

WIRELESS SEMANTIC TRANSMISSION VIA REVISING MODULES IN CONVENTIONAL COMMUNICATIONS

Peiwen Jiang, Chao-Kai Wen, Shi Jin, and Geoffrey Ye Li

ABSTRACT

Semantic communication has become a widely researched area due to its high spectrum efficiency and error correction capabilities. Some studies used deep learning to extract semantic features, typically resulting in end-to-end semantic communication systems that are difficult to adapt to varying wireless environments. Therefore, new semantic-based coding methods and performance metrics were investigated. Designed semantic systems incorporate various modules similar to those for traditional communication but with enhanced functionality. This study discusses recent advancements in state-of-the-art semantic communication, utilizing conventional modules in wireless systems. Moreover, through two examples, this study shows that traditional hybrid automatic repeat request and modulation methods can be re-purposed for novel semantic coding and metrics to further improve the performance of wireless semantic communication. Lastly, this study identifies some open research questions.

INTRODUCTION

Semantic communication can significantly reduce transmission resource requirements. Unlike traditional communication methods, semantic-based techniques commonly rely on a knowledge base (KB) to eliminate redundancy and correct errors during transmission. A KB can be represented by a specific content or a set of trainable neural networks. Compared with bit-level transmission in traditional communication, semantic communication is content related and transmits the intended meaning directly. Deep learning (DL)-based semantic communication can typically achieve content-related coding and decoding based on the same KB in an end-to-end (E2E) manner. A suitable KB is crucial for the spectrum efficiency and error-correction performance of a semantic system. To this end, domain adaptation [1] methods have been developed to update and share a new KB for both the transmitter and the receiver.

Recently, semantic communication has achieved by redesigning or revising the modules in traditional communication systems, which can better adapt to varying wireless environments. In addition to semantic coding and decoding, other modules in traditional communication systems also need to be adjusted due to the change in transmission con-

tent from symbol sequences to semantic meanings and performance metrics. For example, in [2], the modulation method is redesigned to maximize sentence similarity instead of minimizing bit errors. This change in metric significantly affects modulation because words with similar meanings can be modulated into close constellation points. In [3], peak-to-average power ratio (PAPR) is also reduced using semantic coding to improve semantic similarity between received and transmitted sentences. Hybrid automatic repeat request (HARQ) is a key technique to address varying wireless channels in traditional communications and has been adapted to develop semantic-based HARQ in [4]. Furthermore, the semantic transmitter can adaptively transmit different amounts of semantic content based on channel information [5]. To accommodate different performance metrics and requirements, resource allocation [6] for multi-user wireless communications becomes heterogeneous, leading to a sharp increase in complexity. In general, the novel performance metrics and transmission methods for semantic communications require a completely new design for wireless communications.

Unlike an existing survey or tutorial literature, such as [7] and [8], this article focuses on wireless semantic transmission achieved through revisions or redesigns of the modules in traditional communication systems. We first examine the conventional modules presented in a wireless communication system as shown in Fig. 1, and then discuss their limitations. Next, we describe the novel modifications made to facilitate semantic transmission. Overall, semantic communications fundamentally transform the transmission paradigm, as demonstrated by the two examples presented in this article. Since the development of semantic communications is still in its early stages, we highlight some challenges faced in practical wireless semantic communications.

The remainder of this article is structured as follows: The next section provides an overview of a conventional wireless communication system and highlights the increasing trend of wireless terminals and multimodal requirements. We then discuss how semantic transmission impacts the design of various communication system modules. Following that, we offer two examples of semantic channel coding and modulation, and then we address open issues in wireless semantic communications. Lastly, we conclude the article.

