A Novel Task-Oriented Text Corpus in Silent Speech Recognition and its Natural Language Generation Construction Method

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ABSTRACT

Millions of people with severe speech disorders around the world may regain their communication capabilities through techniques of silent speech recognition (SSR). Using electroencephalography (EEG) as a biomarker for speech decoding has been popular for SSR. However, the lack of SSR text corpus has impeded the development of this technique. Here, we construct a novel task-oriented text corpus, which is utilized in the field of SSR. In the process of construction, we propose a task-oriented hybrid construction method based on natural language generation (NLG) algorithm. The algorithm focuses on the strategy of data-to-text generation, and has two advantages including linguistic quality and high diversity. These two advantages use template-based method and deep neural networks respectively. In an SSR experiment with the generated text corpus, analysis results show that the performance of our hybrid construction method outperforms the pure method such as template-based natural language generation or neural natural language generation models.

CCS Concepts

• Information systems → Information systems
applications → Multimedia information systems → Multimedia content creation

Keywords

natural language generation; silent speech recognition; deep neural networks

1. INTRODUCTION

Acoustic speech recognition (ASR) has already become one of the most successful techniques in the era of artificial intelligence (AI) [1], [2]. However, millions of people around the world who lost their abilities to speak cannot enjoy the convenience of ASR [3]. Under certain circumstances such as large background noise or high confidential communications, ASR may lose its advantage or even doesn't work [4].

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NLPIR 2019, June 28–30, 2019, Tokushima, Japan

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ACM ISBN 978-1-4503-6279-5/19/06...\$15.00

DOI: <https://doi.org/10.1145/3342827.3342838>

One possible solution is the silent speech recognition (SSR) which is an alternative for these situations [5], [6]. Many biological indicators has been used as the input for the SSR among which electroencephalography (EEG) is the most promising one [7]–[11]. EEG is a measure of electrical potentials between different locations on the skull. Krishna et.al showed that using EEG can help ASR systems overcome performance loss in the presence of noise [12]. Some studies have also reported that it is possible to decipher imagined speech directly through EEG [13]. Although a huge progress has been made in EEG-based SSR, it is impossible to evaluated the performances of different systems due to the lack of a consensus text corpus for SSR.

In the process of constructing EEG-based SSR text data sets, various NLP methods play an important role. Many methods for attention and neural sequence-to-sequence framework have been proposed [14]–[19]. A method has been proposed that of word-based and character-based sequence-to-sequence models[20]. This model is utilized for data-to-text natural language generation (NLG).

BERT has been successfully applied to a variety of natural language processing tasks such as name entity recognition and machine reading comprehensions[21]–[25]. The literature [26] first proposed to extend the BERT to the sequence generation task, and constructed a new natural language generation model based on the pre-training language model. In order to take full advantage of the BERT's context modeling capabilities, the proposed method uses a two-stage decoding process.

2. TEXT CORPUS FOR SSR

In the field of general speech recognition, there are a large number of mature text corpus available. These texts are organized and complete. The content covers all aspects and application fields of daily conversation. Based on these extensive text corpus, it can be further constructed a rich speech training set for general speech recognition.

Different from the general speech recognition application, the design and construction of training corpus is a challenging task in the field of SSR, because Using EEG as a biomarker for speech decoding has been popular for SSR. We want to build an SSR system based on EEG. Then, there is no ready-made 'EEG-text pair' data set that can be used for model training. We must build such a data set almost from zero. Quantitatively, if you want to build an available system similar to general speech recognition, then the amount of data required must be cumulative tens of thousands of hours of 'EEG-text pair' data sets. For most academic

teams, this is a daunting task that requires a lot of manpower, material and time.

3. HYBRID MODELS FOR TEXT CORPUS

3.1 Task-Oriented Text Corpus

In order to solve the above dilemma, we can choose a compromise approach, considering that in application, the essential needs of SSR are those patients who lose their throat vocal function due to illness. Their outstanding scenario for SSR applications is life support. Therefore, based on this consideration, we avoid the need for a massive ‘EEG-text pair’ data set from the generic scenario SSR. We start with the help of this task-oriented scene to construct the task-oriented text corpus. In this way, the demand for data set size is significantly reduced. Therefore, we need to construct session texts that serve the life support class in a targeted manner. Such texts will be further applied to the EEG signal data collection process to construct a task-oriented ‘EEG-text pair’ data set.

The characteristics of the life-assisted task-oriented session text is that the task-oriented session has a clear purpose relative to the open domain session, requiring high language quality and clear structure. Moreover, with the language habits and language styles of different users, the language presents richness and diversity in a task-oriented session. The special requirements of this kind of task-oriented session text construction bring new challenges to the design and construction of our data set.

we adopt a task-oriented corpus hybrid construction method based on natural language generation algorithm. The algorithm focuses on the strategy of data-to-text generation[20], and has the following two advantages, the first one is linguistic quality based on template-based method and the second is high diversity based on deep neural networks.

