

Deep Source-Channel Coding for Sentence Semantic Transmission with HARQ

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

Abstract

Recently, semantic communication has been brought to the forefront because of its great success in deep learning (DL), especially Transformer. Even if semantic communication has been successfully applied in the sentence transmission to reduce semantic errors, existing architecture is usually fixed in the codeword length and is inefficient and inflexible for the varying sentence length. In this paper, we exploit hybrid automatic repeat request (HARQ) to reduce semantic transmission error further. We first combine semantic coding (SC) with Reed Solomon (RS) channel coding and HARQ, called SC-RS-HARQ, which exploits the superiority of the SC and the reliability of the conventional methods successfully. Although the SC-RS-HARQ is easily applied in the existing HARQ systems, we also develop an end-to-end architecture, called SCHARQ, to pursue the performance further. Numerical results demonstrate that SCHARQ significantly reduces the required number of bits for sentence semantic transmission and sentence error rate. Finally, we attempt to replace error detection from cyclic redundancy check to a similarity detection network called Sim32 to allow the receiver to reserve the wrong sentences with similar semantic information and to save transmission resources.

Index Terms

HARQ, semantic communication, quantization, sentence similarity, joint source-channel coding, Transformer.

P. Jiang and S. Jin are with the National Mobile Communications Research Laboratory, Southeast University, Nanjing 210096, China (e-mail: PeiwenJiang@seu.edu.cn; jinshi@seu.edu.cn).

C.-K. Wen is with the Institute of Communications Engineering, National Sun Yat-sen University, Kaohsiung 80424, Taiwan (e-mail: chaokai.wen@mail.nsysu.edu.tw).

G. Y. Li is with the Department of Electrical and Electronic Engineering, Imperial College London, London, UK (e-mail: geoffrey.li@imperial.ac.uk).

I. INTRODUCTION

Deep learning (DL) has been utilized in the physical layer of communications [1]–[3]. DL-based joint design [4]–[12] has become a potential directions to outperform the conventional communication structure. In [4], a fully connected network is used to replace channel estimation (CE) and signal detection at the receiver. In [5], the pilot is jointly designed with CE to reduce its overhead. In addition, the receiver can also be jointly optimized with beamforming [6] and precoding [7]. In [8], the entire network is combined with different modules, including pilot design, CE, and channel information state feedback. Many modules in the conventional communication systems can be jointly designed to improve their performance, such as DL-based joint encoder-decoder [9]–[11]. However, their reliability still has room for improvement. In the conventional communication system, reliable transmission is commonly guaranteed by hybrid automatic repeat request (HARQ). Among different types of HARQ, incremental redundancy HARQ (IR-HARQ) adjusts its code rate according to the acknowledgment (ACK) feedback and is a channel adaptive method. In [13], the performance of IR-HARQ achieved ergodic channel capacity for fading channels. The existing DL-based methods [14], [15] are proposed to enhance the HARQ but are still designed independently.

Recently, semantic communications [16]–[18] have been brought to the forefront because the great success of DL makes many semantic tasks possible [19]. Traditional communication systems concentrate on the bit or symbol level performance. Semantic communication focuses on transmitting the desired meaning, which is regarded as the second level communication in [20]. Semantic communication usually goes beyond traditional Shannon’s paradigm because the separated source and channel coding approach is not always optimal in practice. The semantic counterparts of Shannon’s source and channel coding theorems have been investigated in [21], where semantic communication is content-related. Thus, shared and local knowledge can help the joint design of source and channel coding and improve transmission efficiency. Specifically, joint source and channel coding for semantic transmission has been effective for image [22]–[27], video [28], speech [29], and text [30], [31] transmissions.

Some architectures for DL-based semantic communications can outperform those based on traditional communications for certain semantic metrics, especially when communication resources are limited and noise is high. At the outset, fully connected and convolutional neural networks

have been initially exploited for some specific transmission tasks, such as image transmission [26], [27]. DL-based joint source and channel coding in [26] improves the peak signal-to-noise ratio while higher image classification accuracy is focused in [27]. The shared knowledge of the transmission task is implicitly stored in the trained weights of the neural networks and makes the DL-based semantic methods better than the conventional encoding methods, which exploit no knowledge of semantics. A recurrent neural network (RNN) in [30] is exploited for sentence transmission under the erasure channel, which demonstrates its superiority under a high bit drop rate. The semantic transceiver in [31], which is called DeepSC, is based on Transformer [32] and is proved to be better than RNN in understanding the meaning of text sentences. DeepSC is extended to the Internet of Things in [33], where more practical issues, such as channel impact, quantization, and network compression, are considered. Furthermore, the novel architecture based on federated edge intelligence in [34] allows the user to offload semantic tasks. However, the impact of semantic coding on HARQ still need further study.

In this paper, we concentrate on SC based on Transformer for semantic transmission of text sentences. However, IR-HARQ is introduced for further performance improvement, which is different from previous works. First, our semantic coding network for source coding, called SC, is combined with the conventional Reed-Solomon (RS) channel coding and HARQ. Then, an end-to-end autoencoder, called SCHARQ, is introduced to improve the transmission efficiency and reduce the sentence-error rate (SER) under a high bit-error-rate (BER). Finally, we replace the conventional error detection method with a Transformer-based network, called Sim32, to detect the meaning error in the estimated sentences. The major contributions of this work are summarized as follows:

- 1) To improve the reliability of sentence semantic transmission, we combine the semantic source coding (SC) with conventional RS channel coding and HARQ, called parallel SC-RS-HARQ. The code length of SC is changeable according to the length of the sentences, thereby enabling SC to perform better than the methods with fixed code length when the required average number of bits is the same. The proposed SC helps reduce SER under high BER but always has minimal wrong words under low BER because DL has no mechanism to guarantee its performance when testing. The proposed parallel SC-RS-HARQ exploits the advantages of the semantic architecture and the conventional RS code and outperforms the competing semantic-

based and conventional methods at word-error rate (WER), SER, and bit consumption.

2) Although the proposed SC is easily applied in the conventional HARQ systems because only source coding is replaced, we also try to reduce the SER and the required bits when transmitting a long sentence further in an end-to-end manner. A Transformer-based joint source and channel coding, called SCHARQ, is proposed. SCHARQ is more flexible than the existing RNN and Transformer-based sentence transmission methods because it can transmit incremental bits according to HARQ. The code length of SCHARQ is controlled by the requirement of the receiver, which is more efficient than the competing methods when transmitting sentences with different lengths. Meanwhile, SCHARQ can cope with high BER better than the separate design.

3) To fully exploit the potential of the proposed semantic coding methods, we introduce a network called Sim32 to detect the meaning error in the received sentences. This error detection enables the received sentences to tolerate some error words as long as their meaning is unchanged. Sim32 can save transmit resources because more lossy sentences can be received without requiring retransmission. However, the proposed error detection still makes mistakes. For example, the replacement of nouns may be ignored by Sim32.

The remainder of this paper is organized as follows. Section II introduces the system model, including conventional RS encoder, IR-HARQ, and classic DL-based autoencoder architectures. The proposed networks are shown and discussed in Section III. In Section IV, we demonstrate the superiority of the proposed networks in terms of SER and the required number of bits. Finally, Section V concludes this paper.

II. SYSTEM MODEL AND RELATED WORKS

In this section, we first introduce a HARQ method for sentence transmission based on RS code. Next, we describe some existing DL-based end-to-end transmission methods. Finally, we discuss the challenges of combining the deep semantic networks with the HARQ system.

A. HARQ System for Sentence Transmission

To transmit a sentence, \mathbf{s} , the conventional transmitter first converts it into bits by source and channel coding, thereby yielding

$$\mathbf{b} = C_{\beta}(S_{\alpha}(\mathbf{s})) \quad (1)$$

where $S_\alpha(\cdot)$ and $C_\beta(\cdot)$ denote the source encoder through α algorithm and channel encoder through β algorithm, respectively. \hat{b} is denoted as the recovered bits at the receiver. Due to channel distortion, the recovered bits at the receiver may be different from those at the transmitter. The received sentence is decoded as

$$\hat{s} = S_\alpha^{-1}(C_\beta^{-1}(\hat{\mathbf{b}})) \quad (2)$$

where $S_\alpha^{-1}(\cdot)$ and $C_\beta^{-1}(\cdot)$ represent the source and channel decoders with the corresponding algorithms, α and β , respectively.

Given the adaptive correction capability of IR-HARQ, it is commonly used in communications, especially in wireless communication. Here, we consider an RS code, a maximum distance separable (MDS) code. An n -symbol RS code with k symbols of information can correct $n - k$ erasure symbols or $(n - k)/2$ error symbols. The corresponding code rate can be calculated by $\frac{k}{n}$. RS codes can be easily used for IR-HARQ because a punctured MDS code is still an MDS code [35], [36]. For example, n total symbols are punctured to n' ($< n$). Correction capability becomes $n' - k$ erasure symbols or $(n' - k)/2$ error symbols. Thus, if transmitting n' symbols is not enough to correct the error symbols, we can transmit $n - n'$ incremental symbols to increase its correction capability from $(n' - k)/2$ to $(n - k)/2$ error symbols.

The HARQ transmission process for sentences is described in Algorithm 1. If the estimated sentences at the receiver are detected to be correct by cyclic redundancy check (CRC) error detection, the acknowledged (ACK) signal will be sent to the transmitter, and the reserved incremental symbols are not required. In contrast, the sentence is unsuccessfully received when all incremental symbols are transmitted, but the full-length codewords still cannot be decoded correctly.

B. DL-based Autoencoder

The joint design has a great potential to improve transmission efficiency. For the DL-based autoencoder, the conventional encoder and decoder, $C_\beta(S_\alpha(\cdot))$ and $S_\alpha^{-1}(C_\beta^{-1}(\cdot))$, are replaced by the DL-based encoder and decoder. To train the encoder-decoder architecture in an end-to-end manner, they are connected by a channel layer, which usually consists of a dropout layer and an AWGN layer if the quantization is not considered. The channel layer can be a bit-erasure or bit-error layer for the quantized encoder and decoder. Also, the channel layer can learn the fading channel through the generative adversarial network [10].

Algorithm 1 HARQ transmission of sentences using RS channel coding.