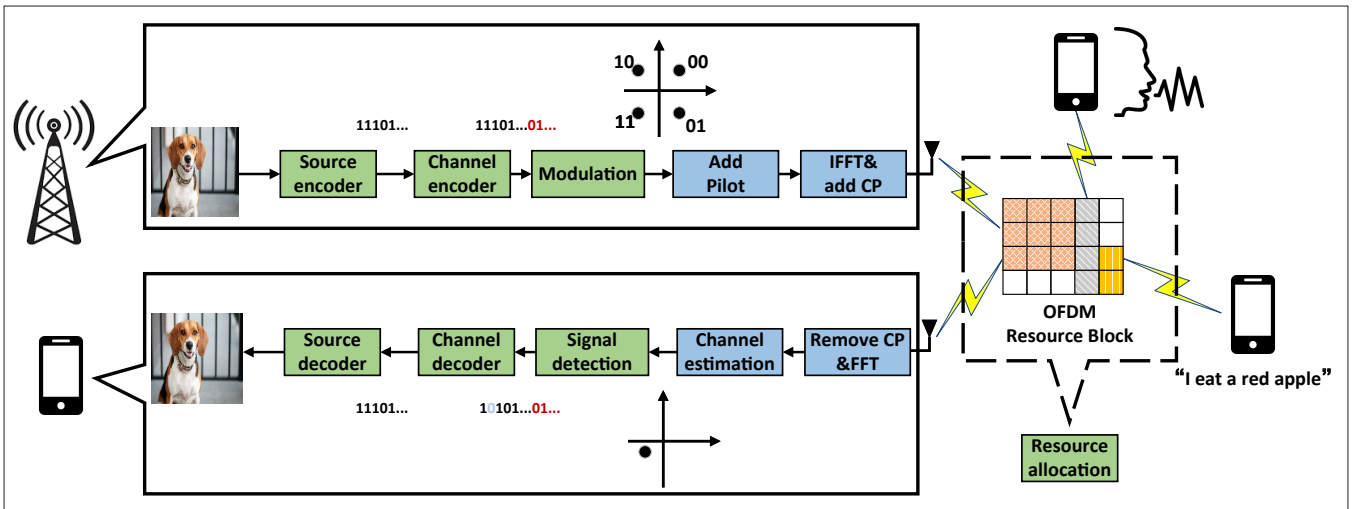


FIGURE 1. A conventional OFDM wireless communication system. The green modules can be potentially redesigned for semantic communications, while the blue modules are still conventional.

MOTIVATION FOR WIRELESS SEMANTIC COMMUNICATION

This section begins by introducing a conventional communication system, followed by a discussion of new communication scenarios and requirements. Finally, the limitations of conventional modules are highlighted.

A CLASSIC WIRELESS COMMUNICATION SYSTEM

We use orthogonal frequency division multiplexing (OFDM) as an example to illustrate the difference between conventional and semantic communication systems. As shown in Fig. 1, the source content, such as images or text, is first compressed and converted into a bit sequence by a source encoder. Redundancy is then added to the bit sequence by a channel encoder to counteract the effects of channel distortion. The bit sequence is then converted into a complex symbol sequence through an appropriate modulation technique. A pilot is inserted for channel estimation before an inverse fast Fourier transform (IFFT) is applied. A cyclic prefix is added to facilitate OFDM demodulation and the signal is sent to wireless channels. In multi-user networks, limited wireless resources, such as bandwidth and transmission power, must be properly allocated to optimize network performance.

Many receiver modules, such as demodulation, channel decoding, and source decoding, perform inverse operations of the corresponding modules at the transmitter. As shown in Fig. 1, the FFT operation, channel estimation, and signal detection address the impact of channels. The channel decoder corrects errors in the detected bits and the source decoder restores the original content, such as an image.

GROWING DEMAND FOR WIRELESS SERVICES

Mobile work and online conferencing have become integral parts of our lives, particularly during the COVID-19 pandemic. For example, transmission traffic has increased by over 60 percent compared to pre-pandemic levels. To meet this overwhelming demand, some service providers, such as YouTube, have been forced to reduce video quality during peak times. However, users expect to have access to high-quality services,

such as high-resolution videos, without restrictions on time and place. As a result, semantic communication, which significantly increases transmission efficiency and improves the user experience, is in high demand.

In addition to enhancing the user experience, wireless networks must also support a large number of devices. For example, autonomous cars rely on thousands of sensors for data collection and communication with other vehicles. The data transmission in vehicular networks typically serves specific purposes, and semantic communications are expected to play a crucial role in these scenarios.

LIMITATION OF SEPARATE MODULE DESIGN

In the classic Shannon paradigm, channel coding does not take into account the semantic meaning of the transmitted content, leading to a divide-and-conquer design approach for conventional modules. However, in low-delay scenarios, such as conferencing and autonomous driving, the code length is limited. Additionally, the transmission characteristics under specific tasks have a strong correlation, making a focus on bit-level transmission inefficient. As a result, content-related semantic methods are becoming increasingly important.