3.2 Task-Oriented Hybrid Models

The literature [20] based on the neural network method realizes the data-to-text natural language generation. Inspired by this method, we construct a task-oriented hybrid construction method based on natural language generation algorithm. This method is used to generate task-oriented text corpus in the field of SSR. The algorithm includes two aspects, first constructing the seed text corpus, then generate task-oriented text corpus based on the seed text corpus using the deep neural network method.

The task-oriented hybrid models are used to construct the corpus. Specific steps are as follows.

Step 1. According to the requirements applied to the life aid class, design the corresponding cycle template, the template needs to be concise and regular, and can basically cover the life assisted scene, with the focus on the relevant high frequency words.

Step 2. Construct the seed text corpus C_{seed} based on the cycle template of natural language generation method.

Step 3. The scale of the seed text corpus needs to be properly controlled. The corpus quality is used as a criterion to control the scale, and the scale adjustment can be returned to the step 2 iterative update.

Step 4. The step 3 result is judged manually, mainly due to the following considerations. The scale of the seed text corpus here is strictly controlled to a small extent, and we have relatively high quality requirements for the seed text corpus.

Step 5. Using the seed text corpus as a training set, training based on the deep neural network model, the model M_C is obtained.

Step 6. Based on the model M_C . Further inference, get the final meet-required task-oriented corpus C_{DN} .

Step 7. The task-oriented corpus C_{DN} generated in step6 may not necessarily meet the requirements in some cases. For example, in the high diversity aspect, we need to go back to step5 and further iterate and optimize until it meets the requirements.

3.3 Constructing Seeds Text Corpus

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who = ['我 (I), 你 (you), 他 (he), 她 (she)']
want = ['想要 (want), 打算 (would like), 不想 (would like not)']
action = ['穿戴 (wear), 吃 (eat), 喝 (drink), 睡觉 (sleep), 去 (go)']
number = ['一 (one), 二 (two), 三 (three), 四 (four)']
coats = ['上衣 (jacket), 毛衣 (sweater), 外套 (coat), 内衣 (underwear), '
        '短袖 (T-shirt), 长袖 (shirt), 羽绒服 (down coat), 大衣 (overcoat), '
        '羊毛衫 (woolen sweater), 套头衫 (pullover), 连体衣 (jumpsuits), '
        '卫衣 (hoodie), 背心 (waistcoat), 雨衣 (raincoat), 西装 (suit), '
        '衬衫 (shirt), 风衣 (dust coat)']
pants = ['裤子 (pants), 牛仔裤 (jeans), 短裤 (short pants), 短裤 (shorts), '
        '秋裤 (long johns), 内裤 (underpants), 裙子 (skirt)']
shoes = ['鞋子 (shoes), 运动鞋 (sneaker), 凉鞋 (sandal), 拖鞋 (slipper), '
        '高跟鞋 (heels), 袜子 (socks)']
decorators = ['帽子 (hat), 头盔 (helmet), 眼镜 (glasses), 墨镜 (sunglasses), '
        '隐形眼镜 (contact lens), 耳环 (earring), 口罩 (mask), 手表 (watch), '
        '戒指 (ring), 围巾 (scarf), 领带 (tie)']
food = ['米饭 (rice), 炒饭 (fried rice), 石锅拌饭 (bibimbab), 粥 (porridge), '
        '蔬菜 (vegetable), 萝卜 (radish), 白菜 (cabbage), 西兰花 (broccoli), '
        '玉米 (corn), 芥蓝 (cabbage mustard), 豆腐 (bean curd), 鸡蛋 (egg), '
        '面包 (bread), 猪肉 (pork), 牛肉 (beef), 羊肉 (mutton), 鱼 (fish), '
        '肉 (meat), 螃蟹 (crab), 虾 (shrimp), 花生 (nuts), 零食 (snacks), '
        '炒面 (fried noodles), 汉堡 (hamburger), 苹果 (apple), 香蕉 (banana), '
        '橘子 (orange), 火龙果 (pitaya), 西瓜 (watermelon), 哈密瓜 (cantaloupe), '
        '猕猴桃 (kiwi)']
drink = ['水 (water), 热水 (hot water), 冰水 (icy water), 酒 (wine), '
        '红酒 (red wine), 威士忌 (whisky), 龙舌兰 (tequila), 饮料 (drinks), '
        '可口可乐 (coca-cola), 果汁 (juice), 酸奶 (yogurt), 牛奶 (milk), '
        '咖啡 (coffee), 茶 (tea), 绿茶 (green tea)']
location = ['房间 (room), 床 (bed), 地板 (floor), 沙发 (sofa), 阳台 (balcony), '
        '楼下 (downstairs), 客厅 (living room), 卧室 (bedroom), 厨房 (kitchen)']
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Figure 1. seed lexicon

In this section, we introduce the method of constructing the seed Text Corpus.

Step 1. Limit the scope of life scenes

Step 2. According to the word frequency, extract common nouns, verbs, adjectives and quantifiers from the established scenes to form a seed lexicon, as shown in Figure 1.

Step 3. According to the rule structure of grammatical subject, predicate and object, the corresponding vocabulary is extracted from the seed lexicon to form a sentence.

