Semantic-Preserved Communication System for Highly Efficient Speech Transmission

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Abstract—Deep learning (DL) based semantic communication methods have been explored for the efficient transmission of images, text, and speech in recent years. In contrast to traditional wireless communication methods that focus on the transmission of abstract symbols, semantic communication approaches attempt to achieve better transmission efficiency by only sending the semantic-related information of the source data. In this paper, we consider semantic-oriented speech transmission which transmits only the semantic-relevant information over the channel for the speech recognition task, and a compact additional set of semantic-irrelevant information for the speech reconstruction task. We propose a novel end-to-end DL-based transceiver which extracts and encodes the semantic information from the input speech spectrums at the transmitter and outputs the corresponding transcriptions from the decoded semantic information at the receiver. In particular, we employ a soft alignment module and a redundancy removal module to extract only the text-related semantic features while dropping semantically redundant content, greatly reducing the amount of semantic redundancy compared to existing methods. We also propose a semantic correction module to further correct the predicted transcription with semantic knowledge by leveraging a pre-trained language model. For the speech to speech transmission, we further include a CTC alignment module that extracts a small number of additional semantic-irrelevant but speech-related information, such as duration, pitch, power and speaker identification of the speech for the better reconstruction of the original speech signals at the receiver. We also introduce a two-stage training scheme which speeds up the training of the proposed DL model. The simulation results confirm that our proposed method outperforms current methods in terms of the accuracy of the predicted text for the speech to text transmission and the quality of the recovered speech signals for the speech to speech transmission, and significantly improves transmission efficiency. More specifically, the proposed method only sends 16% of the amount of the transmitted symbols required by the existing methods while achieving about a 10% reduction in WER for the speech to text transmission. For the speech to speech transmission, it results in an even more remarkable improvement in terms of transmission efficiency with only 0.2% of the amount of the transmitted symbols required by the existing method while preserving the comparable quality of the reconstructed speech signals.

Index Terms—Deep learning, end-to-end communication, semantic communication, speech transmission.

I. INTRODUCTION

The continuously increasing demand for communication causes the explosion of wireless data traffic, and places a heavy burden on the current infrastructure of communication systems. Semantic communication is a promising technology for next generation communications because of its great potential of significantly improving transmission efficiency [1]. Unlike traditional communication systems, which focus on transmitting symbols while ignoring semantic content, semantic communication focuses on gathering semantic information from the source and recovering the same semantic information at the receiver. Therefore, concentrated semantic information will be transmitted to the receiver instead of directly mapped bit sequences from the source. By doing so, to transmit the same amount of information, the required resources for semantic communication will be reduced significantly. Moreover, semantic communication has been proved to be more robust than traditional communication systems [2], especially in harsh channel conditions.

The idea of semantic communication has been proposed by Weaver at the beginning of modern communication [3]. Following this preliminary work, Carnap and Bar-hillel [4] gave an information theoretic definition of semantic information, which uses the logical probability of a sentence to calculate the semantic entropy that measures the amount of semantic information contained in the sentence. Another more recent follow-up work by Floridi [5] proposed to use the truth likeness of a sentence instead of logical probability to quantify the amount of the semantic information. Semantic-aware data compression has been investigated in [6] to design a general transceiver system which encodes and decodes the semantic information at the transmitter and the receiver, respectively. It has been further investigated in [7] by leveraging a shared knowledge base between the transmitter and the receiver to
improve compression efficiency. However, before the boom of deep learning, there has not been an effective way to actually perform semantic communication of content.

With the emergence of deep learning techniques on image processing and language processing, there have been several works on semantic communications which show the superiority over the traditional methods. A CNN model has been presented in [8] to enable joint source and channel coding (JSCC) for wireless image transmission, which can recover images under limited bandwidth and low SNR conditions, and achieves efficient image transmission. In [9], the authors designed a layered wireless image transmission scheme with multiple refinement layers of different compression rates, which can adapt the reconstruction quality of the images according to the bandwidth and channel conditions. Similarly, the authors [10] proposed a multi-level semantic-aware communication for image transmission, which showed the significance of high-level semantic information, such as the image captioning information.

The semantic communication system for text was first proposed in [11], where recurrent neural network (RNN) is used as encoder and decoder to extract the semantic information and recover texts from it. This work has been further extended in [12] which has developed a variable length joint source and channel coding scheme for text that dynamically encodes the input text to transmitted symbols of variable lengths. The authors in [2] have also proposed an efficient and robust semantic-oriented transmission scheme, the deep learning model of which was then further compressed to be able to work on IoT devices [13] using the model quantization and pruning. [14] and [15] designed semantic communication systems that are capable of multimodal data transmission for tasks, such as visual question answering. For the wireless video transmission, a semantic system has been developed in [16] which exploits reinforcement learning to optimize bandwidth allocation and GoP sizes. For the task-oriented communication, the authors in [17] utilized the information bottleneck principle to find a compact representation for a specific task while preserving the semantic-relevant information.

For the transmission of speech, attention-based semantic communication has been developed to recover speech signals at the receiver [18], which views each frame of the speech spectrum as an image, and utilizes convolutional neural network to compress the speech spectrum. A federal learning-based approach has been proposed in [19] to further improve the accuracy of recovered speech signals at the receiver. A speech recognition semantic communication system has been developed in [20], which reconstructs text transcription of the speech signals at the receiver by transmitting text-related semantic features. However, the connectionist temporal classification (CTC) based approach proposed by [21] encodes each speech spectrum frame into the same amount of transmitted symbols, while ignoring the difference in semantic significance of each frame, which may degrade the transmission efficiency.