Input: The transmitted sentence \mathbf{s}

- 1) Choose a low rate RS code. The full length of the codewords is n_R and the number of information bits is k , yielding

$$\mathbf{b}_R \leftarrow C_{RS_{n_R}}(S_\alpha(\mathbf{s})). \quad (3)$$

- 2) Puncture the encoder matrix and obtain different length of codewords, $\mathbf{b}_1, \mathbf{b}_2, \mathbf{b}_3, \dots$, where $k < n_1 < n_2 < n_3 < \dots < n_R$.
- 3) Transmit \mathbf{b}_1 and 32 CRC parity bits.
- 4) $\hat{\mathbf{s}}_1 \leftarrow S_\alpha^{-1} C_{RS_{n_1}}^{-1}(\hat{\mathbf{b}}_1)$.
- 5) **if** CRC detects error, feedback NACK; **else** $\hat{\mathbf{s}} = \hat{\mathbf{s}}_1$ and feedback ACK.

for $i = 2; i \leq R; i++$ **do**

if NACK

- 1) Transmit the incremental symbols, $\mathbf{b}_i - \mathbf{b}_{i-1}$.
- 2) $\hat{\mathbf{s}}_i \leftarrow S_\alpha^{-1} C_{RS_{n_i}}^{-1}(\hat{\mathbf{b}}_i)$.
- 3) **if** CRC detects error, feedback NACK; **else** $\hat{\mathbf{s}} = \hat{\mathbf{s}}_i$ and feedback ACK.

end if

end for

if ACK

Output: $\hat{\mathbf{s}}$.

else

Output: Sentence error.

The DL-based autoencoders perform better than the conventional methods, especially under wired environments with nonlinear interference and limited transmission resources. The joint source-channel coding [30] initiates the words with Glove pre-trained embeddings [37] and uses RNN to learn the semantic information. In [31], the attention mechanism is used for the semantic coder, which is called Transformer in [32]. The first step of the semantic encoder for a sentence is to obtain the word embedding. The sentence with L_s words can be expressed by a positive integer vector, $\mathbf{s} = [w_1, w_2, \dots, w_{L_s}]$. As the input of a DL-based encoder, all the sentences are zero-padded to a length of L . The word embedding process needs a lookup table Ψ and L_Ψ words in the dictionary. Denote M as the length of the word vectors after the word embedding process. Thus, Ψ is an $L_\Psi \times M$ real matrix whose parameters are trainable. The word embedding

process is denoted as $f_{\text{embed}}(\cdot; \cdot)$, and a sentence after wording embedding can be written as

$$\mathbf{V} = f_{\text{embed}}(\mathbf{s}; \Psi) = \begin{bmatrix} \Psi[w_1] \\ \vdots \\ \Psi[w_L] \end{bmatrix} + \mathbf{PE} \quad (4)$$

where $\mathbf{V} \in \mathbb{R}^{L \times M}$, \mathbf{s} is the input sentence, $\Psi[w_1]$ is the vector of the w_1 -th row in the trainable Ψ , and the additive matrix \mathbf{PE} is a constant matrix for position encoding defined in [32]. These word vectors in Ψ contain the meaning of the words because the distance of any two similar-word vectors is usually shorter than that of dissimilar-word vectors. Pre-trained lookup tables are available for extracting semantic information, such as Word2Vec [38] and Glove [37]. The detailed architecture of the Transformer can be referred to [32]. For convenience, we denote the Transformer-based encoder and decoder as $T_{\text{en}}(\cdot)$ and $T_{\text{de}}(\cdot)$, respectively. Here, the trainable parameters in these processes are not shown explicitly, and $f_{\text{embed}}(\mathbf{s}; \Psi)$ is also simplified to $f_{\text{embed}}(\mathbf{s})$. An FC layer converts the output of Transformers in the decoder from $\mathbb{R}^{L \times M}$ to $\mathbb{R}^{L \times L_\Psi}$ via the SoftMax activation. Thus, the decoded sentence $\hat{\mathbf{s}}$ is obtained according to the index of the maximum value at each row. The process is denoted as $f_{\text{argmax}}(\cdot)$. For machine translation, the translated sentence $\hat{\mathbf{s}}$ can be written as

$$\hat{\mathbf{s}} = f_{\text{argmax}}(T_{\text{de}}(T_{\text{en}}(f_{\text{embed}}(\mathbf{s}))))). \quad (5)$$

For semantic communication, several FC layers [31] are used to compress $T_{\text{en}}(f_{\text{embed}}(\mathbf{s}))$ into transmit symbols, and the received symbols are also decompressed by FC layers as

$$\hat{\mathbf{s}} = f_{\text{argmax}}(T_{\text{de}}(f_{\text{de}}(h(f_{\text{en}}(T_{\text{en}}(f_{\text{embed}}(\mathbf{s}))))))), \quad (6)$$

where $h(\cdot)$ is the channel layer, and $f_{\text{en}}(\cdot)$ and $f_{\text{de}}(\cdot)$ are the processes of FC layers. Then, this architecture is trained to cope with the effect of channels.

The semantic networks achieve better performance than conventional coders, especially when the new semantic metrics, such as BLEU [39], are applied. However, the benefits of the semantic methods for the throughout of a sentence transmission system are needed to be investigated further.

C. Challenges on Semantic Coders

The most obvious issue for the semantic coders is the fixed network architecture for different sentence lengths, which decreases coding efficiency. The fixed bit transmission in [30] performs

better for short sentences than long ones. The fixed symbol transmission in [31] also faces a similar issue if we add the quantization module.

In addition, they lack combination with HARQ, which is vitally important for successful transmission. The superiority of the semantic networks are exhibited not only in lossless compression but also in lossy transmission. The sentences with wrong words estimated by the semantic networks also contain useful semantic information under extreme hostile environments. To adapt to this content-related encoder-decoder, the HARQ method should also be refined.

III. HARQ BASED ON SEMANTIC CODER

In this section, we propose different semantic architectures, that are combined with IR-HARQ in different extents. In the beginning, the design of the semantic network is independent of the HARQ framework. Then, all the source-channel coding and the incremental encoded bits are generated by the neural networks. Finally, we replace the CRC with the similarity detection to reserve the incorrect but similar sentences at the receiver.

A. Semantic Source Coding for Transmitter with RS Channel Coding

Joint semantic source and channel coding have been studied in [30], [31]. These existing methods have shown their superiority under low SNR and the limited number of bits for each sentence. However, the fixed architectures are not flexible and efficient because sentences usually have different lengths. Meanwhile, these joint designs make the combination channel coding and HARQ difficult because DL-based coding is inexplicable.

As shown in Fig. 1(a), we first designed SC separately without the combination of conventional RS coding and IR-HARQ, and IR-HARQ (not shown in the figure) is directly based on the RS coding. The two proposed methods are called series and parallel SC-RS-HARQ. These methods exploit conventional RS coding in different stages. For series SC-RS-HARQ, the RS coding is used to protect the coded bits of the SC. That is, the received sentences are directly decoded by SC. Thus, this method may still commit mistakes under no transmission errors because the performance of the DL-based SC is not guaranteed when testing. For parallel SC-RS-HARQ, the sentence is encoded by SC and RS, and the parity bits of the RS coding are transmitted directly. Therefore, the RS coding is used to protect the original sentence and the correct sentence decoded by the SC. Thus, the received sentences are directly decoded by RS coding, and their performance is guaranteed under low BER. Overall, these methods can achieve better performance under high BER due to the introduction of SC.

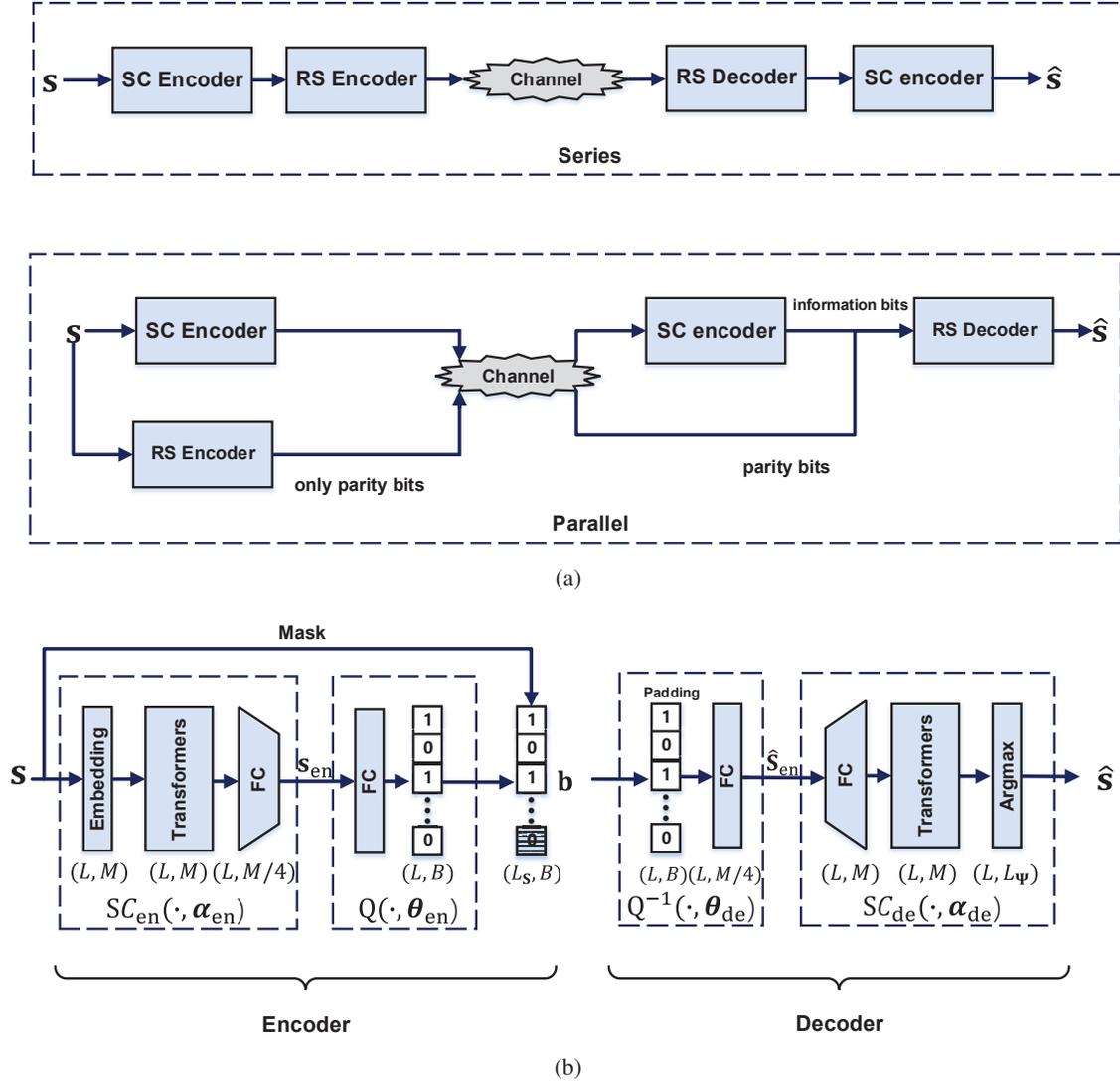


Fig. 1. (a) Two combination methods of SC- and RS- based IR-HARQ. (b) Architecture of the Transformer-based SC. The encoded bits are masked according to the input sentence length.