Step 4. The statement is expanded to include appropriate quantifiers and adjectives before the corresponding nouns.

Example:

- a1. I want to wear a coat
- a2. I want to wear a long coat
- a3. I want to wear a long coat with velvet
- b1. He wants to drink water
- b2. He wants to drink a glass of water
- b3. He wants to drink a cup of warm water.
- b4. He wants to drink a cup of warm water with sugar.

3.4 Constructing Text Corpus Based on Deep Neural Networks NLG Method

In this section, we designed the NLG model to implement non-fixed length input and generate non-fixed length output text. We

need to construct the sequence-to-sequence structure. First implement embeddings for inputting non-fixed length text.

We use BERT[25][26] to implement the encoding function, where the BERT stands for means bidirectional encoder representations from transformers. In the process of using BERT, due to the use of language models for transformer learning, empirical improvements have shown that unsupervised pre-training is an important integral part of many natural language processing systems. The BERT method suggests that a general language model may exist. Prior to this, when people solved NLP problems, they often customized specific models for specific problems. However, BERT successfully solves a wide range of NLP tasks. Based on the above description, our structure is shown in Figure 2.

Figure 2. Embedding based on BERT

Based on the idea of these literature [20][27]-[29], We implement the natural language generation transformer model for specific text to text. Furthermore, we have adopted a method based on these documents[30]-[33]. The detailed process is described below. The basic structure of LSTM is as follows. Where ζ_t , ζ_t , ξ_t and ψ_t represent input gate, forget gate, output gate and memory cell, respectively.

$$\begin{aligned}\zeta_t &= \sigma(\Xi_\zeta \mathcal{R}_{t-1} + \Im_\zeta \vartheta_{x_t} + \beta_\zeta) \\ \zeta_t &= \sigma(\Xi_\zeta \mathcal{R}_{t-1} + \Im_\zeta \vartheta_{x_t} + \beta_\zeta) \\ \xi_t &= \sigma(\Xi_\xi \mathcal{R}_{t-1} + \Im_\xi \vartheta_{x_t} + \beta_\xi) \\ \varphi_t &= \tanh(\Xi_\varphi \mathcal{R}_{t-1} + \Im_\varphi \vartheta_{x_t} + \beta_\varphi) \\ \psi_t &= \zeta_t \odot \psi_{t-1} + \zeta_t \odot \varphi_t \\ \mathcal{R}_t &= \xi_t \odot \tanh(\psi_t)\end{aligned}$$

Where ϑ_{x_t} stand for the embedding of input. Ξ and $\Im$ stand for corresponding matrix, and β represent bias. They are all trainable parameters. $\mathcal{R}_t$ stand for the hidden state of LSTM.

Utilizing bi-directional LSTM structure[31], we can extract text context information from both forward and backward directions. The hidden state can be expressed as follows.

$$\mathcal{R}_t = \mathcal{R}_{L_t} \oplus \mathcal{R}_{R_t}$$

where $\mathcal{R}_{L_t}$ and $\mathcal{R}_{R_t}$ represent hidden state of backward direction and hidden state of forward direction, respectively. and $\oplus$ stands for the concat operation.

Output text sequence $\mathcal{L}_1, \mathcal{L}_2, \dots, \mathcal{L}_N$, has a defined generation rule[20][34]. The elements $\mathcal{L}_k, (k = 1, 2, \dots, N)$ are generated as follows.

$$p(\mathcal{L}_k | \mathcal{L}_1 \mathcal{L}_2 \dots \mathcal{L}_{k-1}) = \text{softmax}(W(\sum_{e=1}^M ((\text{softmax}(s_k \mathcal{W} \mathcal{R}_e)) \mathcal{R}_e)))$$

Where s_k has the following representation.

$$s_k = bi\sim LSTM((W^{out}(\mathcal{L}_{k-1}) \oplus \sum_{e=1}^M ((\text{softmax}(s_{k-1} \mathcal{W} \mathcal{R}_e)) \mathcal{R}_e)), s_{k-1})$$

Wherein, input text sequence $\vartheta_x = (\vartheta_{x_1}, \vartheta_{x_2}, \dots, \vartheta_{x_M})$. where W , $\mathcal{W}$ and W^{out} represent output matrix, attention matrix and output embedding matrices, respectively.

4. RESULTS AND ANALYSIS

Based on the methods presented in Sections 3.3 and 3.4, we combine the above two methods to construct a hybrid algorithm for task-oriented corpus.

Task-oriented hybrid model can learn to express structured input in an appropriate way. These advantages mainly come from the exquisite and elegant seeds text corpus design and deep neural networks natural language generation method. The hybrid model has two advantages including linguistic quality and high diversity.

In the field of SSR experiment, analysis results show that the performance of our hybrid model outperforms the pure method such as template-based natural language generation or neural natural language generation models.

5. ACKNOWLEDGMENTS

We are very grateful to DeepBlue Technology (Shanghai) Co., Ltd. and DeepBlue Academy of Sciences for their support. Thanks to the support of the Equipment pre-research project (No. 31511060502).

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