We propose a novel semantic communication system for the transmission of speech for both the speech recognition and recovery tasks in this paper. Inspired by [21], which is the first to propose transmitting only the text-related semantic features for speech recognition task, we further extend this semantic-focus transmission mechanism for speech recovery. Also inspired by the deep learning based machine translation methods [22], which use attention mechanisms to learn the alignment between two languages with different lengths of compared translations, we employ an attention-based alignment module to enforce the amount of the semantic features to be transmitted to be close to that of the corresponding text content of the input speech spectrum. All the repeated and semantically irrelevant features are further dropped by a redundancy removal module. In this way, only the semantic-relevant information is extracted from the input speech spectrum and sent over the channel. To enhance the correctness of the predicted transcription at the receiver, we use a beam search decoder to find the most possible subwords sequences, and a semantic corrector to avoid semantic errors by leveraging a pretrained language model. For the successful recovery of the speech signal at the receiver, we also propose an additional speech information extractor that extracts a compact set of additional speech related information from the speech spectrums at the transmitter, which contains the duration, pitch and power information. The simulation results illustrate the remarkable improvement in the transmission efficiency of the proposed approach over the existing methods while boosting the accuracy of the predicted transcription and preserving the reconstruction quality of the speech signals at the same time.

The main contributions of this paper can be summarized as follows:

- We propose a highly semantic-focus communication system for both the speech to text transmission and the speech to speech transmission, which, in particular, exploits an attention-based soft alignment module and a redundancy removal module, which extracts only the text-related semantic features and drops semantically irrelevant features to significantly improve the transmission efficiency. Different from the existing methods that use characters or words as tokens, we use subwords instead, which preserves semantic meaning and avoids the problem of unseen words at the same time, thus further improving the accuracy of the predicted transcription.

- For the successful prediction of the corresponding transcription, We employ a beam search semantic decoder to obtain the most possible transcription of the speech signals by exploring the semantic correlation among the recovered sequence of subwords. We also employ a language model based semantic corrector, which has been pretrained on a large natural language dataset. This semantic corrector would help correct both the semantic and syntax errors that would make the recovered transcripts unnatural with the language knowledge learnt form the external text examples. To the best of our knowledge, we are the first to exploit background knowledge to improve the accuracy of the speech to text transmission in the literature of semantic communications.

- For the successful recovery of the speech signal at the receiver, we also adopt a CTC alignment based additional speech information extractor that extracts a compact set of additional speech related information, including the
duration, pitch and power information, from the speech spectrums at the transmitter, which are then utilized to synthesize the speech signals by a deep generative model based speech reconstructor module at the receiver.

- We propose a two-stage training method, which speeds up the training of the proposed model by training different parts at each stage. The numerical results validate the effectiveness and efficiency of the proposed method in both the text recognition performance and speech recovery.

The rest of this article is organised as follows. Section II introduces the system model of the considered semantic communication problem and the performance metrics. Section III details the proposed deep learning-based approach semantic communication. Simulation results are presented in Section IV and Section V concludes the paper.

Notation: The boldface letters are used to represent vectors and matrices, and single plain letters denote scalars. Given a vector $x$, $x_i$ indicates its $i$th component, $\|x\|$ denotes its Euclidean norm. Given a matrix $Y$, $\mathbf{Y} \in \mathbb{R}^{M \times N}$ indicates that $Y$ is a matrix of size $M \times N$. $\mathcal{CN}(m, V)$ denotes multivariate circular complex Gaussian distribution with mean vector $m$ and co-variance matrix $V$.

II. SYSTEM MODEL

In this section, we present the system model of the considered semantic communication system for highly efficient speech transmission, which aims to send compact semantic information of the input speech over the channel. This system is able to accomplish two different transmission tasks of speech signals, where one is to recover the corresponding text at the receiver, referred to as speech to text transmission, and the other is to recover the speech signal, referred to as speech to speech transmission. We also introduce the metrics to evaluate the performance of the proposed model for speech text and speech to speech transmission.

A. Speech Transmission System

The considered semantic communication system for speech transmission consists of two parts as shown in Fig. 1: the transmitter and the receiver. The speech signal is sampled at 16 KHz, where we apply a 25 ms Hamming window and 10 ms shift. Then we compute fast Fourier transform (FFT) and filter banks (fbanks) [23] of each Hamming window to get the speech spectrum, which is then input to the transmitter, denoted by $S = [S_1, S_2, \ldots, S_n]$, where $n$ is the number of frames. For the speech to text transmission, the receiver aims to output the corresponding transcription of the input speech, denoted by $G = [G_1, G_2, \ldots, G_m]$, where $G_i \in \mathcal{V}$ is the $i$th subword in the transcription, $m$ is the number of subwords in the transcription, and $\mathcal{V}$ denotes the vocabulary, which contains all the possible subwords in the speech. The mapping between $S$ and $G$ is called alignment [22], which is a core task for speech recognition. For the speech to speech transmission, the receiver aims to recover the speech spectrum $\hat{S} = [\hat{S}_1, \hat{S}_2, \ldots, \hat{S}_n]$ with the recovered text $G$ and the additional speech related information received, which is then input to a generative adversarial network (GAN) to synthesize the speech.

We note that subwords [24] are used here as the tokens to construct the corresponding transcriptions of the input speech instead of characters or words. For example, subwords $te$, $le$, $s$, $c$, $o$, $pe$ constitute the word “telescope”. Compared to using words as tokens as in our previous work [25], it solves the problem of unknown or out-of-vocabulary (OOV) words since any new word can be tokenized into a set of subwords. It also has the advantage of preserving more semantic information than the methods that use characters as tokens in existing work [20]. For example, subwords $er$ and $est$ often serve as the suffixes of adjectives to obtain their comparatives and superlatives, respectively, which are more semantically meaningful than simply the characters, such as ‘e’ and ‘r’. Besides, subword-based systems do not need an extra token blank to separate words, which may further improve the transmission efficiency. We also note that the word-based scheme is more robust to the transmission errors since we may completely lose the word if one character in it is not correctly received for the character-based scheme. However, the subword-based scheme would be able to correct the transmission error by looking at the semantic meaning. For example, if ‘est’ is incorrectly received as ‘emt’, the carefully designed receiver would be able to correct this to ‘est’ by looking up the vocabulary of subwords and the context. In this paper, we employ a pretrained subword model that has learnt a set of subword units from a text dataset [26].