DEEP SEMANTIC SYSTEM DESIGNS

Currently, a majority of research in semantic communication focuses on the design of joint source-channel coding (JSCC). Some approaches involve redesigning traditional communication system components, such as modulation, signal detection, PAPR reduction, and resource allocation, for semantic communications. In this section, we will explore how these components can be semantized, including:

- Semantic Segmentation and Extraction for Source Coding.
- Joint Design and Training for Channel Coding.
- Minimizing Semantic Errors in Physical Modules.
- Resource Allocation for Semantic Needs of Various Users.

It is noteworthy that all semantic systems are powered by deep learning, as it is currently the only method for extracting semantic meaning from the source content. Table 1 provides a high-level comparison of the advantages and disadvantages

	Conventional	Semantic
Source coding	Pros: Reduced transmission payload and robust to any content. Cons: Inefficiency in specific tasks and content where semantic correlation is strong and most information can be known in advance.	Pros: Significantly save the transmission bandwidth by exploiting semantic correlation and meaning. Cons: Rely on an accurate KB shared in advance, which can be challenging in dynamic and diverse environments.
Channel coding	Pros: Errors are corrected based on bit redundancy, ensuring high accuracy. Cons: Poor performance when errors exceed correction capability	Pros: Error correction is done by semantic correlation, providing more effective protection for crucial transmission features. Cons: Dependent on precise KB for specific tasks and content, which can be difficult to keep current and updated.
Physical modules	Pros: Bit error rate and physical complexity are reduced. Cons: Separate design may not be optimal for specific contents and tasks	Pros: Directly improve the semantic similarity or task performance. Cons: Semantic similarity varies under different contents and tasks and rely on accurate KB shared in advance.
Resource allocation	Pros: Bit rate optimization for users. Cons: Inefficient use of increased bit rate without knowledge of task requirements.	Pros: User task performances are met effectively. Cons: Resource allocation is uneven and complicated due to the diversity of user content and tasks.

TABLE 1. Comparison of conventional and semantic modules.

es of these conventional and semantic modules. Before delving into the implementation of these semantic modules in the following subsections, we first define the KB, a key aspect for setting up a semantic communication system.

The KB guides the semantic extractor to transmit only compressed unknown information and the semantic decoder to correct errors. In [9], each transmitter and receiver pair have their local KB in addition to a KB shared by all transceivers when considering the consensus and disagreement of different equipment sets or users. In Fig. 2a, the local and shared KBs are categorized into implicit and explicit KBs.

Explicit KB can be shared in specific tasks. For example, in a talking-head video, there is usually a static background and a specific speaker. The photo of the speaker can be shared with the receiver as an explicit KB [10], which contains unchanged semantic information, such as the appearance of the speaker. This explicit KB can be replaced with a new photo easily once the speaker is changed.

Implicit KB is extracted automatically by DL methods and is represented by the trained parameters. Thus, implicit KB is established automatically after the E2E training of the semantic transmitter and receiver. However, implicit KB is not easily interpretable and is not as flexible. In order to adapt to new semantic scenarios, retraining or transfer learning is required to form a new KB.

Once a KB is established, various semantic-based operations can be designed, such as semantic extraction, reconstruction, and metrics. One such metric, called sentence similarity, is shown in Fig. 2b and is used in many studies, such as [2–4, 6]. Sentence similarity is based on a pre-trained model called BERT, which extracts knowledge from billions of sentences. After BERT has learned sentence correlation well, the distance between the embedded word vectors can be used as a measure of sentence similarity. The value of sentence similarity is at its maximum, 1, if the two sentences are exactly the same.

In reality, most semantic features are hard to represent explicitly and depend on the development of DL. Attention-based DL techniques have gained attention as these networks can distinguish the importance of different source parts.

SEMANTIC SEGMENTATION AND EXTRACTION FOR SOURCE CODING

Source coding aims to compress the original source content in order to reduce the transmission payload. This goal can be achieved through the use of semantic segmentation and extraction techniques, as demonstrated in Fig. 3.

Semantic segmentation involves dividing the source into different semantic parts, with varying degrees of importance. This segmentation is based on the KB of the specific scenario. For example, in a sentence, nouns and verbs may be considered more important than adjectives and adverbs, while in an image, objects may be considered more important than the background. After semantic segmentation, different parts of the source are protected with varying degrees of protection, with the most important semantic parts receiving the best channel conditions.

Semantic extraction reduces the redundancy of the source by taking into account the shared KB. By utilizing the shared KB, certain semantic information can be inferred, allowing only the key semantic information to be transmitted. For example, in the case of a talking-head video, only a few key points representing the facial expression need to be transmitted, as the rest of the appearance can be inferred using the shared KB [10].

