Chain-Talker: Chain Understanding and Rendering for Empathetic Conversational Speech Synthesis

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Abstract

Conversational Speech Synthesis (CSS) aims to align synthesized speech with the emotional and stylistic context of user-agent interactions to achieve empathy. Current generative CSS models face interpretability limitations due to insufficient emotional perception and redundant discrete speech coding. To address the above issues, we present **Chain-Talker**, a three-stage framework mimicking human cognition: *Emotion Understanding* derives context-aware emotion descriptors from dialogue history; *Semantic Understanding* generates compact semantic codes via serialized prediction; and *Empathetic Rendering* synthesizes expressive speech by integrating both components. To support emotion modeling, we develop **CSS-EmCap**, an LLM-driven automated pipeline for generating precise conversational speech emotion captions. Experiments on three benchmark datasets demonstrate that Chain-Talker produces more expressive and empathetic speech than existing methods, with CSS-EmCap contributing to reliable emotion modeling. The code and demos are available at: https://github.com/AI-S2-Lab/Chain-Talker.

1 Introduction

Conversational speech synthesis (CSS) aims to express a target utterance with the proper linguistic and affective prosody in a user-agent conversational context (Guo et al., 2021). This task not only requires the agent to accurately perceive the user's emotion but also to ensure that the generated speech's emotion and style align with the conversational situation. In recent years, with the development of human-computer interaction (HCI), CSS has become an integral part of intelligent interactive systems and plays an important role in areas such as virtual assistants (Jain et al., 2024) and voice agents (Jaber et al., 2024).

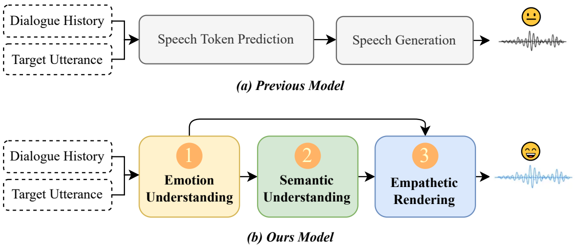

Figure 1: (a) Previous methods predict speech tokens directly based on context. (b) Our approach progressively realizes empathetic CSS through three stages: Emotion Understanding, Semantic Understanding, and Empathetic Rendering.

Traditional CSS attempts mainly focus on taking the multi-modal dialogue history, including the text and speech modalities, to predict the speech representations of the speech to be synthesized. Afterward, these representations are fed to the speech synthesizer to decode the target conversational speech. In this process, elaborate encoding modules were introduced to enhance speech quality by incorporating style embeddings (Guo et al., 2021; Nishimura et al., 2022; Xue et al., 2023) or emotional category information (Liu et al., 2023b; Deng et al., 2023; Liu et al., 2024a) into the representations. Recently, advanced CSS models like GPT-Talker (Liu et al., 2024b), based on Generative Pre-trained Transformer (GPT) (Radford, 2018), have significantly enhanced the naturalness and expressiveness of synthesized speech by directly predicting speech token sequences (such as HuBERT encoding (Hsu et al., 2021)) from dialogue contexts, as shown in Fig. 1 (a). Such a process lacks interpretability in two ways: 1) Speech generation does not fully understand the emotion of the conversation, making it difficult to achieve true empathy. However, using natural language descriptions allows easier control and representation of style and emotion in speech (Guo et al., 2023; Ji et al., 2024). This approach directly establishes

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a strong correlation between the semantic content and the acoustic expressiveness (Yang et al., 2024). Therefore, understanding captions enables the comprehension of emotional changes in the dialogue. 2) General discrete speech codes contain too much redundant information. They are often obtained by quantizing intermediate representations from pre-trained models (Hsu et al., 2021) or using Neural Audio Codec models (Zeghidour et al., 2022), which mix semantic and acoustic information and have limited expressive capacity.

To address the above issues, we propose a Chain Understanding and Rendering scheme for Empathetic CSS, termed **Chain-Talker**. Drawing on the chain-like human thinking process (Zheng et al., 2023; Imani et al., 2023; Huang et al., 2024), Chain-Talker decomposes CSS into a three-link thinking chain including *Emotion Understanding*, *Semantic Understanding*, and *Empathetic Rendering*. As shown in the Fig. 1 (b), the emotion understanding module perceives the emotion description of the current utterance based on the conversation history with the conversation-related speech emotion description. The semantic understanding module continues to generate purely semantic codes of the speech by means of serialization prediction, and then the emotion description and semantic codes are used for the final empathetic CSS. This cognitive chain architecture ensures precise comprehension of contextual emotional states, enabling accurate affective responses in human-machine dialogues. By decoupling emotion and semantics into modularized processes (emotion understanding and semantic understanding), the system achieves independent yet synergistic modeling, forming an interpretable empathetic CSS framework with transparent decision-making mechanisms.