In addition, we develop the SC to encode the sentence into different lengths of bits according to the length of this sentence (Fig. 1(b)), which is beneficial for code efficiency. The encoder and decoder are based on Transformer [32]. The sentence is mapped to a vector of positive integers $s = [w_1, w_2, \dots, w_L]$ as an input. The SC encoder embeds s as (4), and then the embedded word vectors are processed by six Transformers with M units. The output of the Transformers is compressed by an FC layer, and the entire process is denoted as $SC_{en}(\cdot)$ with output

$$s_{en} = SC_{en}(s; \alpha_{en}), \quad (7)$$

where $\mathbf{s}_{\text{en}} \in \mathbb{R}^{L \times M/4}$ and $\boldsymbol{\alpha}_{\text{en}}$ represent all the trainable parameters. The one-bit quantization module first converts \mathbf{s}_{en} into $\mathbb{R}^{L \times B}$ with an FC layer, where B is the number of bits for each word. Different from the existing methods, the quantization module also masks part of the bits in accordance to sentence length L_s . We denote the quantization process as $Q(\cdot)$, and its output can be expressed as

$$\mathbf{b} = Q(\mathbf{s}_{\text{en}}; \boldsymbol{\theta}_{\text{en}}), \quad (8)$$

where \mathbf{b} is an $L_s \times B$ bit vector if the sentence length is L_s . The other $(L - L_s) \times B$ bits are not transmitted to save transmission resources.

The dequantization module pads input bits to an $L \times B$ binary matrix with zeros. Then, an FC layer is used for reshaping, and its output is $\hat{\mathbf{s}}_{\text{en}} \in \mathbb{R}^{L \times M/4}$, thereby yielding

$$\hat{\mathbf{s}}_{\text{en}} = Q^{-1}(\mathbf{b}; \boldsymbol{\theta}_{\text{de}}). \quad (9)$$

Then, $\hat{\mathbf{s}}_{\text{en}}$ is decompressed into $\mathbb{R}^{L \times M}$ with an FC layer and then goes through six Transformers with M units. At last, the argmax layer uses an FC layer with SoftMax activation and outputs $L \times L_\Psi$ vectors of probabilities in the dictionary. The estimated sentence is composed of the max possible words. Similar to the encoder process, the estimated sentence can be written as

$$\hat{\mathbf{s}} = SC_{\text{de}}(\hat{\mathbf{s}}_{\text{en}}; \boldsymbol{\alpha}_{\text{de}}). \quad (10)$$

The number of bits for each word, B , is difficult to choose to balance the coding efficiency and bit consumption; thus, an end-to-end training process costs too much time. The entire training process is also divided into three steps.

1) The parameters in $SC_{\text{en}}(\cdot)$ and $SC_{\text{de}}(\cdot)$ are trained without quantization layers $Q(\cdot)$ and $Q^{-1}(\cdot)$, i.e., $\hat{\mathbf{s}}_{\text{en}} = \mathbf{s}_{\text{en}}$. This training process can be expressed as

$$(\hat{\boldsymbol{\alpha}}_{\text{en}}, \hat{\boldsymbol{\alpha}}_{\text{de}}) = \arg \min_{\boldsymbol{\alpha}_{\text{en}}, \boldsymbol{\alpha}_{\text{de}}} L_{\text{CE}}(\mathbf{s}, SC_{\text{de}}(SC_{\text{en}}(\mathbf{s}; \boldsymbol{\alpha}_{\text{en}}); \boldsymbol{\alpha}_{\text{de}})), \quad (11)$$

where $L_{\text{CE}}(\cdot)$ denotes the cross-entropy (CE) loss function.

2) Try B repeatedly until transmit bits are enough to carry the information in $\mathbf{s}_{\text{en}} = SC_{\text{en}}(\mathbf{s}; \hat{\boldsymbol{\alpha}}_{\text{en}})$. The loss function is the mean-squared error (MSE), and the training process can be expressed as

$$(\hat{\boldsymbol{\theta}}_{\text{en}}, \hat{\boldsymbol{\theta}}_{\text{de}}) = \arg \min_{\boldsymbol{\theta}_{\text{en}}, \boldsymbol{\theta}_{\text{de}}} L_{\text{MSE}}(\mathbf{s}_{\text{en}}, Q^{-1}(Q(\mathbf{s}_{\text{en}}; \boldsymbol{\theta}_{\text{en}}); \boldsymbol{\theta}_{\text{de}})). \quad (12)$$

3) Finetune all trainable parameters in an end-to-end manner,

$$(\hat{\boldsymbol{\alpha}}_{\text{en}}, \hat{\boldsymbol{\alpha}}_{\text{de}}, \hat{\boldsymbol{\theta}}_{\text{en}}, \hat{\boldsymbol{\theta}}_{\text{de}}) = \arg \min_{\boldsymbol{\alpha}_{\text{en}}, \boldsymbol{\alpha}_{\text{de}}, \boldsymbol{\theta}_{\text{en}}, \boldsymbol{\theta}_{\text{de}}} L_{\text{CE}}(\mathbf{s}, \hat{\mathbf{s}}). \quad (13)$$

The two methods design SC and conventional IR-HARQ modules separately so that they can be applied easily. The advantages of SC are exploited under high BER. Meanwhile, the conventional method shows its superiority under the lossless transmission, and this combination can cover the shortage of the AI method. However, joint optimization is also a potential strategy for reducing transmission resources further, and thus joint source-channel coding and HARQ architecture will be studied further.

B. Semantic-based End-to-End HARQ

The long sentences can also be dealt through transmitting incremental bits because of the adjustable length of IR-HARQ. Thus, we propose an end-to-end semantic framework similar to the IR-HARQ framework, and it is called SCHARQ, which transmits the incremental bits until the receiver estimates sentence successfully or reach the maximum number of retransmissions. These incremental bits can not only improve correction capability but can also carry extra information for complex sentences. Overall, this framework is flexible under varying channels and different lengths of sentences.

There are R SC-based encoders and decoders for R transmissions are shown in Fig. 2. Here, the encoder and decoder architectures are different from those in Fig. 1. The quantization process $Q_i(\cdot; \boldsymbol{\theta}_{\text{en},i})$ in SCHARQ does not need to mask part of bits, but it converts the output of $SC_{\text{en}}(\cdot; \boldsymbol{\alpha}_{\text{en},i})$ to $\mathbb{R}^{1 \times (n_i - n_{i-1})}$ with a dense layer and then uses one-bit quantization. An n_1 -bit vector \mathbf{b}_1 is transmitted first, and the following transmissions use the similar architecture. The i -th transmission can be expressed as

$$\mathbf{b}_i = Q_i(SC_{\text{en}}(\mathbf{s}; \boldsymbol{\alpha}_{\text{en},i}); \boldsymbol{\theta}_{\text{en},i}), \quad (14)$$

and the previous transmitted bits are connected with the incremental bits $\hat{\mathbf{b}}_i$ and decoded together, yielding

$$\hat{\mathbf{s}}_i = SC_{\text{de}}(Q_i^{-1}([\hat{\mathbf{b}}_1, \dots, \hat{\mathbf{b}}_i]; \boldsymbol{\theta}_{\text{de},i}); \boldsymbol{\alpha}_{\text{de},i}), \quad (15)$$

where $Q_i^{-1}(\cdot)$ reshapes these bits with a dense layer and $SC_{\text{de}}(\cdot)$ has the same architecture as in Fig. 1.