At the receiver, the source decoder uses the received semantic parts of the source, as well as the semantic information from the shared KB, to reconstruct the original content. The traditional goal is to restore the source completely, but when the receiver has a specific task in mind, such as object recognition, the priority of transmission would be given to objects and sketches over background when resources are limited. The use of semantic segmentation and extraction, which are based on the shared KB between the transmitter and receiver, allows for a significant reduction in the transmission payload compared to conventional source coding methods that only compress the source at the bit-level.

JOINT DESIGN AND TRAINING FOR CHANNEL CODING

The compressed source can be protected using conventional channel coding techniques, such as Reed-Solomon code [4]. However, the use of

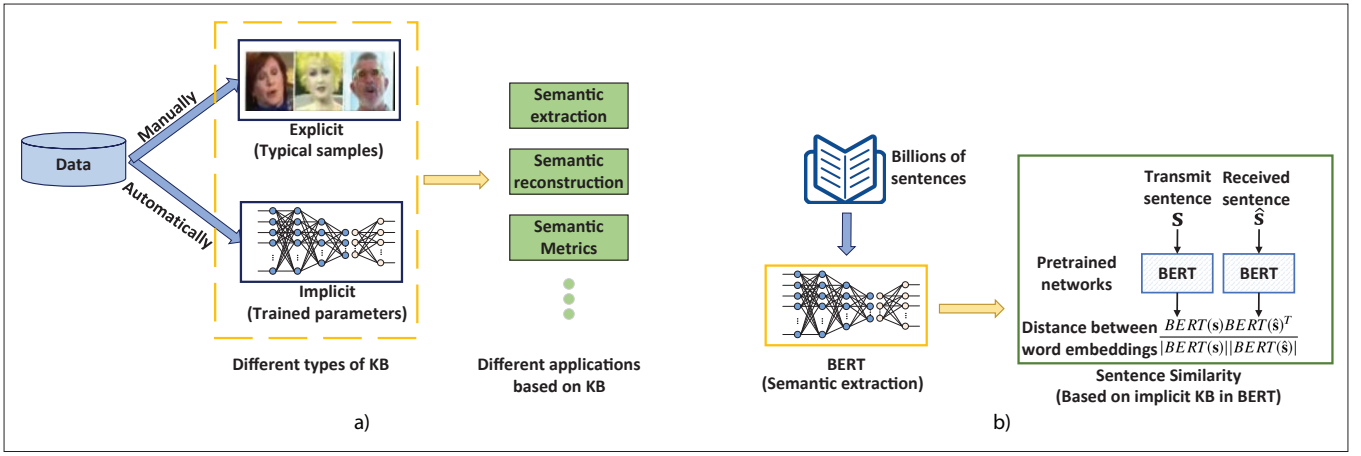


FIGURE 2. a) Two types of KB: explicit and implicit KBs; b) An example of a KB application: a semantic similarity metric using a pre-trained BERT model, trained on billions of sentences to create an implicit KB.

