dB, and 21 dB SNR. Figs. 5, 6, and 7 show that the proposed ISSC system can effectively avoid the “cliff effect”.

In Fig. 8, we further implement PNG as source coding in traditional methods. From Fig. 8, we can see that, using PNG gets the similar curves as that of JPEG but the steep lines have no intact outputs because the damaged PNG image cannot be segmented. From Fig. 6 and Fig. 8, we can see that the ISSC system has a better performance at low SNR, because ISSC...
In this paper, we propose an ISSC system for vehicular wireless image transmission, which transmits the semantic features of images to achieve more reliable and efficient communication than traditional methods. Additionally, the neural networks based on Swin Transformer which broadens the receptive area of image data and extracts semantic features more effectively. In the ISSC system, the codecs are jointly designed and trained to achieve global optimization of the model parameters. According to experiments, the ISSC system performs better in low SNR, and its performance does not suffer much from deteriorating channel conditions and high compression ratios. It is a competitive choice for image transmission over the IoV since it can handle the complex traffic communication environment and reduce the amount of data transmission.

V. CONCLUSION

Fig. 9 shows that the proposed ISSC system can achieve a higher compression ratio, thus reducing the transmission data amount.

REFERENCES

[1] J. Choi, V. Va, N. Gonzalez-Prelcic, R. Daniels, C. R. Bhat, and R. W. Heath, “Millimeter-wave vehicular communication to support massive automotive sensing,” IEEE Communications Magazine, vol. 54, no. 12, pp. 160–167, Dec. 2016.
[2] A. Gad and A. Nayak, “An adaptive high-fidelity image compression framework for internet of vehicles,” in Proc. IEEE International Conference on Communications, Seoul, South Korea, May. 2022.
[3] W. Saad, M. Benais, and M. Chen, “A vision of 5G wireless systems: Applications, trends, technologies, and open research challenges,” IEEE Network, vol. 34, no. 3, pp. 134–142, Jun. 2020.
[4] G. Shi, Y. Xiao, Y. Li, and X. Xie, “From semantic communication to semantic-aware networking: Model, architecture, and open problems,” IEEE Communications Magazine, vol. 59, no. 8, pp. 44–50, Aug. 2021.
[5] R. Barnap, Y. Bar-Hillel et al., “An outline of a theory of semantic information,” Research Laboratory of Electronics, Massachusetts Institute of Technology, Oct. 1952.
[6] J. Bao, P. Basu, M. Dean, C. Partridge, A. Swami, W. Leland, and J. A. Hendler, “Towards a theory of semantic communication,” in Proc. 2011 IEEE Network Science Workshop, NW Washington, DC, United States, June. 2011.
[7] G. Güler, A. Yener, and A. Swami, “The semantic communication game,” IEEE Transactions on Cognitive Communications and Networking, vol. 4, no. 4, pp. 787–802, Dec. 2018.
[8] H. Xie, J. Qin, G. Y. Li, and B.-H. Jiang, “Deep learning enabled semantic communication systems,” IEEE Transactions on Signal Processing, vol. 69, pp. 2663–2675, 2021.
[9] H. Tong, Z. Yang, S. Wang, Y. Hu, W. Saad, and C. Yin, “Federated learning based audio semantic communication over wireless networks,” in Proc. IEEE Global Communications Conference (GLOBECOM), Madrid, Spain, Dec. 2021.
[10] X. Bouroulletze, D. B. Kurka, and D. Guindiz, “Deep joint source-channel coding for wireless image transmission,” IEEE Transactions on Cognitive Communications and Networking, vol. 5, no. 3, pp. 567–579, Sept. 2019.
[11] D. B. Kurka and D. Guindiz, “Deepsource: Deep joint source-channel coding of images with feedback,” arXiv preprint arXiv:2010.11925.
[12] Y. Yang, C. Guo, F. Liu, C. Liu, L. Sun, Q. Sun, and J. Chen, “Semantic communications with ai tasks,” arXiv preprint arXiv:2109.14170, Sept. 2021.
[13] Y. Kang, B. Song, J. Guo, Z. Qin, and F. R. Yu, “Task-oriented image transmission for scene classification in unmanned aerial systems,” IEEE Transactions on Communications, vol. 70, no. 8, pp. 5181–5192, Dec. 2022.
[14] A. Dosovitskiy, L. Beyer, A. Kolesnikov, D. Weissenborn, X. Zhai, T. Unterthiner, M. Dehghani, M. Minderer, G. Heigold, S. Gelly et al., “An image is worth 16x16 words: Transformers for image recognition at scale,” arXiv preprint arXiv:2010.11929, 2020.
[15] Z. Liu, Y. Lin, Y. Cao, H. Hu, Y. Wei, Z. Zhang, S. Lin, and B. Guo, “Swin transformer: Hierarchical vision transformer using shifted windows,” in Proc. IEEE/CVF International Conference on Computer Vision, Montréal, Canada, Oct. 2021.
[16] M. Cordts, M. Omran, S. Ramos, T. Rehfeld, M. Enzweiler, R. Benenson, U. Franke, S. Roth, and B. Schiele, “The cityscapes dataset for semantic urban scene understanding,” in Proc. IEEE Conference on computer vision and pattern recognition, Las Vegas, USA, June. 2016.