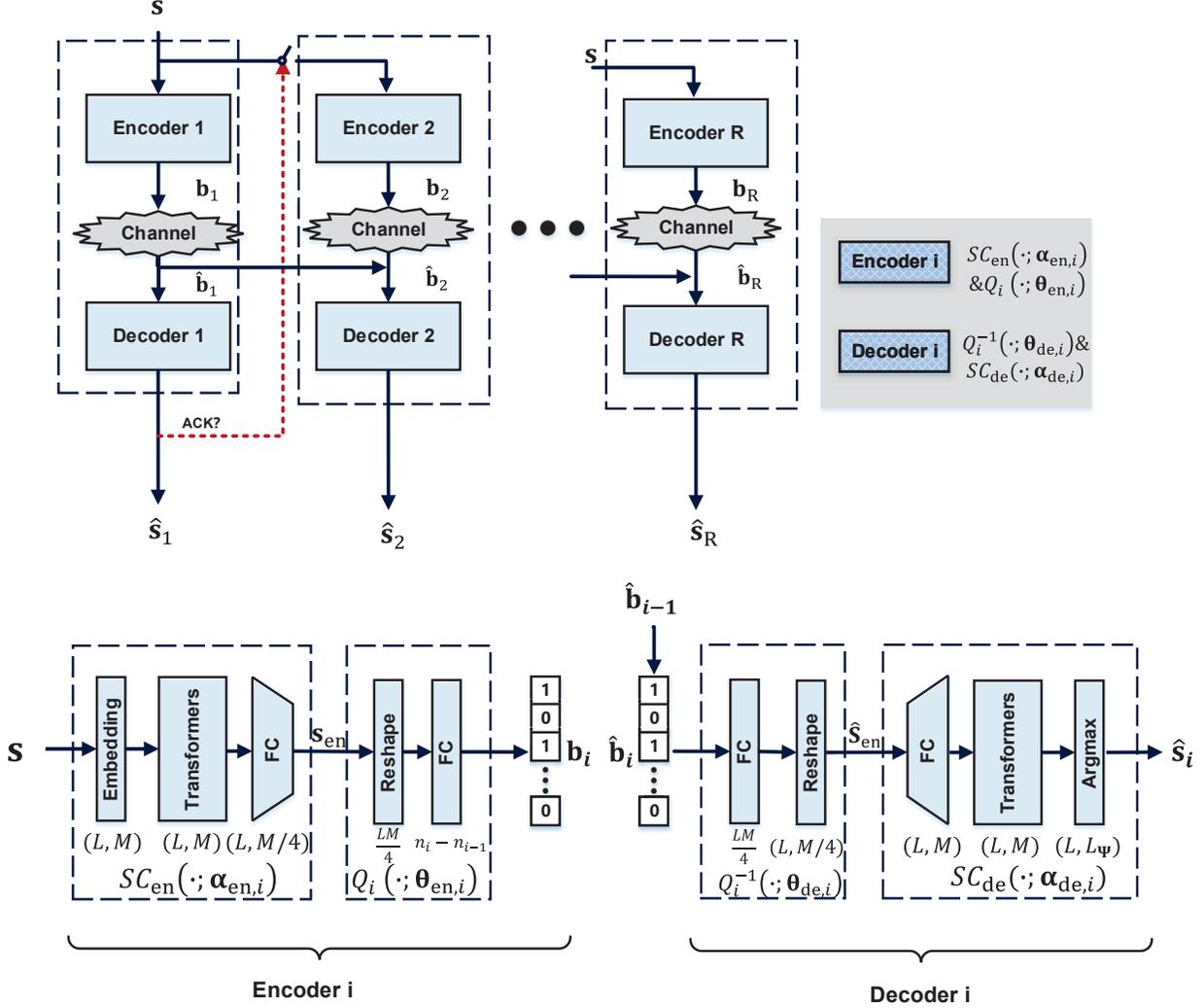


Fig. 2. Structure of SCHARQ, which can transmit R times in maximum.

The training process uses $\hat{\alpha}_{\text{en}}$ and $\hat{\alpha}_{\text{de}}$ trained in Section III A as the initiation of $\alpha_{\text{en},i}$ and $\alpha_{\text{de},i}$, respectively. For the first transmission, the training process is similar to Steps 2 and 3 in Section II A, but the channel condition should be considered here, and 5% bits are in error. For the i -th transmission ($i > 1$), the trainable parameters of the previous transmissions are fixed and the training process can be expressed as

$$(\hat{\alpha}_{\text{en},i}, \hat{\alpha}_{\text{de},i}, \hat{\theta}_{\text{en},i}, \hat{\theta}_{\text{de},i}) = \arg \min_{\alpha_{\text{en},i}, \alpha_{\text{de},i}, \theta_{\text{en},i}, \theta_{\text{de},i}} L_{\text{CE}}(\mathbf{s}, \hat{\mathbf{s}}_i), i > 1. \quad (16)$$

The application of this framework is naturally the same as the conventional IR-HARQ shown in Alg. 1. After the i -th transmission, we check $\hat{\mathbf{s}}_i$ with CRC and then transmit \mathbf{b}_{i+1} if this

transmission cannot obtain the correct sentence. If the i -th transmission passes the CRC error detection, then $\hat{s} = \hat{s}_i$, and the subsequent transmission is not required.

C. Similarity Detection

The above joint design with HARQ makes the network more flexible under varying channels and sentences, but the system still aims at minimizing word error rather than the semantic error in transmission. To fully exploit the potential of semantic architecture, we attempt to change the CRC to a similarity detection in this section.

Conventional transmission systems usually rely on the CRC error detection to repeat requests automatically to receive the correct sentences and feedback ACK. However, the traditional CRC error detection will regard a sentence with an error if it contains error words but with the same or similar meaning as the original one. Similar sentences are also useful for semantic transmission, especially in hostile environments.

Although some methods for the similarity measurement of sentences, such as Levenshtein distance and BLEU, have been proposed. They only calculate the change of words between two sentences and have no insight into the meaning of different words. Recently, BERT [40], a pre-trained model under billions of words and sentences, achieved great success in extracting semantic information. This architecture has been applied in measuring the similarity of sentences, such as [31]. $BERT(s)$ converts the input sentences, s , into real vectors, and the cosine similarity is used to measure the similarity in their semantic information, which is defined as

$$Sim(s, \hat{s}) = \frac{BERT(s)BERT(\hat{s})^T}{|BERT(s)||BERT(\hat{s})|}. \quad (17)$$

However, the true sentence s in HARQ systems is unavailable at the receiver. Thus, a new method that is similar to CRC is proposed, and it is called Sim32. In Fig. 3, 32 bits are transmitted to the receiver for similarity detection. At the transmitter, the 32 bits is encoded as

$$\mathbf{b}_{sim} = Q_{sim}(SC_{en}(s; \alpha_{sim,1}); \theta_{sim,1}), \quad (18)$$

where $Q_{sim}(\cdot; \theta_{sim,1})$ converts the output of $SC_{en}(\cdot; \alpha_{sim,1})$ into 32 bits, and $\alpha_{sim,1}$ and $\theta_{sim,1}$ are the trainable parameters in these processes. At the receiver, similarity detection is based on two inputs, namely, $\hat{\mathbf{b}}_{sim}$ and \hat{s} , which can be expressed as

$$Sim32(\hat{s}, \hat{\mathbf{b}}_{sim}) = f_{sim}(\hat{\mathbf{b}}_{sim}, SC_{en}(\hat{s}; \alpha_{sim,2}); \mathbf{W}_{sim}), \quad (19)$$

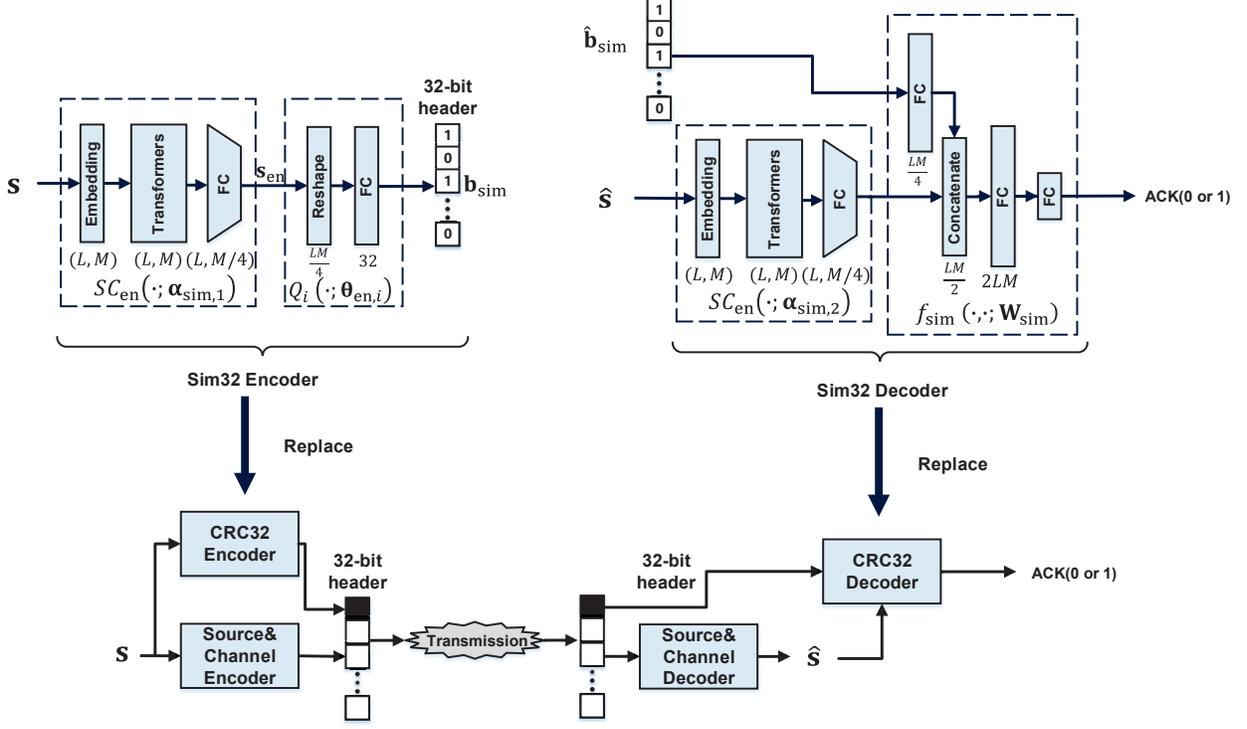


Fig. 3. Structure of similarity detection method. The estimated sentence \hat{s} is received by the proposed methods, such as SC-RS-HARQ and SCHARQ.

where f_{sim} has two FC layers and the trainable parameters, $\alpha_{sim,2}$ and \mathbf{W}_{sim} are introduced. Its hidden layer has four times the size of the input and ReLU activation function, and it only outputs one value using the sigmoid activation function.

The training process of this architecture will collect the estimated sentences from the aforementioned frameworks under different channel conditions and retransmission stages. The label is based on (19), and it satisfies

$$label(\mathbf{s}, \hat{\mathbf{s}}) = \begin{cases} 1, & Sim(\mathbf{s}, \hat{\mathbf{s}}) > 0.98, \\ 0, & Sim(\mathbf{s}, \hat{\mathbf{s}}) \leq 0.98, \end{cases} \quad (20)$$

where $Sim(\mathbf{s}, \hat{\mathbf{s}}) > 0.98$ indicates that the estimated sentences are similar enough to express the semantic information and their labels are 1. The training process can be written as

$$\begin{aligned} & (\hat{\alpha}_{sim,1}, \hat{\alpha}_{sim,2}, \hat{\theta}_{sim,1}, \hat{\mathbf{W}}_{sim}) \\ & = \arg \min_{\alpha_{sim,1}, \alpha_{sim,2}, \theta_{sim,1}, \mathbf{W}_{sim}} L_{CE} \left(label(\mathbf{s}, \hat{\mathbf{s}}), Sim32(\hat{\mathbf{s}}, \hat{\mathbf{b}}_{sim}) \right). \end{aligned} \quad (21)$$

After training, 32 bit CRC can be replaced with Sim32. Similar to CRC, Sim32 needs to judge the similarity from the estimated sentence and only 32 encoded bits from the true sentence. The transmission is considered successful when $Sim32(\hat{s}, \hat{\mathbf{b}}_{sim}) > 0.5$.

IV. NUMERICAL RESULTS

In this section, we will present the numerical results of different frameworks and discuss the pros and cons of the semantic-based HARQ. We will also compare their bit consumption with competing ones.