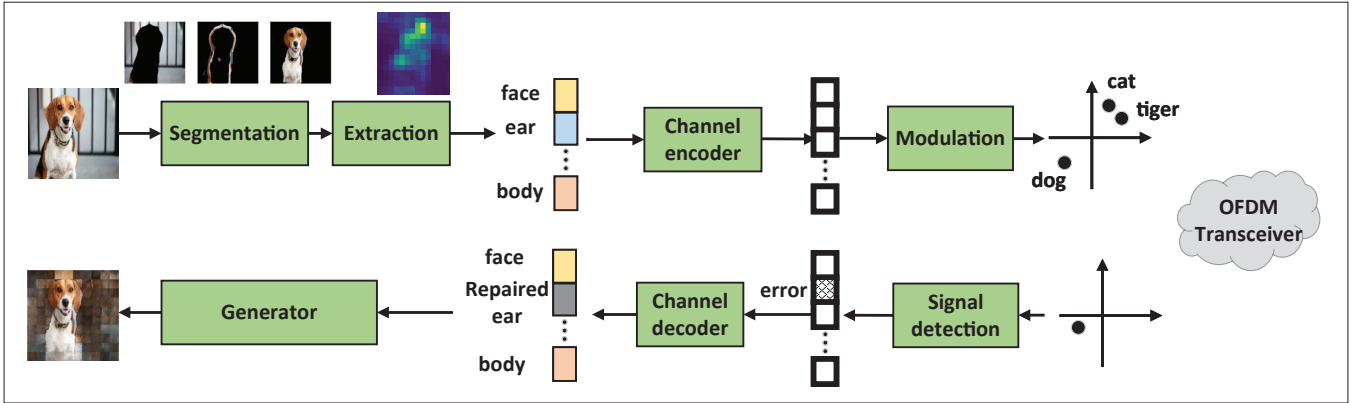


FIGURE 3. Examples of source-channel coding and modulation utilizing semantic extraction, segmentation, and metrics. The green modules represent the semantic methods used.

KB JSCC can significantly enhance the error correction capabilities. The joint design allows for the automatic protection of different parts of the source with different code rates [5]. In situations where the transmission bandwidth is limited, JSCC focuses on important semantic features, minimizing the loss of semantic similarity.

Figure 3 illustrates the mechanism of channel coding. The channel encoder takes into account the importance of different parts of a dog, such as the face, ears, and body, and applies varying degrees of protection to them. If errors occur in the received codeword corresponding to the ear in the dog's image, a conventional channel decoder can only correct the errors by utilizing redundancy, but it has no knowledge of the actual content. On the other hand, a semantic channel decoder can further correct errors by leveraging KB information, thereby restoring the dog's ear if the other parts of the dog have been accurately identified.

In summary, semantic-based channel coding offers more options for protecting the transmitted content and correcting transmission errors, thanks to the use of a KB. As a result, even in harsh channel environments where transmission errors exceed the correction capability of conventional channel coding, semantic coding can still preserve some semantic features.

MINIMIZING SEMANTIC ERRORS IN PHYSICAL MODULES

In traditional communication systems, physical modules, such as modulation, signal detection, and

channel estimation are optimized independently to minimize metrics, such as bit error rate (BER) and mean-squared error (MSE). However, in semantic communication systems, the optimization goal is to improve semantic similarity or task performance. Conventional systems transmit independent bits, while semantic systems transmit semantic features, some of which can be omitted if not essential for performance improvement. Conventional techniques, such as modulation, PAPR reduction, HARQ, and CSI feedback methods must be adapted to meet the needs of semantic communication. These adaptations are explained as follows:

Modulation: Due to the different semantic metrics used in wireless semantic communication, modulation techniques must be reevaluated. Conventional modulation methods, such as quadrature amplitude modulation (QAM), aim to reduce BER but are not aware of the content being transmitted. In fact, the transmitted features are not of equal importance. For example, in semantic text transmission as described in [2], constellation points are reorganized to enhance sentence similarity.

PAPR: PAPR can also be lowered while enhancing semantic performance, as high PAPR can strain hardware devices. In [3], PAPR is treated as an additional loss function, and the semantic network is trained to minimize both semantic and PAPR losses simultaneously, balancing PAPR reduction and semantic performance metrics.

HARQ: In varying channel conditions, HARQ with acknowledgment (ACK) feedback is crucial

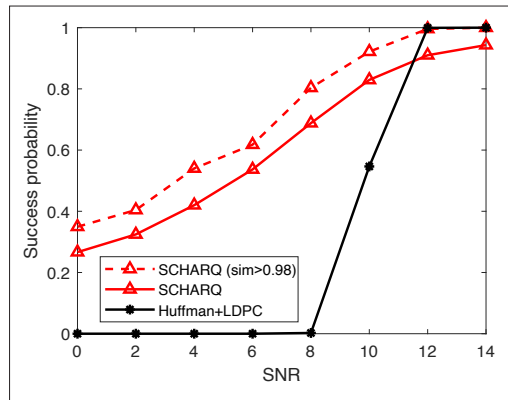


FIGURE 4. Comparison of transmission success rates for semantic-based and conventional Huffman+LDPC-based HARQ methods. SCHARQ (sim > 0.98) indicates that successful transmission is achieved when sentence similarity is greater than 0.98.

for successful transmission. Conventional HARQ relies on channel coding for forward error correction (FEC) and a cyclic redundancy check (CRC) code for error detection. In [4], FEC is substituted with semantic-based coding, and the CRC is redesigned based on semantic similarity.

Channel State Information (CSI) Feedback: Semantic methods, such as data hiding [11], can reduce the payload of CSI feedback. Additionally, important semantic features can be transmitted over favorable subchannels guided by CSI feedback [10].