The transmitter of the considered semantic communication system consists of a semantic encoder, an additional speech information extractor, and a channel encoder. The semantic encoder derives a compact latent semantic representation $L$ and an intermediate semantic representation $H$ from the input spectrum $S$. Then the intermediate semantic representation $H$ is input to the additional speech information extractor together with the input spectrum $S$ to compute all the additional speech information, such as speech duration, pitch and power, denoted by $D$. Then, the channel encoder maps $L$ and $D$ into symbols, denoted by $X$, to be transmitted over physical channels. The received signals at the receiver are given by

$$Y = h * X + w,$$  \hspace{1cm} (1)

where $h$ represents the channel coefficients, and $w \sim \mathcal{CN}(0, \sigma^2 I)$ denotes the independent and identically distributed (i.i.d.) complex Gaussian noise, where $\sigma^2$ is the noise variance, and $I$ is the identity matrix.

The receiver consists of a channel decoder, a semantic decoder, a semantic corrector, a speech reconstructor and a pretrained GAN vocoder [27]. The received signal, $Y$, is first
mapped additional speech information $\hat{D}$ by a channel decoder. $\hat{L}$ is then converted into the predicted transcriptions $\hat{G}$ by the semantic decoder with the help of a semantic corrector which keeps semantic information from previous context. For the speech to speech transmission, the predicted transcription $\hat{G}$ is then further processed to recover the speech spectrum by the semantic reconstructor with the received additional speech information $\hat{D}$ including speech duration, pitch and power. Then a pretrained GAN vocoder recovers the desired speech signals from the reconstructed speech spectrum. We note here that in this considered communication system, only the meaning related information is transmitted even for the speech to speech transmission, with a compact set of additional speech related features. Experimental results, which will be presented in the sequel, reveal that this semantic-oriented transmission significantly improves the transmission efficiency while preserving the reconstruction qualities of either the corresponding transcription or the speech signals.

B. Performance Metrics

We employ the word-error-rate (WER [28]) and the semantic similarity score [2] as the performance metrics to evaluate the performance of the considered speech to text transmission. WER is calculated by

$$\text{WER} = \frac{S + D + I}{N},$$

(2)

where $S$, $D$, $I$ and $N$ denote the numbers of word substitutions, word deletions, word insertions, and the number of words in the transcription $G$ respectively.

The semantic similarity score that quantifies the sentence similarity between the predicted transcription $\hat{G}$, and the original transcription, $G$, is given by

$$\text{similarity}(\hat{G}, G) = \frac{B(\hat{G}) \cdot B(G)^T}{||B(\hat{G})|| \cdot ||B(G)||},$$

(3)

where $B(\cdot)$ represents sentence embedding by a pre-trained text embedding model, i.e., Bidirectional Encoder Representations from Transformers (BERT) [29]. This sentence similarity score is a number between 0 and 1, which indicates how similar one sentence is to another, with 1 representing semantically equivalent and 0 representing not relevant at all.

For the speech to speech transmission, We use the Mel cepstral distortion (MCD) [30] as the performance metrics to evaluate the reconstruction quality of the speech spectrum. The smaller the MCD is, the closer the reconstructed speech is to the original speech. Recall that $S$ and $\hat{S}$ denote the input spectrum and predicted spectrum, respectively. We align $S$ and $\hat{S}$ using Dynamic Time Warping (DTW) algorithm, and calculate MCD by:

$$\text{MCD}(S, \hat{S}) = \frac{10}{\ln(10)} \sqrt{2 \sum_{t=1}^{T} ||S_t - \hat{S}_t||},$$

(4)

where $t$ denotes the index of the timestep, and $T$ is the total number of timesteps.

In addition to the MCD, we also employ a subjective quality evaluation test, that is, Mean opinion score (MOS) [31], as another performance metric to further evaluate the quality of the recovered speech. The MOS rates the naturalness of the synthesized speech, which is obtained by having a group of raters, who are the native speakers of the same language, listening to the generated audio through the same headphones. The rates give scores in a five-point numeric scale, as shown in Table I, according to the naturalness of the speech samples, with 5 representing the highest perceived quality and 1 representing the lowest perceived quality.

| Description | Score |
|-------------|-------|
| Excellent - Completely natural speech | 5 |
| Good - Mostly natural speech | 4 |
| Fair - Equally natural and unnatural speech | 3 |
| Poor - Mostly unnatural speech | 2 |
| Bad - Completely unnatural speech | 1 |

III. PROPOSED SEMANTIC COMMUNICATION FOR SPEECH TRANSMISSION

The proposed semantic communication system contains two subsystems for speech transmission as shown in Fig. 2. The basic subsystem is for speech to text transmission, which extracts the semantic-related information from the speech spectrums and eliminates semantic-irrelevant redundancy in it. This semantic information is sent over the channel to the receiver, and then used to reconstruct the corresponding transcription of the original speech. The second subsystem, which is built upon the basic subsystem, aims for the speech to speech transmission. In addition to the semantic-related information, a set of semantic irrelevant information, which, however, helps the reconstruction of the speech signal at the receiver, is also extracted from the speech signals and sent to the receiver including the duration, pitch and power information of the speech. We describe the component that constitutes these two subsystems in detail in the sequel.

A. Speech to Text Transmission

As depicted in Fig. 2, the basis subsystem for the speech to text transmission consists of a semantic encoder, a channel encoder, a channel decoder, and a semantic decoder and corrector, where the semantic encoder extracts the semantic relevant information and removes the redundancy from the speech spectrums, and the channel encoder then processes this information into transmitted symbols. The received symbols at the receiver are then decoded by the channel decoder back to the semantic information, which is then used to reconstruct the transcriptions by the semantic decoder and corrector. We introduce each module in detail in the following.