A. Configurations of the simulation system

The English version of the proceedings of the European Parliament [41] is chosen as the dataset, which has 2.2 million sentences and 53 million words. We set up the dictionary using 30,000 most common words. Thus, these words can be denoted by 2-byte integers. The length of the sentences is restricted between 4 and 30. After this pre-processing, these sentences are split into a training set of 500,000 sentences and a test set of 50,000 sentences. The input sentences s are padded to their max length $L = 30$ with zeros, and the number of units in the hidden layers M is 128. The detailed settings of the proposed networks are shown in Table I.

Huffman coding is used as the conventional source coding, and the average length of coded bits are compared with the SC in Table II. Due to different lengths of sentences, the SC is still not efficient compared with the Huffman code. Meanwhile, the SC has no mechanism to guarantee no error, and it costs numerous bits to reduce WER further when WER is already very small. For example, SC with $B = 40$ needs 1/3 more bits than that with $B = 30$, but WER only decreases by nearly 1%. In the following simulations, $B = 30$ is chosen to balance bit consumption and WER. The semantic encoder with fixed bit length, called fixed SC, encodes the sentence into 500 bits. The WER of the fixed SC is much higher than the SC with an average of 490 bits per sentence because it is weak in dealing with long sentences.

Binary symmetric channel, where transmit bits are randomly inversed, is used. The WER and SER are analyzed along with the change in BER. The transmission using Huffman source coding, RS channel coding, and HARQ is called Huffman-RS-HARQ, where the number of the SC coders is $R = 4$, and the code rates of each transmission are $\frac{k}{n_1} = \frac{5}{7}$, $\frac{k}{n_2} = \frac{5}{11}$, $\frac{k}{n_3} = \frac{5}{15}$ and $\frac{k}{n_4} = \frac{5}{19}$. Thus, $n_R = 1508$. The series and parallel SC-RS-HARQ methods only transmit three times at most and the corresponding $n_R = 490 \times \frac{n_3}{k} = 1470$, which is lightly fewer than the conventional one. For SCHARQ, $R = 3$ and the code lengths are set as $n_1 = 300$, $n_2 = 500$, and $n_3 = 1000$, respectively.

TABLE I. Settings of the proposed Networks.

Networks	Modules	Layer	Output dimensions	Activation function	
SC	INPUT	s	30	/	
	SC_{en}	Embedding	(30,128)	None	
		$6 \times$ Transformer	(30,128)	None	
		FC	(30,32)	ReLU	
	Q	FC	(30,30)	ReLU	
		1-bit quantization	(30,30)	/	
		Mask	$(L_s, 30)$	/	
Q^{-1}	Padding	(30,30)			
	FC	(30,32)	ReLU		
SC_{de}	FC	(30,128)	ReLU		
	$6 \times$ Transformer	(30,128)	None		
	FC	(30,30000)	SoftMax		
OUTPUT	\hat{s}	30	Argmax		
SCHARQ	INPUT	s	30	/	
	Encoder i	SC_{en}	(30,32)		
		Reshape	960	/	
		FC	b_i	ReLU	
		1-bit quantization	b_i	/	
	bit error channel				
	Decoder i	FC	960	ReLU	
Reshape		(30,32)	ReLU		
SC_{de}		(30,30000)	SoftMax		
OUTPUT	\hat{s}_i	30	Argmax		

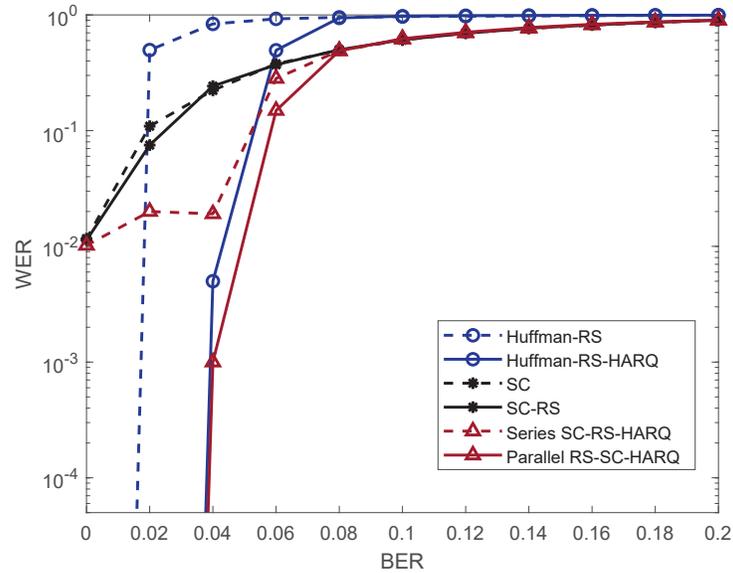
* For convenience, SC_{en} is directly used in the layer column to represent the same layers shown in the SC_{en} module of the SC. Sim32 only consists of the proposed modules and some FC layers; thus, its detailed architecture is omitted here.

TABLE II. SC source coding with different B .

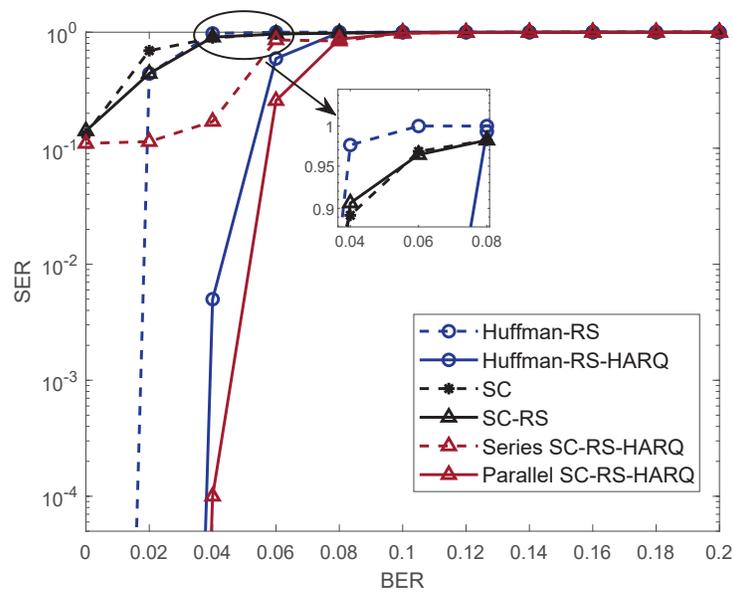
	B	Bits/Sentence	WER
SC	40	654	0.01%
	30	490	1.03%
Fixed SC	/	500	9.81%
Huffman	/	397	/

B. Performance of SC Combined with Conventional Methods

In Fig. 4(a), Huffman-RS represents the first transmission of Huffman-RS-HARQ with code rate $\frac{5}{7}$ and code length of approximately 555 bits. The Huffman-RS has the worst capability to



(a)



(b)

Fig. 4. (a) WER performance of the different semantic competing conventional methods. (b) SER performance of the different semantic competing conventional methods.

cope with the change in BER. SC requires fewer bits (approximately 490 bits) but has better performance than the Huffman-RS, especially when BER is high. This phenomenon demonstrates the SC can handle bit errors even if it does not learn to do it. The series and parallel SC-RS-HARQ both perform better than Huffman-RS-HARQ when $BER > 0.04$. However, the Huffman-

RS-HARQ and parallel SC-RS-HARQ can guarantee almost zero WER when $BER < 0.04$ because the estimated sentences are directly decoded by the conventional method, whereas the series SC-RS-HARQ always has tiny errors when testing. Due to the SC source coding, the series and parallel SC-RS-HARQ is better than the Huffman-RS-HARQ when $BER \geq 0.06$, and its performance is the same as the SC when $BER \geq 0.08$. Therefore, the semantic-based SC is still effective when the conventional method cannot work.

In Fig. 4(b), the SC has a higher SER than the Huffman-RS when $BER < 0.03$ because nearly 1% of the error words randomly spread out the estimated sentences and causes about 10% of estimated sentences with one or two error words even when the conventional Huffman-RS-HARQ has no errors. The series SC-RS-HARQ also has the same phenomenon, and its SER can only reach 0.1 while its WER is around 0.01. In contrast, the conventional methods can estimate sentences perfectly if the number of wrong bits is below their error correction capability. The parallel SC-RS-HARQ can correct the error words after the SC decoder; thus, it can achieve perfect transmission when $BER < 0.04$. Meanwhile, the SER of the parallel SC-RS-HARQ always decreases earlier with BER than the competing methods, which shows its superiority when facing high BER conditions.

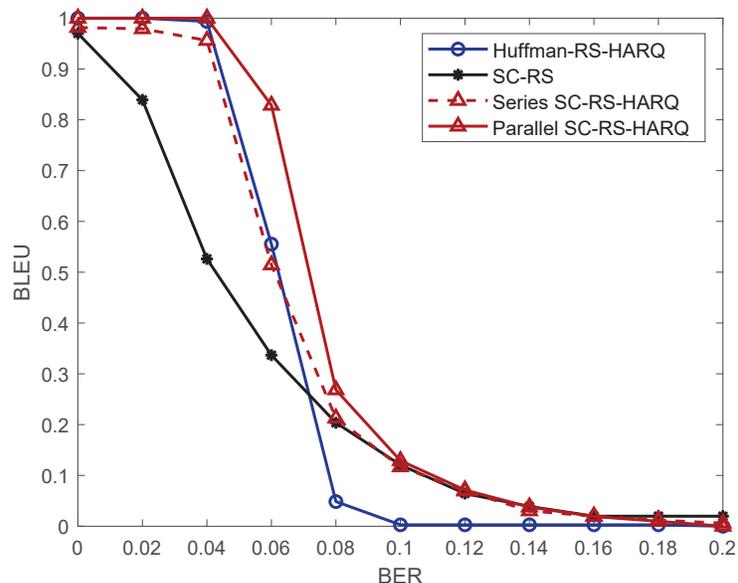


Fig. 5. BLEU performance of the proposed SC-RS-HARQ methods and conventional Huffman-RS-HARQ method.