RESOURCE ALLOCATION FOR SEMANTIC NEEDS OF VARIOUS USERS

Resource allocation is becoming increasingly important as the number of users and terminals continues to grow. By using appropriate allocation methods, the quality of service for all users can be ensured, and transmission resources can be conserved. Traditional resource allocation aims to transmit the necessary bits within the required time for a user. However, in semantic communications, the goal of resource allocation is shifting from reducing the number of bit errors to improving semantic performance metrics, such as sentence similarity. Therefore, the resource allocation method must be adapted accordingly.

Resource allocation in semantic communication has been initially studied in [6], where the metric is changed to sentence similarity and task success probability is maximized. A successful transmission requires an adequate level of sentence similarity to prevent misinterpretation. However, semantic performance metrics vary based on content and task. This property results in heterogeneous resource allocation and increased complexity. For example, text, image, and speech transmitted to three different users have different levels of importance. When transmission resources are limited, the most important semantic requirements must be met, such as maintaining text and speech meaning and keeping the main object in the image clear. When resources are plentiful, they can be used for high-quality service, such as accurate sentences and speech and full image restoration. Semantic resource allocation should consider varying levels of importance

for different parts and allocate resources adaptively based on channel conditions and user needs.

TWO EXAMPLES OF WIRELESS SEMANTIC COMMUNICATIONS

In this section, we showcase the advantages of wireless semantic communications and the impact it has on communication systems. We highlight the importance of error correction in challenging channel conditions by presenting examples of channel coding and modulation techniques.

SUCCESS RATE OF SENTENCE TRANSMISSION UNDER VARYING CHANNELS

The traditional HARQ method relies on FEC and a CRC to detect and correct transmission errors at the bit level. However, a semantic-based coding approach utilizes semantic correlation to correct errors at the sentence level. This method also allows for the detection of sentences with altered meaning, eliminating the need for the retransmission of unchanged sentences. As a result, the success rate of transmission can be improved through the use of these novel FEC and error detection methods. The specifics of the implementation are outlined below.

Database: This study uses sentences from the European Parliament, with lengths ranging from four to 30 words. A total of 100,000 sentences are used for training and 10,000 for testing.

Huffman+LDPC-based HARQ: The input sentences are first compressed using Huffman coding and then protected by Low-Density Parity-Check (LDPC) coding. The LDPC-based HARQ method is achieved by puncturing the LDPC codeword into different code rates. After Huffman coding, the average number of bits per sentence is approximately 460. The maximum code rate of the LDPC codeword is 5/16 and the maximum code length is 1,470 bits.

SCHARQ: The semantic coding (SC)-based incremental redundancy HARQ method, proposed in [4], encodes the input sentence into different codewords using a Transformer-based JSCC to extract semantic correlation. The error detection method can also be replaced by a sentence similarity measure. According to the ACK feedback, varying numbers of codewords are transmitted, resulting in an adaptive code rate. The maximum code length for a single sentence is 1,000 bits.

Experimental Setup: Both of these methods are integrated into an OFDM system with 16 QAM. Each block contains eight OFDM symbols, each of which comprises 64 subcarriers. The first OFDM symbol is used for piloting, while the remaining are for data. The channel is modeled with three paths located at [0, 4, 10] sampling points of delay spread, with a power profile of [0 -5 -10] dB, each path following an independent complex Gaussian distribution. The channel is assumed to vary between OFDM blocks. The success rate of transmission is calculated by transmitting 10,000 sentences.

As shown in Fig. 4, under time-varying channels, when the SNR is low, the SCHARQ method improves the number of correctly received sentences significantly, whereas the conventional Huffman+LDPC method is unable to correct the received sentences because the number of errors

exceeds its correction capability. However, when the SNR is larger than 12 dB, the SCHARQ method has a lower successful transmission probability. This result suggests that there is a small performance degradation due to the difference between the training and testing data.

The term SCHARQ ($\text{sim} > 0.98$) denotes that the transmission can be considered a success when the sentence similarity is greater than 0.98. A similarity value of 0.98 is very close to 1, indicating that the sentence meaning has not changed. As a result, SCHARQ ($\text{sim} > 0.98$) always transmits more sentences than those transmitted by SCHARQ and Huffman+LDPC.