1) Semantic Encoder: The semantic encoder has five components, including a VGG module [32], a bidirectional Long Short Term Memory (BLSTM) module, a FC module, a soft alignment module, and a redundancy removal module. We recall that the input speech spectrums, $S \in \mathbb{R}^{B \times N \times 40}$ are acquired by applying 25 ms Hamming window and 10 ms
shift on the speech signals, and then computing FFT to get 40 fbanks coefficients, where $B$ is the batch size, $N$ is the number of frames, and 40 is the number of coefficients. The sequence of speech spectrums $S$ is first fed into the VGG module to obtain a latent representation $S' \in \mathbb{R}^{B \times \frac{N}{4} \times 256}$, that is, 256 feature maps of size $\frac{N}{4} \times 10$ for each input. And the reshape layer concatenates all the 256 channels of $S'$ and reshapes the latent representation to $S'' \in \mathbb{R}^{B \times \frac{N}{4} \times 2560}$. Then, $S''$ is input into the BLSTM module, which generates the intermediate features that preserve the temporal correlation in the input sequence. The followed FC module further compresses these intermediate features into a representation $H \in \mathbb{R}^{B \times 1024}$, which is then fed into the soft alignment module. The soft alignment module then extracts the transcription-related information, and outputs latent semantic representations $Z \in \mathbb{R}^{B \times q \times 1024}$, which is further input to the redundancy removal module to remove the semantic-irrelevant redundancy and generate a more compact latent semantic representation $L \in \mathbb{R}^{B \times c \times 1024}$, where $c$ is the length of this representation after removing the redundant parts.

The soft alignment module uses an attention mechanism together with an LSTM layer to extract semantic features, as shown in Fig. 3. The attention mechanism [33] is adopted for our soft alignment module to get the alignment of speech with its semantic text. In order to acquire the alignment, we need to compute the weight, also referred to as attention scores, assigned to each element of the input latent features, $H$, by the query information and the corresponding key information. The query information is derived by passing the hidden states of the LSTM layer through a fully connected layer, and the key information is derived by another fully connected layer with $H$ as the input. The query and key information are then combined with the feedback information through element-wise addition, as shown in Fig. 3. Then this combined information is fed into a FC layer and then a softmax layer to get the normalization scores $A$, which feedback through a 1D convolution layer and a FC layer to derive the location information. Each value in the normalized attention scores $A \in \mathbb{R}^{B \times q \times 512}$ multiplies its corresponding value in $H$ to get the latent semantic representation, $H' \in \mathbb{R}^{B \times q \times 512}$, where $q$ is the length of latent semantic representation, which depends on the semantic information the signal is carrying. We note that the value of $q$ approaches the length of the corresponding text content of input speech by the soft alignment module and redundancy removal module. Hence, the value of $q$ depends on the semantic content of different speech input, and how much redundancy is removed by the soft alignment module and redundancy removal module. And $H'$, concatenated with the feedbacked embeddings from the next redundancy removal module, is fed into a LSTM layer, which outputs $Z \in \mathbb{R}^{B \times q \times 1024}$ as the input to the redundancy removal module. We present one example of the derived attention scores matrix $A$ in the form of a heat map in Fig. 4. We can observe that only a few elements of this matrix are with values that are not close to zero. A speech-related latent representation with the length of 260 is mapped into a text latent representation with the length of 16. As it is revealed by the numerical results, $q$ is always smaller than 10 percent of $N$. So the proposed soft alignment module leads to better transmission efficiency because the derived attention scores push the transmission resource allocated to semantic significant parts. In addition, it is worth noting that the speech-text attention mechanism is difficult to converge during the training process. It is necessary to use the teacher forcing technique, which takes the true value of the label as the output of the attention module at the beginning of the training and feeds this result into the LSTM layer of the attention mechanism, so that the training of the whole network quickly approximates the converged result. In the final stage of the training, the frequency of teacher forcing is gradually reduced, so that the attention mechanism can be trained quickly and accurately.

The redundancy removal module consists of a FC layer, as shown in Fig. 3, which outputs a probability matrix of size $B \times q \times 1001$, and each element of the last dimension represents a token in the vocabulary list. The vocabulary list contains 1000 subwords and a special token, which represents both the symbol $EOS$ and $BOS$, where $EOS$ marks the end of a sentence, and $BOS$ is used at the beginning of a sentence. The largest value in last dimension of the output probability matrix specifies the subword the corresponding element in $Z$ belongs to. We note here we use the subwords.
as tokens instead of the words as in our previous work, which reduces the size of the vocabulary from 15003 (the most frequent 15000 words and three special symbols) to 1001. With the output of the FC layer, which indicates the corresponding subword of each element in the input sequence \( Z \), the redundancy removal module removes from \( Z \) the special tokens and the sequences after the first special token in the sequence excepting the one that may be at the beginning of the sequence, which represents the symbols EOS. This is because the parts after EOS are without any semantic meaning. Then the redundancy removal module output the reduced sequence of \( Z \) to the channel encoder as shown in Fig. 2. The experiments reveal that cutting off the sequences after the symbol EOS saves about 59.4% of the transmission length, and removing the special saves approximately 4.5%. We note that the output of the FC layer in this redundancy removal module is also fed into an embedding layer to get an embedding of size \( B \times q \times 128 \) to be concatenated with \( H' \) of the next time stamp before feeding into the LSTM layer in the soft alignment module, which passes the semantic information from the current time stamp to the next one.

2) Channel Encoder and Channel Decoder: In the channel encoder at the transmitter side, two cascaded FC layers map \( L \) to symbol sequences \( X \in \mathbb{R}^{B \times c \times 64} \), which is then reshaped into \( X' \in \mathbb{R}^{B \times q \times 2} \), where the first and second channels are the real parts and imaginary parts of the wireless signals to be transmitted, respectively. The received symbol sequences, \( Y \in \mathbb{R}^{B \times q \times 2} \) at the receiver, are first reshaped into \( Y' \in \mathbb{R}^{B \times c \times 64} \), which are then input to two cascaded FC layers to recover the text-related semantic features, denoted by \( \hat{L} \in \mathbb{R}^{B \times c \times 1024} \). \( \hat{L} \) is then fed into the semantic decoder to recover the transcription of the input speech signals. We note here, in contrast to the conventional channel coding, the proposed channel encoder reduces the dimension of the transmit symbols instead of introducing redundancy to combat. This is because the proposed learning based channel encoder and decoder mitigate the effect of channel noises by adapting the neural network weights through end to end optimization.