We also compare the BLEU performance of these methods in Fig. 5. Similar to their SER performance, the parallel SC-RS-HARQ always has the best BLEU performance while that of

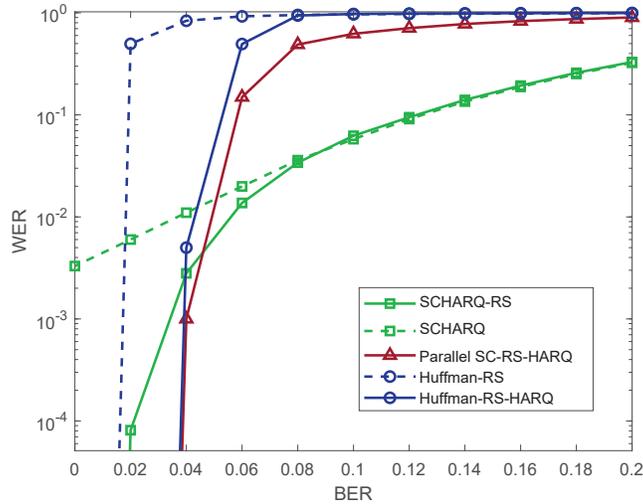
the series SC-RS-HARQ is worse than that of the conventional Huffman-RS-HARQ when $\text{BER} \leq 0.06$. However, the performance gap between the series SC-RS-HARQ and the Huffman-RS-HARQ is smaller than that in Fig. 4(b) because the wrong sentences still reserve some correct semantic information. The three SC-based methods have the same performance when $\text{BER} > 0.1$ because the SC network plays a major role in high BER. Overall, the series SC-RS-HARQ is not too bad under the BLEU measurement because the reserved tiny error words when $\text{BER} < 0.03$ have little impact on its semantic information.

In the above simulation, the semantic methods have better WER performance than the conventional methods if they are combined with conventional RS coding and HARQ properly. The SER performance of parallel SC-RS-HARQ is guaranteed to surpass the conventional Huffman-RS-HARQ while that of the series one has worse SER. Overall, the proposed methods are easily applied in the conventional HARQ systems, and the performance is improved for high BER.

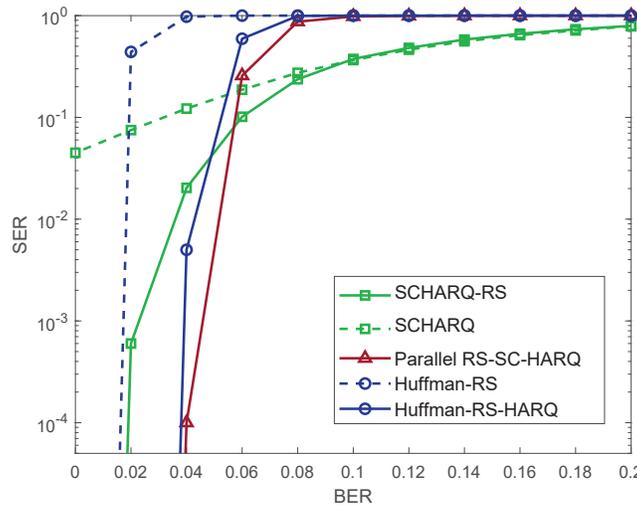
C. Performance of SCHARQ

In Fig. 6(a), SCHARQ methods show their superiority when BER is between 0.04 and 0.2, and increasing the transmit bit limit is helpful to improve the WER of SCHARQ. Because avoiding the tiny error is difficult when $\text{BER} \leq 0.04$, we also transmit extra parity bits coded by the RS encoder to correct the estimated sentences similar to the parallel SC-RS-HARQ. The SCHARQ with the RS code is called SCHARQ-RS, which has $\frac{5}{7}$ code rate for RS coding. Similarly, the SCHARQ methods always have better capability to cope with high BER, as shown in Fig. 6(b). $n_R = 1000$ is adequate for SCHARQ to approach almost zero WER when $\text{BER} \leq 0.04$, but its SER can only reach 0.05 at most due to tiny WER. The conventional RS code helps improve the performance and guarantees the perfect transmission when the error in the SCHARQ does not surpass the capability of the RS code. Thus, SCHARQ-RS can reach 0 WER and 0 SER when $\text{BER}=0$ and surpass SCHARQ when $\text{BER} \leq 0.1$. However, the error that appears in the redundancy bits of the RS code may also misapprehend the correct estimated sentences, which makes SCHARQ-RS become a little worse than SCHARQ when BER is between 0.1 and 0.2. The parallel SC-RS-HARQ is the best method to use when $\text{BER} \leq 0.04$, where the SER is guaranteed to be zero, but it performs worse than the SCHARQ methods when $\text{BER} > 0.06$.

In Fig. 7, the average required number of bits for a sentence transmission are compared. The conventional Huffman-RS-HARQ and series SC-RS-HARQ reach the upper limit of transmission times at $\text{BER}=0.06$, and thus its SER is close to 1 when $\text{BER} \geq 0.08$. In contrast, the parallel SC-RS-HARQ performs better when BER is low and reaches bit consumption limit at $\text{BER}=0.08$.



(a)



(b)

Fig. 6. (a) WER of the proposed SCHARQ and the competing methods. (b) SER of the proposed SCHARQ and the competing methods.

The series SC-RS-HARQ requires more bits than the parallel one when $BER \leq 0.06$ because the series one cannot reach zero SER, and some error sentences need to be retransmitted. The SCHARQ methods show the superiority of the joint design of semantic source-channel coding and HARQ in reducing transmit bit consumption, especially when BER is high. Especially, SCHARQ-RS needs fewer bits than SCHARQ when $BER \leq 0.05$ even though it transmits extra redundancy bits. This phenomenon is owed to the reduced times of retransmission with the help of RS code when BER is low. However, the redundancy bits of the RS code cannot bring benefit

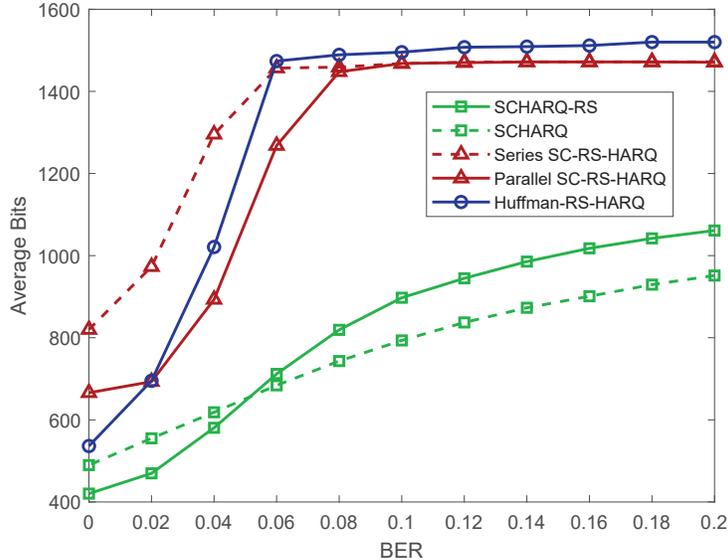


Fig. 7. Average bit consumption per sentence of different methods.

for high BER but introduces more errors (Fig. 6(b)); thus, the SCHARQ-RS needs more bits than the SCHARQ when $BER=0.05 - 0.2$.

From the above discussion, we find the joint design of source-channel coding and HARQ has a significant advantage in reducing bit consumption and improving the SER performance under high BER. The proposed methods show their superiority at different BER scales. However, these designs cannot make full use of the semantic coder because the retransmission decision is still CRC that needs the estimated sentences to error-free. Although the semantic method cannot surpass the conventional methods if the BER is low and no error transmission is needed, it brings the possibility to protect the sentence meaning when some words are incorrect. In the following, CRC is replaced with similarity detection to study the pros and cons of semantic transmission.

D. Pros and Cons of Similarity Detection

We first show the decision error rate of Sim32 in Fig. 8. We calculate the similarity according to (17) of 50,000 estimated sentences under two different BER settings. The decision error means the estimated sentences with similarity larger than 0.98 have Sim32 decision of 0, and those with similarity less than 0.98 have Sim32 decision of 1. As shown in Fig. 8, the error rate is high in the adjacent area of 0.98, which demonstrates that Sim32 cannot obtain an accurate similarity because the semantic information of the true sentence is compressed into 32 bits in the transmission. In general, this similarity detection efficiently refuses the estimated sentences with

a similarity less than 0.9 and is robust to the change in BER. However, approximately 2% of the correct sentences are mistaken as dissimilar sentences by Sim32 under BER=0.05. To solve this issue, we only use Sim32 to find similar sentences after CRC detection, and it ensures that the correct sentences are directly received at the CRC process, and is called CRC-Sim32.

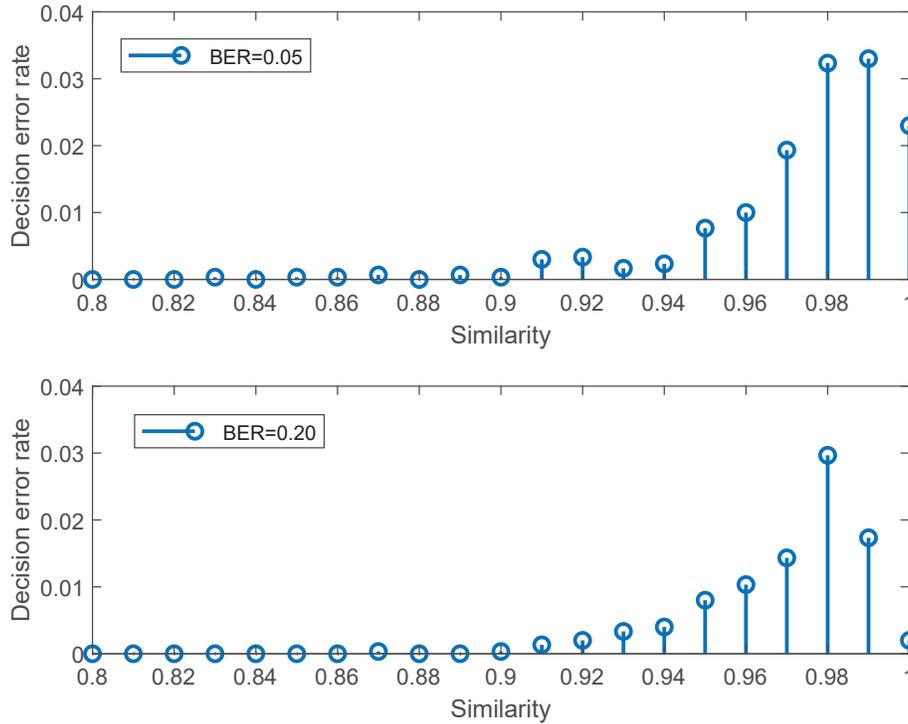


Fig. 8. Decision error rate of the Sim32 error detection method.