SEMANTIC TRANSMISSION MODULATION

The traditional approach to constellation point distribution in modulation techniques, such as QAM and PSK, is to distribute them uniformly, assuming that all bits have equal importance. However, an alternative approach is to consider an E2E semantic JSCC method [12] that takes into account the semantic similarity of sentences. This method encodes each symbol into four bits, which are then mapped to two real numbers through a dense layer with a tanh activation function. These two real numbers represent a two-dimensional coordinate, resulting in a constellation point with 16 locations. The sentence is modulated into 80 constellation points through E2E training, with the goal of maximizing sentence similarity. As a result, two similar sentences may be mapped to constellation points that are close to each other.

As seen in Fig. 5a, the trained constellation points differ from those of the conventional QAM method, as the distance between points varies based on sentence similarity. If a point is mistakenly detected as another, but the meaning of the sentence is not affected, the points will be close to each other.

In Fig. 5b, we observe that the trained modulation method has improved performance in sentence similarity compared to 16-QAM, particularly at low SNR. However, at higher SNR, the performance of the trained modulation is slightly worse than 16-QAM. This is because some points are too close to others and cannot be correctly detected when SNR is between 15 and 20 dB.

The use of semantic methods in communication systems offers a unique approach for transmitting the meaning of the content, rather than just reducing bit errors. These methods involve a shift in performance metrics to prioritize maintaining semantic information and redesigning transmission modules to protect these features. As a result, semantic methods have the ability to operate effectively in challenging channel conditions and limited bandwidth environments.

OPEN ISSUES

Recent advancements in semantic communication have seen significant success, but have also introduced new challenges. Some newer transmission methods rely on KBs and E2E training, which can be difficult to understand and inflexible. Additionally, the use of new metrics in semantic communication has made the design process more complex. Further research is required to develop a practical wireless semantic communication system.

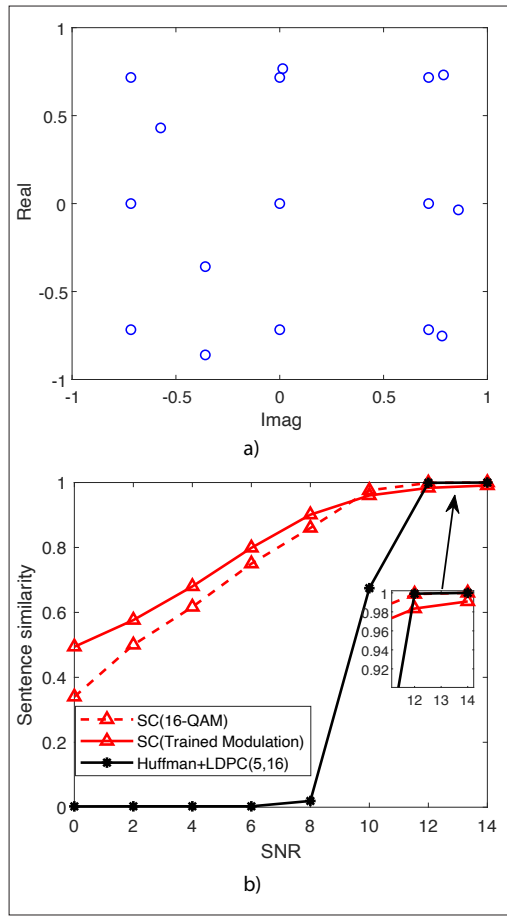


FIGURE 5. a) The 16 learned constellation points for maximizing sentence similarity, which are not uniformly distributed; b) sentence similarity performance of semantic methods using 16-QAM and trained modulation.

CREATING AND UPDATING A KB FOR SEMANTIC COMMUNICATION

The design of a KB plays a crucial role in semantic communication and affects transmission performance. However, a large portion of a KB is implicit in the trained parameters, making it hard to interpret. This design principle can result in KBs that work well with content in the same domain as the training data, but fail with new content. It is important to consider the specific task and transmission content when creating a KB. For example, a KB optimized for talking-head videos saves bandwidth by transmitting only keypoints, but is not suitable for general-purpose videos with changing backgrounds and characters. Varying transmission content and tasks require different KB designs, which is a challenge. Regular KB updates are also necessary, as offline training cannot cover all semantic scenarios, and collecting online data is difficult. In such cases, few-shot training methods, like domain adaptation and federated learning, can help share KBs across terminals.