To ensure that Chain-Talker learns a robust understanding of expressiveness such as emotion and style during training, we propose an LLM-driven automatic dialog-aware empathetic captioning pipeline, **CSS-EmCap**, for conversational speech. We employ the CSS-EmCap pipeline to generate emotional descriptions for three benchmarking CSS datasets, including NCSSD (Liu et al., 2024b), MultiDialog (Park et al., 2024) and DailyTalk (Lee et al., 2023). Three datasets with emotional descriptive information are consolidated as the final training data for Chain-Talker. Subjective and objective experiments are conducted to verify the reliability of the proposed pipeline and the effectiveness of Chain-Talker. The results indicate that Chain-Talker outperforms other CSS baseline models by synthesizing more appropriate and empathetic conversational speech, highlighting the necessity of the proposed pipeline. In summary, the main contributions of this paper are:

- We introduce Chain-Talker, which employs a three-stage chain modeling process. After perceiving the emotions in the dialogue and serially generating semantic codes, it collaboratively produces empathetic response speech.
- We propose CSS-EmCap, an LLM-driven automatic dialog-aware empathetic captions annotation pipeline for dialogue speech. A total of approximately 384 hours across three benchmarking CSS datasets were annotated.
- Comprehensive experiments prove the reliability of CSS-EmCap and the effectiveness of Chain-Talker.

2 Related Works

2.1 Chain Modeling in Conversation

Recently, using chain modeling to solve complex problems step-by-step has been very successful in dialogue-related tasks. For instance, in generating text responses, Chen et al. (2021) and Lin et al. (2024) incorporate reading comprehension and sentiment analysis, enabling models to focus on key information and emotional cues, thereby improving response accuracy and relevance. In speech response tasks, systems like USDM (Kim et al., 2024) and Spectron (Nachmani et al., 2024) perform speech recognition before generating responses. This sequential approach within a unified LLM reduces errors from multi-module setups and enhances semantic coherence. Drawing inspiration from these successes, we pioneer the application of chain modeling to CSS tasks. This approach enables more empathetic conversations by step-by-step understanding context and rendering.

2.2 Speech Emotion Description

Accurately describing emotion and style in speech using natural language becomes a key research area. Traditionally, this task relies heavily on manual annotation, where annotators write adjectives or sentences based on the speech. This method is inefficient, costly, and the quality of annotations declines with prolonged manual labeling (Yang et al., 2024; Liu et al., 2023a; Kawamura et al., 2024).

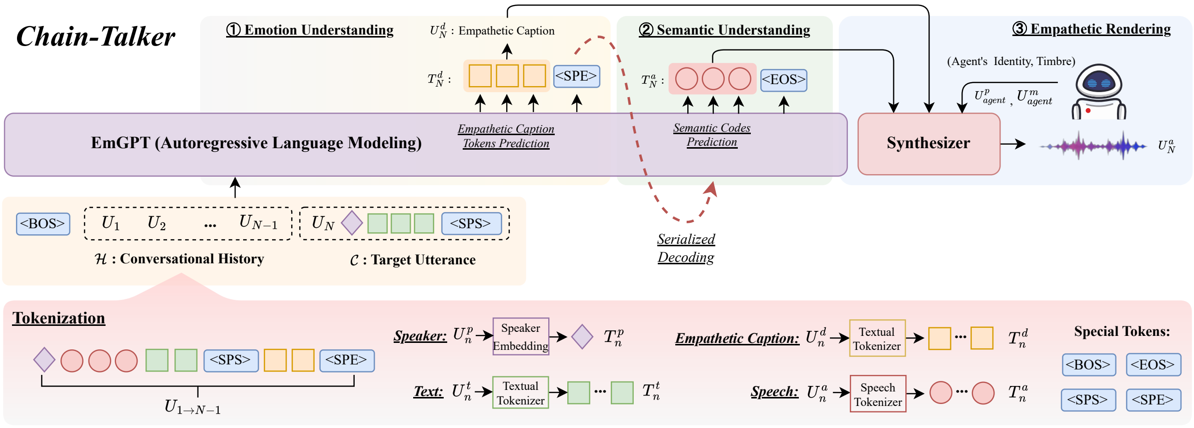

Figure 2: The overall architecture of Chain-Talker. Chain-Talker comprises two main components: EmGPT and Synthesizer. EmGPT is responsible for emotion and semantic understanding, while the Synthesizer handles the generation of empathetic speech rendering.