In Fig. 9, the first two transmissions of SCHARQ still use CRC error detection, and that of the last transmission is changed into Sim32, and CRC-Sim32. Thus, the change in error detection has no influence on reducing retransmission times. The CRC-Sim32 uses CRC first and then uses Sim32 to decide the sentences that fail in CRC. The CRC-Sim32 needs extra 32 bits but can ensure that the correct sentences are not considered dissimilar sentences. The detected error sentences means that these estimated sentences cannot pass the decision after the last transmission, and this error rate is shown in Fig. 9. The performance of CRC can represent the SER performance of SCHARQ in Fig. 6(b). The Sim32 detection at the last transmission allows that some estimated sentences with error words are received as similar sentences. This method increases the number of the received sentences, especially when BER is high. However, some correct sentences are mistakenly decided as dissimilar sentences. Thus, Sim32 receives fewer sentences than CRC when $BER \leq 0.04$. CRC-Sim32 performs best when BER is low and

approaches Sim32 when BER=0.2 because only few correct sentences are mistakenly rejected by Sim32 when BER=0.2.

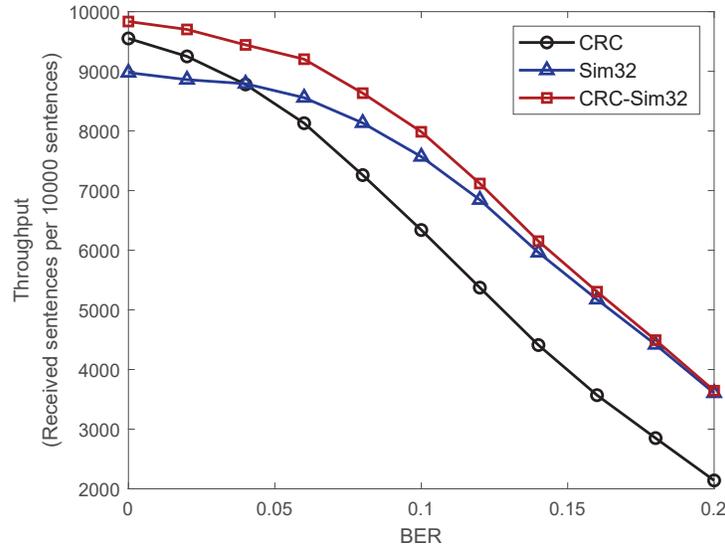


Fig. 9. Received sentences from 10000 transmit sentences with different error detection methods. Only the error detection method at the last transmission is replaced.

Replacing CRC with CRC-Sim32 at all transmission can reduce the bit consumption further by reducing the times of retransmission. For example, the received sentences can be increased by 18%, and the average bit consumption is reduced by nearly 40 bits when replacing CRC with CRC-Sim32 at all transmission when BER=0.2.

Finally, the BLEU performances of SCHARQ-based methods are compared in Fig. 10. The SCHARQ-RS, SCHARQ, and Huffman-RS-HARQ use CRC error detection while CRC-Sim32 is the SCHARQ that uses CRC-Sim32 for all the transmission times. Although SCHARQ-RS has an obvious SER performance gap with SCHARQ in Fig. 6(b), they have similar BLEU performance because the few error words that can be corrected by RS code have little influence on the semantic information. Thus, CRC-Sim32 only needs the received sentences to be understood rather than a high BLEU score, thereby causing some sentences to need fewer bits than the SCHARQ with CRC error detection. The performance gap between SCHARQ with CRC and CRC-Sim32 under low BER is larger than that under high BER because more received sentences have a chance to reach a higher BLEU score under low BER.

The proposed similarity detection aims at adopting an estimated sentence with error words as long as its semantic meaning is unchanged. However, similarity detection is such a difficult task

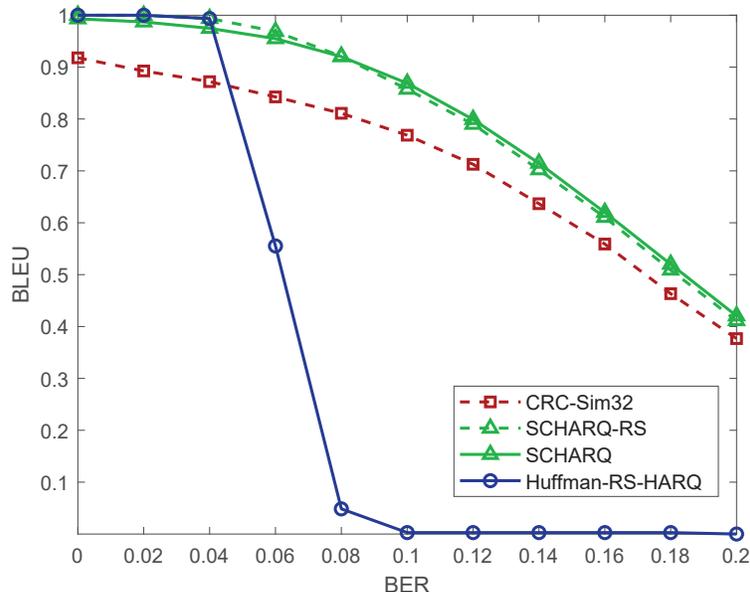


Fig. 10. BLEU performance of the proposed joint source-channel coding and HARQ methods. CRC-Sim32 means that BLEU performance of SCHARQ, whose the error detection methods of all transmissions are replaced with CRC-Sim32.

because the true sentences are unknown to the receiver. A lot of work must still be done before the similarity detection becomes reliable in the sentence transmission.

E. Similar Sentences Received by Similarity Detection

Here, we will analyze some common mistakes that appear in the "similar sentences" decided by the proposed methods. As shown in Table III, some similar sentences of SCHARQ are collected under four settings. Here, CRC in the bracket means the first two transmissions are decided by CRC, and the last transmission is detected by CRC-Sim32. CRC-Sim32 means that all the transmissions are detected by CRC-Sim32. TX is the transmitted sentence, and RX is the received sentence after SCHARQ. Three pairs of TX and RX sentences are shown under different settings.

Most of the similar sentences under BER=0 (CRC) contain only one or two error words. Meanwhile, these mistakes only happen in long sentences because the 1000-bit limitation of the semantic network may not be enough for these sentences. These three received sentences demonstrate that the wrong nouns are difficult to judge for similarity detection because replacing a noun usually has no influence on the grammar. For Sentence 1, "acquis" is replaced with "aviation", which may associate with "travel freely without barrier". For Sentence 2, the noun

TABLE III. The sentences pass the Sim32 but contain error words.

BER=0 (CRC)	
1	RX: this aviation means a lot to eastern and central european countries also for historical reasons because it provides the opportunity to travel freely without barriers TX: this acquis means a lot to eastern and central european countries also for historical reasons because it provides the opportunity to travel freely without barriers
2	RX: today we must welcome an important result which is that we consider the citizens of bulgaria and romania to be among those who can benefit from this fundamental that TX: today we must welcome an important result which is that we consider the citizens of bulgaria and romania to be among those who can benefit from this fundamental instrument
3	RX: the problem must be treated at its roots by providing better employment and education opportunities for them this internal migration pressure will also reconciliation within the european union TX: the problem must be treated at its roots by providing better employment and education opportunities for them this internal migration pressure will also decrease within the european union
BER=0.2 (CRC)	
1	RX: the disputes just do not back this idea up either TX: the facts just do not back this idea up either
2	RX: romania has invested more vote eur 1 billion and the results have undertaken countries positive in all this communities are TX: romania has invested more than eur 1 billion and the results have definitely been positive in all the evaluation reports
3	RX: no one are interested freely in a two track europe TX: no one is interested nowadays in a two track Europe
BER=0 (CRC-Sim32)	
1	RX: it was already established in 2007 that once the technical negotiations were fulfilled bulgaria and romania would join the schengen area in 2008 TX: it was already established in 2007 that once the technical criteria were fulfilled bulgaria and romania would join the schengen area in 2011
2	RX: fellow members bulgaria and romania have completed their development and we are building on greater security systems in cooperation with our schengen partners TX: fellow members bulgaria and romania have completed their job and they are building on these security systems in cooperation with their schengen partners
3	RX: what is the situation when it comes to the judicial reform and anti corruption measures that are still achieved TX: what is the situation when it comes to the judicial reform and anti corruption measures that are still needed
BER=0.2(CRC-Sim32)	
1	RX: bulgaria and romania are absolutely not preparations for schengen TX: bulgaria and romania are absolutely not ready for Schengen
2	RX: we are on double standards TX: we cannot allow double standards
3	RX: what president is the commission giving that this rappporteur will be resolved effectively TX: what guarantees is the commission giving that this problem will be tackled effectively

“instrument” becomes pronoun “that” and its meaning is vague. For Sentence 3, its meaning has no change but its grammar contains a mistake. Pressure “reconciliation” can also be considered

pressure “decrease”.

When BER=0.2 (CRC), more wrong words appear in similar sentences, and the similarity detection may also make mistakes. For example, Sentence 2 is decided as a similar sentence, but its meaning has been damaged by the error words. Sentence 1 also has wrong noun and its meaning is changed to some extent. Meanwhile, Sentence 3 can be understood.

The use of CRC-Sim32 as a retransmission decision saves bit consumption further but introduces more similar sentences with more wrong words than CRC. When BER=0, Sentences 1 and 2 face the change of words, and these words may lead a serious misunderstanding. For example, the year “2011” is replaced with “2008” in Sentence 1, and this mistake directly affects the behavior of the receiver. This phenomenon also exists when BER=0.2. Thus, similarity detection is still not very reliable. Although similar sentences with error words replaced with synonyms are received, some sentences with changing semantic information are also difficult to be found and rejected.