ADAPTING TO DYNAMIC WIRELESS CHANNELS FOR SEMANTIC TRANSMISSION

In practical communication systems, wireless channels are often imperfect and unpredictable. Additionally, multiplicative wireless channels can

After channel estimation and signal equalization, an OFDM system can be treated as multiple flat subchannels with additive noise, enabling E2E training of semantic networks. However, most existing networks are fixed after E2E training, making them unsuitable for time-varying wireless channels. This approach can result in subpar performance when each transmit symbol carries a fixed amount of semantic features.

block the gradient from passing through. Some studies (e.g., [13]) have shown that explicit channel estimation can improve the performance of semantic methods. After channel estimation and signal equalization, an OFDM system can be treated as multiple flat subchannels with additive noise, enabling E2E training of semantic networks. However, most existing networks are fixed after E2E training, making them unsuitable for time-varying wireless channels. This approach can result in subpar performance when each transmit symbol carries a fixed amount of semantic features. A potential solution is to use variable code lengths, where each coded symbol carries adaptive transmit features, to adapt to changing channel conditions in wireless semantic transmission.

COORDINATING MULTIMODAL SOURCES FOR EFFICIENT SEMANTIC TRANSMISSION IN MULTI-USER SYSTEMS

Contrary to conventional systems that focus on increasing bit rate, multimodal sources for the same user can collaborate for certain tasks as they share some common semantic information [14]. For instance, a single object can be described using a picture, speech, and text. This enables E2E training to extract these semantic features and save a substantial transmission payload. However, different users may have diverse requirements, and the multiple sources may have varying definitions of semantic similarities. These conditions result in multiple semantic metrics and pose new challenges compared to traditional systems with a single metric. Some semantic metrics may not be differentiable, and reinforcement learning has been explored to address this issue [15]. With various metrics in a multi-user system, resource allocation becomes much more complex to accommodate personalized requirements, requiring further research.

CONCLUSIONS

This article has highlighted the limitations of traditional communication methods and the growing need for semantic communication. With the increasing number of wireless devices and diverse communication needs, semantic communication is becoming increasingly crucial for reducing data transmission and focusing on important semantic information through the use of a shared KB. We have introduced the concept of semantic communication, examined ways to improve or redesign conventional communication modules, and provided examples to demonstrate the superiority of semantic-based JSCC and modulation over traditional methods. Furthermore, we have identified important areas for future research in this field.

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BIOGRAPHIES

PEIWEN JIANG [S'21] (peiwenjiang@seu.edu.cn) received his B.S. degree from Southeast University, Nanjing, China, in 2019. He is currently working toward his Ph.D. in information and communications engineering, Southeast University, China. His research interests include deep learning based channel estimation, signal detection, and semantic transmission in communications.

CHAO-KAI WEN [SM'20] (chaokai.wen@mail.nsysu.edu.tw) received his Ph.D. from the Institute of Communications Engineering, National Tsing Hua University, Taiwan, in 2004. He was with Industrial Technology Research Institute, Hsinchu, Taiwan, and MediaTek Inc., Hsinchu, Taiwan, from 2004 to 2009, where he was engaged in broadband digital transceiver design. In 2009, he joined the Institute of Communications Engineering, National Sun Yat-sen University, Kaohsiung, Taiwan, where he is currently Professor. His research interests center around the optimization of wireless multimedia networks.

SHI JIN [SM'17] (jinshi@seu.edu.cn) received his Ph.D. in communications and information systems from Southeast University in 2007. From June 2007 to October 2009, he was a research fellow with the Adastral Park Research Campus, University College London, United Kingdom. He is currently with the faculty of the National Mobile Communications Research Laboratory, Southeast University. His research interests include space-time wireless communications, information theory, intelligent communications, and RIS. He and his coauthors received the 2010 Young Author Best Paper Award from the IEEE Signal Processing Society and the 2011 IEEE Communications Society Stephen O. Rice Prize Paper Award in the field of communication theory.

GEOFFREY LI [F'06] (geoffrey.li@imperial.ac.uk) is a Chair Professor with Imperial College London. His general research is in signal processing and machine learning for wireless communications. In the related areas, he has published over 600 articles with over 59,000 citations with H-index over 110 and been listed as a Highly Cited Researcher by Web of Science almost every year since 2001. He is an IEEE Fellow and an IET Fellow. He won Distinguished ECE Faculty Achievement Award from Georgia Institute of Technology and several prestigious awards from IEEE Communications, Signal Processing, and Vehicular Technology Societies, including IEEE ComSoc Edwin Howard Armstrong Achievement Award.