3) Semantic Decoder: The semantic decoder, as shown in Fig. 5, first takes in the text-related semantic features \( \hat{L} \) and derives a coarse prediction on the distribution of subwords \( \hat{G} \in \mathbb{R}^{B \times q \times 1001} \) by a FC layer, which is then further modified by a semantic corrector through a beam search algorithm to improve the prediction accuracy. The semantic corrector consists of an embedding layer, two LSTM layers, and two FC layers, which has been pretrained on a large text dataset, Librispeech [34], which contains 14500 public domain books, to further correct possible semantic errors by leveraging the learnt external semantic knowledge. At each time step \( t \), \( t = 1, \ldots, c \), the most possible \( K \) subwords for the \( t \)th element in the predicted sequence are input to the embedding layer one by one. We note that, for \( t = 1 \), special token BOS is input implying the beginning of a sentence. The embedding layer then outputs the semantic embedding of each input subword, denoted by \( E \in \mathbb{R}^{128} \). \( \hat{E} \) is then feed into the two LSTM layers to generate the intermediate latent representation \( \hat{R} \in \mathbb{R}^{1024} \). Finally, \( \hat{R} \) is processed by two FC layers to get the predicted distribution of the subword at time step \( t \) for each of the \( K \) most possible subwords at time step \( t - 1 \). These \( K \) distributions are then averaged to obtain the prediction at time step \( t \), denoted by \( G_{Cor,t} \in \mathbb{R}^{1001} \). \( G_{Cor,t} \) is then summed up with the corresponding row of \( \hat{G} \) with given weights \( Weight_{Cor} \) and \( \text{Weight} \) to generate the combined distribution of this time step \( \tilde{G}_t \in \mathbb{R}^{1001} \). This combined distribution \( \tilde{G}_t \) is then used to select the most possible \( K \) subwords at time step \( t \) by beam search algorithm, which we will introduce in detail in the sequel. These \( K \) subwords are again input to the semantic corrector in an one by one manner to obtain the predicted distribution of subwords at time step \( t + 1 \) following the same procedure. We emphasize that the semantic corrector has been pretrained on a large and comprehensive text dataset [34], hence containing substantial knowledge on natural language that helps prediction of the transcription. As the numerical
results reveal, the semantic corrector remarkably improves the system’s overall performance and corrects the semantic mistakes which may be caused by the channel noise.

The beam search decoder operates as follows. It starts with the beginning of the input sequence, corresponding to the special token BOS, which is fed BOS into the semantic corrector to calculate the combined distribution \( G_1 \). Then \( K \) most likely subwords are selected according to this combined distribution \( G_1 \), and added to the beam that forms \( K \) partial transcriptions of this initial time step. Then the following step is repeated until the whole input sequence has been processed: at each iteration it calculates all possible conditional distributions over the vocabulary given each of the current \( K \) partial transcriptions in the beam. According to these conditional distributions, we select the new \( K \) most likely partial transcriptions from all the possible extended transcriptions, and replace the previous \( K \) most likely partial transcriptions. At last, the beam search decoder outputs the most likely transcription in its beam. We note that the beam decoder exploits the long time dependency in the semantic sequence by keeping \( k \) candidates in the beam and evaluating the conditional distribution given the previous context at each iteration, which improves the accuracy of the predicted transcriptions as revealed by the numerical results.

**B. Speech to Speech Transmission**

For the speech to speech transmission, we further include an additional speech information extractor at the transmitter side and speech reconstructor at the receiver side on top of the subsystem for the speech to text transmission, as shown in Fig. 2, where the additional speech information extractor generates the additional speech related information, such as speech duration, pitch and power, to send over the channel, for better reconstruction of the speech signals, and the speech reconstructor synthesizes speech from the received text and additional speech information. We introduce each module in detail in the following.

1) **Additional Speech Information Extractor**: The additional speech information extractor takes the intermediate features \( H \) from the FC module in the semantic encoder as input and outputs the frame-level alignment to obtain duration information of the speech sequence \( C \in \mathbb{R}^{B \times c' \times 1} \), where \( c' \) is the total number of predicted phonemes, and each element in \( C \) represents the duration of each phoneme. In particular, a FC layer is employed to compute the probabilities of subwords for each frame in the sequence input. Then the CTC alignment module, based on the Viterbi algorithm [35], decides the most possible subword for each frame, and outputs the start time and the ending time as the duration of each predicted subword. We also utilize a pretrained subword to phoneme model [36] to acquire the corresponding phoneme of each subword. We also compute the pitch and power information of each phoneme from the input speech spectrums, which are concatenated with the duration information \( C \) to form the set of speech related information \( D \in \mathbb{R}^{B \times c' \times 3} \) to be sent to the receiver for the purpose of speech recovery. We note that compared to the semantic information to be sent, which is of dimension \( L \in \mathbb{R}^{B \times c \times 1024} \), the amount of the additional speech information is negligible, which is thus transmitted over the channel using the traditional channel coding scheme, and can be recovered losslessly at the receiver.

The CTC based alignment method finds the duration of each phoneme by the following two steps. First, it finds the possibilities of the corresponding phonemes of every spectrum frame. Then, the Viterbi algorithm is applied to find spikes when the phonemes change. Then we have the time between two spikes as the duration of a phoneme. We then apply the DIO algorithm[37] to obtain pitch information of each frame and compute the average pitch of all frames of the same phoneme. Then we also compute the vector norm of each frame to obtain power information, and then compute the average power of all frames of the same phoneme. Thus, we obtain the pitch and power information of each phoneme.

2) **Speech Reconstructor**: The speech reconstructor, as shown in Fig.6, takes the predicted transcription from the semantic decoder and corrector as input and outputs the recovered speech signal with the help of the additional speech information from the transmitter. We adopt the non autoregressive model FastSpeech2 [27] and get a \( 270 \times \) speed up than the autoregressive model [37], [38]. In particular, a text embedding layer is first employed to transform the input text to an embedding, which is then fed to a text-to-speech(TTS) encoder containing four transformer layers to obtain a latent representation of each token in the input text sequence, together with the prediction of the duration, power and pitch of the corresponding phonemes. Then a text to speech alignment module is exploited that takes in the predicted duration information and the real duration information received from the receiver, and modifies the number of frames of each token in the latent representation output by the TTS encoder. This latent representation is then combined with the power information embedding and pitch information embedding, which embeds both the transmitted and predicted power and pitch information, respectively, as shown in Fig.6, to generate latent representation that contains both the semantic relevant text information and speech-related information. This combined information is then input to the TTS decoder, which consists of 6 transformer layers, to recover the speech spectrums. Finally, we use a pretrained GAN, that is, HiFiGAN vocoder [39], to generate the speech signals from the recovered spectrums.