In general, the proposed Sim32 is a good attempt to exploit the capability of semantic architectures, which can protect the semantic information when facing mistakes and trying to repair the sentences according to semantic relation. However, some similar sentences decided by Sim32 may still lead to misunderstanding

V. CONCLUSIONS

In this paper, we have investigated semantic coding. We have combined it with conventional RS channel coding and IR-HARQ and developed two different frameworks, namely, series SC-RS-HARQ and parallel SC-RS-HARQ. By comparing the two proposed frameworks and conventional methods, we find that the semantic encoder has better performance when facing high BER. However, it cannot guarantee error-free transmission. The parallel SC-RS-HARQ exploits the different advantages of the semantic architecture and the conventional method and outperforms the conventional IR-HARQ method. We have also designed a joint source-channel coding and HARQ framework called SCHARQ. This framework is more flexible and efficient because it can transmit incremental bits to solve the issues of different sentence lengths and varying channel conditions. Thus, it has the best performance among the other competing methods when BER is high but a little weaker when BER is low. To exploit the full potential of the semantic coder, we have proposed a similarity detection called Sim32 to detect the semantic error in the estimated sentences and combined it with CRC called CRC-Sim32. The proposed error detection methods allow similar sentences to be received so that more sentences can be transmitted, especially when

BER is high. However, some sentences with changing semantic information are still mistakenly received. In the future, more work is needed to improve its reliability.

REFERENCES

- [1] T. J. O' Shea and J. Hoydis, "An introduction to deep learning for the physical layer," *IEEE Trans. Cogn. Commun. Netw.*, vol. 3, no. 4, pp. 563–575, Dec. 2017.
- [2] Z.-J. Qin, H. Ye, G. Y. Li, and B.-H. Juang, "Deep learning in physical layer communications," *IEEE Wireless Commun.*, vol. 26, no. 2, Apr. 2019.
- [3] H. He, S. Jin, C. Wen, F. Gao, G. Y. Li, and Z. Xu, "Model-driven deep learning for physical layer communications," *IEEE Wireless Commun.*, vol. 26, no. 5, pp. 77–83, Oct. 2019.
- [4] H. Ye, G. Y. Li, and B. H. Juang, "Power of deep learning for channel estimation and signal detection in OFDM systems," *IEEE Wireless Commun. Lett.*, vol. 7, no. 1, pp. 114–117, Feb. 2018.
- [5] C.-J. Chun, J.-M. Kang, and I.-M. Kim, "Deep learning-based joint pilot design and channel estimation for multiuser MIMO channels," *IEEE Commun. Lett.*, vol. 23, no. 11, pp. 1999–2003, Nov. 2019.
- [6] A. M. Elbir and K. V. Mishra, "Online and offline deep learning strategies for channel estimation and hybrid beamforming in multi-carrier mm-Wave massive MIMO systems," *arXiv preprint arXiv:1912.10036*, 2019.
- [7] W. Ma, C. Qi, Z. Zhang, and J. Cheng, "Sparse channel estimation and hybrid precoding using deep learning for millimeter wave massive MIMO," *IEEE Trans. Commun.*, vol. 68, no. 5, pp. 2838–2849, May 2020.
- [8] J. Guo, C.-K. Wen, and S. Jin, "CANet: Uplink-aided downlink channel acquisition in FDD massive MIMO using deep learning," *arXiv preprint arXiv:2101.04377*, 2021.
- [9] S. Dörner, S. Cammerer, J. Hoydis, and S. t. Brink, "Deep learning-based communication over the air," *IEEE J. Sel. Topics Signal Process.*, vol. 12, no. 1, pp. 132–143, Dec. 2018.
- [10] H. Ye, L. Liang, G. Y. Li, and B.-H. Juang, "Deep learning-based end-to-end wireless communication systems with conditional GANs as unknown channels," *IEEE Trans. Wireless Commun.*, vol. 19, no. 5, pp. 3133–3143, May 2020.
- [11] H. Ye, G. Y. Li, and B.-H. F. Juang, "Deep learning based end-to-end wireless communication systems without pilots," *IEEE Trans. Cognitive Commun. Network.*, Early access.
- [12] H. He, C.-K. Wen, S. Jin, and G. Y. Li, "Model-driven deep learning for MIMO detection," *IEEE Trans. Signal Process.*, vol. 68, pp. 1702–1715, Feb. 2020.
- [13] G. Caire and D. Tuninetti, "The throughput of hybrid-ARQ protocols for the Gaussian collision channel," *IEEE Trans. on Inf. Theory*, vol. 47, no. 5, pp. 1971–1988, Jul. 2001.
- [14] N. Strodthoff, B. Göktepe, T. Schierl, C. Hellge, and W. Samek, "Enhanced machine learning techniques for early HARQ feedback prediction in 5G," *IEEE J. Sel. Areas Commun.*, vol. 37, no. 11, pp. 2573–2587, Aug. 2019.
- [15] G. Qiu, M. M. Zhao, M. Lei, and M. J. Zhao, "Throughput maximization for polar coded IR-HARQ using deep reinforcement learning," in *2020 IEEE 31st Annual International Symposium on Personal, Indoor and Mobile Radio Communications*, Oct. 2020, pp. 1–6.
- [16] E. C. Strinati and S. Barbarossa, "6G networks: Beyond shannon towards semantic and goal-oriented communications," *Computer Networks*, p. 107930, 2021.
- [17] B. Güler, A. Yener, and A. Swami, "The semantic communication game," *IEEE Trans. Cognitive Commun. Network.*, vol. 4, no. 4, pp. 787–802, Sep. 2018.
- [18] G. Shi, D. Gao, X. Song, J. Chai, M. Yang, X. Xie, L. Li, and X. Li, "A new communication paradigm: from bit accuracy to semantic fidelity," *arXiv preprint arXiv:2101.12649*, 2021.

- [19] K. Cho, B. Van Merriënboer, C. Gulcehre, D. Bahdanau, F. Bougares, H. Schwenk, and Y. Bengio, “Learning phrase representations using rnn encoder-decoder for statistical machine translation,” *arXiv preprint arXiv:1406.1078*, 2014.
- [20] C. E. Shannon, W. Weaver, and N. Wiener, “The mathematical theory of communication,” *Physics Today*, vol. 3, no. 9, p. 31, 1950.
- [21] J. Bao, P. Basu, M. Dean, C. Partridge, A. Swami, W. Leland, and J. A. Hendler, “Towards a theory of semantic communication,” in *2011 IEEE Network Science Workshop*. IEEE, 2011, pp. 110–117.
- [22] G. M. Davis and J. M. Danskin, “Joint source and channel coding for image transmission over lossy packet networks,” in *Applications of Digital Image Processing XIX*, vol. 2847, 1996, pp. 376–387.
- [23] O. Y. Bursalioglu, G. Caire, and D. Divsalar, “Joint source-channel coding for deep-space image transmission using rateless codes,” *IEEE Trans. Commun.*, vol. 61, no. 8, pp. 3448–3461, Jun. 2013.
- [24] D. B. Kurka and D. Gündüz, “DeepJSCC-f: Deep joint source-channel coding of images with feedback,” *IEEE J. Sel. Areas Inf. Theory*, vol. 1, no. 1, pp. 178–193, Apr. 2020.
- [25] M. Yang, C. Bian, and H.-S. Kim, “Deep joint source channel coding for wireless image transmission with OFDM,” *arXiv preprint arXiv:2101.03909*, 2021.
- [26] E. Bourtsoulatze, D. B. Kurka, and D. Gündüz, “Deep joint source-channel coding for wireless image transmission,” *IEEE Trans. Cogn. Commun. Netw.*, vol. 5, no. 3, pp. 567–579, Sep. 2019.
- [27] C. Lee, J. Lin, P. Chen, and Y. Chang, “Deep learning-constructed joint transmission-recognition for internet of things,” *IEEE Access*, vol. 7, pp. 76 547–76 561, Jun. 2019.
- [28] F. Zhai, Y. Eisenberg, and A. K. Katsaggelos, “Joint source-channel coding for video communications,” *Handbook of Image and Video Processing*, pp. 1065–1082, 2005.
- [29] Z. Weng and Z. Qin, “Semantic communication systems for speech transmission,” *IEEE J. Sel. Areas Commun.*, Jan. 2021.
- [30] N. Farsad, M. Rao, and A. Goldsmith, “Deep learning for joint source-channel coding of text,” in *Proc Int. Conf. Acoustics Speech Signal Process. (ICASSP)*. IEEE, 2018, pp. 2326–2330.
- [31] H. Xie, Z. Qin, G. Y. Li, and B.-H. Juang, “Deep learning enabled semantic communication systems,” *IEEE Trans. Signal Process.*, vol. 69, pp. 2663–2675, Apr. 2021.
- [32] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, Ł. Kaiser, and I. Polosukhin, “Attention is all you need,” in *Proc. Int. Conf. Neural Inf. Syst.*, Dec 2017, pp. 5998–6008.
- [33] H. Xie and Z. Qin, “A lite distributed semantic communication system for internet of things,” *IEEE J. Sel. Areas Commun.*, vol. 39, no. 1, pp. 142–153, 2021.
- [34] G. Shi, Y. Xiao, Y. Li, and X. Xie, “From semantic communication to semantic-aware networking: Model, architecture, and open problems,” *arXiv preprint arXiv:2012.15405*, 2020.
- [35] S. B. Wicker and M. J. Bartz, “Type-II hybrid-ARQ protocols using punctured MDS codes,” *IEEE Trans. Commun.*, vol. 42, no. 234, pp. 1431–1440, Apr. 1994.
- [36] M. L. B. Riediger and P. K. M. Ho, “Application of Reed-Solomon codes with erasure decoding to type-II hybrid ARQ transmission,” in *Proc. Global Commun. Conf.*, vol. 1, Dec. 2003, pp. 55–59 Vol.1.
- [37] J. Pennington, R. Socher, and C. D. Manning, “Glove: Global vectors for word representation,” in *Proc. Conf. on Empirical Methods Natural Language Process. (EMNLP)*, Oct. 2014, pp. 1532–1543.
- [38] T. Mikolov, K. Chen, G. Corrado, and J. Dean, “Efficient estimation of word representations in vector space,” *arXiv preprint arXiv:1301.3781*, 2013.
- [39] K. Papineni, S. Roukos, T. Ward, and W.-J. Zhu, “BLEU: a method for automatic evaluation of machine translation,” in *Proc. Annual Meeting Assoc. Comput. Linguistics (ACL’02)*, Jul. 2002, pp. 311–318.

- [40] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, “BERT: Pre-training of deep bidirectional transformers for language understanding,” *arXiv preprint arXiv:1810.04805*, 2018.
- [41] P. Koehn, “Europarl: A parallel corpus for statistical machine translation,” *MT Summit*, vol. 5, pp. 79–86, Sep. 2005.