**C. Model Training and Testing**

In this section, we describe the training and testing of the proposed DL-based semantic communication system.

1) **Data Argument Strategies**: We employ data argument strategies to enrich the training dataset in order to improve
1 month, as revealed by experiments. In the first stage, we train a network as a whole in an end-to-end manner for more than 10 days than training the following loss function using the Adadelta optimizer by directly inputting the output of the semantic encoder to the channel decoder, and semantic decoder under physical channel transmission. We consider the communication systems for speech transmission. We exploit the performance of the existing deep learning-based semantic communication systems for speech transmission. We consider the AWGN and Rayleigh channels for the evaluation. We use the Librispeech dataset [34] for training and testing, which is a large dataset for speech to speech transmission and the text transmission are illustrated in Algorithm 3 and 4, where we note that the speech sample sequences used for testing are different from that used for training.

IV. EXPERIMENT AND NUMERICAL RESULTS

In this section, we compare the proposed method's performance to the existing deep learning-based semantic communication systems for speech transmission. We consider the AWGN and Rayleigh channels for the evaluation. We use the Librispeech dataset [34] for training and testing, which is a speech to text library based on public domain audiobooks containing 960 hours of speech for training and 2703 utterances
TABLE II
PARAMETER SETTINGS OF THE PROPOSED SEMANTIC COMMUNICATION NETWORK FOR SPEECH RECOGNITION

| Layer Name     | Parameters | Activation |
|----------------|------------|------------|
| 2×CNN          | 3×3/1/28   | LeakyReLU  |
| MaxPool        | 2×2        | None       |
| 2×CNN          | 3×3/256    | LeakyReLU  |
| MaxPool        | 2×2        | None       |
| Reshape        | None       | None       |
| 4×BLSTM        | 1024       | None       |
| FC             | 1024       | LeakyReLU  |
| Query FC       | 300        | None       |
| Key FC         | 300        | None       |
| Conv1d         | 201/10/100 | None       |
| FC             | 300        | None       |
| FC             | 1          | Tanh       |
| GRU            | 1024       | None       |
| Embedding      | 1000/128   | None       |
| FC             | 1001       | logsoftmax |
| FC             | 1003       | logsoftmax |
| FC             | 236        | ReLU       |
| Reshape        | None       | None       |
| Reshape        | None       | None       |
| FC             | 64         | LeakyReLU  |
| FC             | 256        | LeakyReLU  |
| FC             | 1000       | LogSoftmax |
| 2×LSTM         | 2048       | None       |
| PC             | 512        | LeakyReLU  |
| FC             | 4×transformer | 256/2 heads | None |
| text embedding | 256        | None       |
| pitch embedding| 256        | None       |
| text embedding | 256        | None       |
| speaker embedding| 256     | None       |
| text embedding | 256        | None       |
| 6×transformer  | 256/2 (heads)| None |

for testing. For the speech to text transmission, we compare to the following three benchmarks: the existing DL-based speech to text transmission approach by [20], referred to as DeepSC-SR; the semantic communication approach for the text to text transmission proposed in [2], which transmits and recovers text at the receiver, combined with the proposed semantic encoder, which transfers the speech signal to semantic text, referred to as SE-DeepSC; the semantic communication for speech transmission proposed in [18], which transmits and recovers speech, combined with the proposed semantic encoder, which transfers the received speech signal to text at the receiver, referred to as DeepSC-S-SR. For a fair comparison, we use the same dimension of the input spectrum and training data augmentation strategies. We also use the proposed semantic encoder and decoder, while ignoring the noisy channel as well as channel encoder and decoder, as the Baseline, which provides the upper-bound performance. For the speech to speech transmission, we also compare with the speech transmission scheme proposed in [18], but without the proposed semantic encoder applied, referred to as DeepSC-S. The detailed setting of our proposed network is shown in table II, which lists the neural layers and the numbers of parameters in each module, as well as the type of activation functions applied. We note that the proposed approaches and all the methods for comparison are trained and tested with the same datasets. During training, we set channel conditions with SNR varying randomly from 5dB to 10dB. We use the two Gaussian random variables with 0 mean and $0.5 \times 10^{-4}$ $N(\sigma^2)$ Square of the variance for the real and imaginary parts of noise for the AWGN channel, which ensures the sum of the transmission power equal to one. We use the Rayleigh fading channel for simulation and the real and imaginary parts of channel coefficients are Gaussian random variables with 0 mean and one variance. And the noise for Rayleigh fading channel is the same as the AWGN channel. And we assume perfect CSI at the receiver. And we set $\lambda = 0.1$ in 5. The training time of stage one is 250 hours with a NVIDIA RTX 3090 GPU and the training time of stage two is about 6 hours.

A. Performance Comparison of the Speech to Text Transmission

We compare the text prediction performance of the proposed approaches with the aforementioned three benchmarks, the baseline with and without the proposed semantic corrector module, denoted by Baseline w/ semcor and Baseline w/o semcor, respectively, and our previous approach [25] as well. We present the performance comparison in terms of WER and sentence similarity in Fig. 7 and Fig. 8, respectively. We can see that the proposed method significantly outperforms the other methods under both channel conditions in terms of both WER and sentence similarity. We can also note that our proposed method performs steadily and closer to the baseline, while the performance of the SE-DeepSC approach is poor under a low SNR regime. We note that we get the WER of around 15% instead of 40% for DeepSC-SR as reported in...
Algorithm 3 Testing Algorithm of the Proposed Speech to Text Transmission
1: **Input:** Speech signals and transcriptions \( G \) from dataset, fading channel \( h \), noise \( w \).
2: Set fading channel \( h \) = Rayleigh or AWGN
3: for each SNR value do
4: Generate Gaussian noise \( W \) under the SNR value.
5: Generate spectrum sequences \( S \) from input speech signals.
6: Output \( L \) from \( S \) by the semantic encoder.
7: Output \( X \) from \( L \prime \) by the channel encoder.
8: Transmit \( X \) and receive \( Y \) via (1).
9: Output \( L \) from \( Y \) by the channel decoder.
10: Output \( G \) from \( L \prime \) by the semantic decoder.
11: **Output:** compare \( \hat{G} \) and \( G \) and compute WER and sentence similarity via (7) and (8)

Algorithm 4 Testing Algorithm of the Proposed Speech to Speech Transmission
1: **Input:** Speech signals from dataset, fading channel \( h \), noise \( w \).
2: Set fading channel \( h \) = Rayleigh or AWGN
3: for each SNR value do
4: Generate Gaussian noise \( W \) under the SNR value.
5: Generate spectrum sequences \( S \) from input speech signals.
6: Output \( L \) and \( C \) from \( S \) by the semantic encoder.
7: Output \( X \) from \( L \) by the channel encoder.
8: Transmit \( D \) from \( C \) by the Additional speech information extractor
9: Transmit \( X \) and receive \( Y \) via (1).
10: Transmit \( D \) in a lossless manner.
11: Output \( L \) from \( Y \) by the channel decoder.
12: Output \( G \) from \( L \prime \) by the semantic decoder.
13: Output the recovered speech signal form \( \hat{G} \) and \( D \) with the speech reconstructor.
14: **Output:** compare the recovered speech signal and input speech signal and compute MCD with DTW via (4). Mos can be tested using Amazon Mturk.

We can observe a significant improvement over our previous approach, which may come from the following several aspects. First is the use of subwords as tokens instead of the natural words, which avoids the errors of unseen words. Then it may also be due to the data argument strategies employed, which enriches the training dataset by several times. The usage of subword tokens contributes about 7% WER reduction. The other reason is the introduction of the beam search decoder and the semantic corrector, which fixes semantic errors utilizing the internal and external semantic knowledge. The benefit of semantic corrector is validated by the results shown in Fig. 7 and Fig. 8, where we can see a clear performance gap between the baseline with and without semantic corrector. And the usage of greedy semantic decoder, denoted as Greedy semdec, shows worse performance than both our proposed methods. The usage of the beam search decoder and the semantic corrector contributes 0.68% and 1.61% WER reduction, respectively.
the semantics of the transmitted symbols more, thus causing a more dramatic increase in WER, as we observe in Fig. 8. However, we can observe our result is still much better than that of all the other works. And we also observe that if we use the same dimension of the transmitted vector as in our prior work, our method is much less sensitive to the noise than our method with the smaller dimension of the transmitted vector.

We further present text output examples by greedy decoder used by DeepSC-SR and our semantic decoder with and without the semantic corrector in Table IV, where highlight the mistaken parts with different colors for different methods. It can be seen that the beam search semantic decoder avoids some word errors occurring to the greedy decoder, while the semantic corrector further fixes the other mistakes, and pushes the output closer to ground truth. We further present the performance comparison between the proposed approach with and without semantic corrector, and also the proposed approach with the semantic decoder replaced with the greedy decoder, in terms of WER and sentence similarity over different channels in Fig. 9. The results imply that the beam search decoder performs closely to the greedy semantic decoder, while the semantic corrector brings remarkable performance gain under different channels in terms of both the WER and sentence similarity. We can conclude that the semantic corrector can correct the mistake from noisy channel, because the curve of the beam search decoder with semantic corrector changes most gently when channel noise gets larger.
TABLE V
EXAMPLES OF INPUT SPEECH AND THEIR TRANSCRIPTIONS BEFORE AND AFTER THE REDUNDANCY REMOVAL MODULE

| Example 1 | The number of speech spectrum frames: 497 |
|---------------------------------|---------------------------------|
| Transcription: (Length:36)     | BOSS RANDAL HE SAID YOU KNOW WHERE SYDNEY IS EOS x 27 |
| saved: 77.8%                   | |
| Example 2 | The number of speech spectrum frames: 9845 |
| Transcription: (Length:96)     | BOSS I HAVE DRAWN UP A LIST OF ALL THE PEOPLE WHO OUGHT TO GIVE US A PRESENT AND I SHALL TELL THEM WHAT THEY OUGHT TO GIVE IT WON'T BE MY FAULT IF I DON'T GET IT EOS EOS EOS EOS EOS EOS EOS EOS EOS EOS EOS EOS EOS EOS OF ALL THE PEOPLE WHO OUGHT TO GIVE US A PRESENT AND I SHALL TELL THEM WHAT THEY OUGHT TO GI |
| saved: 61.5%                   | E IT WON'T BE MY FAULT IF I DON'T GET IT |

TABLE VI

| Transmitter | Receiver | Total |
|-------------|----------|-------|
| Speech to Text | | |
| Proposed | 464M | 0.012 | 209M | 0.134 | 673M | 0.146 |
| DeepSC-SR | 336M | 0.033 | 9M | 0.0001 | 245M | 0.033 |
| SE-DeepSC | 776M | 0.07 | 135M | 0.225 | 881M | 0.295 |
| DeepSC-S-SE | 14M | 0.063 | 661M | 0.272 | 675M | 0.335 |
| Speech to Speech | | |
| Proposed | 464M | 0.012 | 671M | 0.134 + 0.140 = 0.274 | 1115M | 0.286 |
| + autoregressive TTS | 464M | 0.012 | 412M | 0.134 + 6.66 = 6.794 | 576M | 6.806 |
| DeepSC-S | 14M | 0.063 | 14M | 0.126 | 28M | 0.189 |

B. Transmission Efficiency

We present the length of the transmitted symbol vector and the average number of the transmitted symbols per sentence on the same testing dataset of different approaches in Table III. The length of each transmitted symbol vector is half of the dimension of each channel encoder output since two elements are combined into a complex value to transmit. We can see from this table that although our proposed model has slightly longer symbol vectors, i.e., a larger dimension of the output of the channel encoder, the average number of transmitted symbols per sentence by the proposed model is 16% of that by DeepSC-SR, significantly improving the transmission efficiency while achieving about 10% WER reduction as shown in Fig. 7. The reason may be that DeepSC-SR encodes every single speech spectrum frame into the same amount of transmitted symbols, while the proposed method ignores the redundant content, and only sends the text-related semantic information.

Two examples of the speech signals and their corresponding transcriptions as well as the transcription after redundancy removal are shown in Table V. Both of the examples show that the number of the speech spectrum frames is much larger than the length of the transcription, which implies that many of the frames are semantically irrelevant. We also observe that the redundancy removal module significantly reduces the length of the transcription while preserving the semantic meaning.

C. Performance Comparison of the Speech to Speech Transmission

We then compare the quality of the recovered speech by the proposed approach and DeepSC-S in terms of MOS and MCD, as shown in Fig. 10 and Fig. 11, respectively. The MOS scores presented in Fig. 10 are obtained by 20 native speakers listening to 40 generated speech samples by each approach and rating the scores according to Table I. As it can be observed from Fig. 10, our system achieves comparable results with DeepSC-S. However, surprisingly, the MOS score of our proposed method without additional speech information is better than with additional information, and very close to the ground truth results. The reason may be that the MOS score measures the naturalness of the generated speech instead of the closeness to the original speech. And the adopted pre-trained GAN vocoder is powerful to convert the spectrum into natural speech. However, we can observe significant performance gain achieved by the additional information provided in Fig. 11 in terms of MCD, which measures the distance between the recovered speech spectrums and the original ones. This implies the additional speech information helps the recovery of the original speech spectrums. We note the DeepSC-S results in much lower MCD compared to the proposed approach. This is due to the fact that DeepSC-S views speech spectrums as images, and aims for exact recovery of the spectrums including the noises in the spectrum. However, our approach focuses on the successful transmission of semantic information while eliminating the semantic irrelevant factors in the speech spectrum, such as environment noises. We also present the predicted speech spectrums by the proposed approach and the original spectrums in Fig. 12. We can see that the predicted spectrum without the additional speech information provided is longer than the original speech, and the pitch and power less similar to the ground truth compared to that by the proposed approach with additional information provided. We provide the recovered audio samples at https://txhan.github.io/speech-to-text/.

In terms of transmission efficiency, we note that the additional information only needs to be sent once for each utterances, and is of a small dimension of 64, which can be neglected compared to the amount of the semantic information sent over the channel. We can see from the Table III that the proposed approach for the speech to speech transmission sends 1120 transmitted symbols per sentence over the channel, less
than 0.2\% of that by the existing method, DeepSC-S, which results in 655360 transmitted symbols per sentence.

**D. Model Size and Runtime**

We compare the computational complexities and memory cost of the proposed model and the other benchmark approaches for both the speech to text transmission and speech-to-speech transmission in this section. We also include an additional benchmark approach, which replaces the text to speech generator in the proposed approach with an autoregressive text to speech method [38] while the other parts remain the same, referred to as Proposed + AR. All the experiments are run on the same server with a NVIDIA RTX 3090 GPU and the same version of deep learning libraries. We present the average runtime per speech input and the model sizes of all the approaches in Table. VI. For the speech-to-text transmission, we note that the proposed method has a longer runtime than the existing method DeepSC-SR. We observe that the proposed transmitter has a much smaller cost than that of DeepSC-SR, while the proposed receiver takes much longer to recover the text than DeepSC-SR. This is because DeepSC-SR accomplishes most of the speech recognition task at the transmitter side, and the proposed scheme relies more on the receiver to correctly recover the corresponding transcript with the computational-intense semantic corrector. As we show above, the introduction of a semantic corrector significantly improves the accuracy of the recovered transcripts. For the speech-to-speech transmission, we can see the overall runtime of the proposed scheme is close to the existing method, DeepSC-S, while the transmission cost is only thousandths, as shown above. We also observe that our transmitter is less computational-intense than that of DeepSC-S, which also implies that the proposed method relies more on the speech generator at the receiver to recover the speech signals. It can also be seen that the model runs much longer when we replace the proposed text to speech generator with the autoregressive...
TTS method. This is due to that the proposed method is able to parallel the generation of multiple frames. We note that the proposed model is relatively large, which, for the future work, can be reduced in size by utilizing model compression methods, like model quantization and model pruning.

V. Conclusion

In this paper, we proposed a semantic-oriented communication system for speech transmission, which transmits only the semantic-relevant information over the channel for the speech recognition task, and a compact additional set of semantic-irrelevant information for the speech reconstruction task to improve transmission efficiency. In particular, for the speech to text transmission, we employed an attention-based soft alignment module and a redundancy removal module to extract only the text-related semantic features while dropping semantically redundant content, which reduces the 90% of the latent semantic features by the semantic encoder as revealed by the numerical results. We also introduced a beam search semantic decoder to find the most possible transcription exploiting the long time dependency in the input sequences, and a semantic correction module based on a pretrained language model to further correct the predicted transcription with semantic knowledge learnt from a large and comprehensive text dataset. For the speech to speech transmission, we further included a CTC alignment module at the transmitter side to extract additional information from the original speech that helps the recovery of the speech including the duration, pitch and power information of each phoneme, and a speech reconstructor at the receiver which leverages a text to speech decoder and a pretrained GAN to reconstruct the speech signals by combining the received semantic information and the additional speech-related information. We also introduced a two-stage training scheme, which trains different parts of the proposed model at each stage, and, thus, speeds up the training of the model as revealed by experiments. Simulation results demonstrate that our proposed method outperforms our previous work and the existing methods in terms of the accuracy of the predicted text for the speech to text transmission, and achieves comparable results with the existing approach in terms of the quality of the recovered speech signals for the speech to speech transmission. It is worth mentioning that the proposed approach significantly improves the transmission efficiency over the existing methods with only 16% of the number of transmitted symbols per sentence required by the state-of-the-art approach for the speech to text transmission, and only transmits shockingly 0.2% of the amount of transmitted symbols by the existing method for the speech to speech transmission.

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