To address these issues, some studies rely on limited manual annotations and expand the data using pre-trained models such as SimBERT or GPT-3.5 Turbo (Guo et al., 2023; Ji et al., 2024). However, these models lack genuine speech understanding and merely rewrite sentences based on keywords, often resulting in inaccurate descriptions of emotion or speaking style. Other approaches (Chu et al., 2024; Xu et al., 2024; Lian et al., 2024) attempt to train models capable of labeling speech style, but they typically overlook the need for emotional understanding in conversational contexts. To overcome these issues, we develop an automated, dialog-aware empathetic description process using LLMs. Specifically, the proposed method first extracts stylistic attributes at the sentence-level and emotions at the dialog-level. It then prompts the LLM to generate basic descriptions, which are subsequently optimized into empathetic captions. Throughout the process, it continually prompts the LLM to reference diverse contextual information to ensure consistency between descriptions and speech.

2.3 Speech Discrete Encoding

Speech tokens extracted through unsupervised learning (Hsu et al., 2021; Zeghidour et al., 2022) enable the synthesis of relatively natural-sounding speech (GPT-SoVITS, 2024; Wang et al., 2023). However, training language models with these tokens often results in slow convergence and poor stability. To address this, research has shown that semantic tokens derived from supervised learning—by capturing clear semantic information in speech and aligning it with text—can improve model stability (Du et al., 2024). In CSS tasks, the input sequence includes various modalities, making the modeling process challenging unless it is performed within the same semantic space. Therefore, following CosyVoice, we employ a supervised automatic speech recognition (ASR) model to create a supervised semantic speech tokenizer.

3 Task Definition

In user-agent spoken dialogue interactions, the user initiates the conversation, followed by the agent responding within the context of the dialogue. As the conversation progresses with alternating turns, the accumulated spoken content forms the dialogue history. The current dialogue turn is denoted by N, the utterance to be synthesized is represented as $\mathcal{C} = (U_N^p, U_N^t)$, and the dialogue history can be defined as $\mathcal{H} = \{U_1^{p,a,t,d}, U_2^{p,a,t,d}, \ldots, U_{N-1}^{p,a,t,d}\}$. Here, U_n^p, U_n^a, U_n^t, and U_n^d represent the speaker, speech, text, and emotional description of the utterance at the n-th turn, respectively. To generate empathetic speech, the Chain-Talker first determines the empathetic caption U_N^d based on the dialogue history $\mathcal{H}$ and the current utterance $\mathcal{C}$. Next, it serially generates the semantic codes T_N^a, and finally synthesizes the corresponding expressive speech U_N^a that aligns with the inferred empathetic caption.

4 Methodlogy: Chain-Talker

This section offers a detailed description of our proposed Chain-Talker. We begin by outlining the data input format for the model, referred to as the *Unified Context Tokenization* method. Building on the chain modeling, our approach has three main processes: 1) *Emotion Understanding*, which focuses on predicting empathetic captions, 2) *Semantic Understanding*, which aims at inferring speech codes that include semantic information, and 3) *Empathetic Rendering*, which synthesizes the empathetic response speech. Finally, we conclude by discussing the model's training strategy: *Multi-Stage Training*.

4.1 Unified Context Tokenization

To better model the context of dialogues, we follow the method of GPT-Talker, which involves the alternating concatenation of user and agent utterances to simulate a real dialogue flow. In particular, each utterance is concatenated in the order of speaker information, speech, textual content, and empathetic captions. This allows the model to first understand the context and predict the emotion before generating the corresponding speech. Therefore, the input to Chain-Talker can be represented as $\mathcal{Q}$:

$$\mathcal{Q} = (\langle \text{BOS} \rangle, \mathcal{H}, \mathcal{C}, \langle \text{EOS} \rangle) \tag{1}$$

where $\mathcal{H}$ denotes the dialogue history, consisting of $N-1$ sextuples $(U_n^p, U_n^a, U_n^t, \langle\text{SPS}\rangle, U_n^d, \langle\text{SPE}\rangle)$. $\mathcal{C}$ represents the target utterance to be synthesized, comprising a triple $(U_n^p, U_n^t, \langle\text{SPS}\rangle)$. The special tokens (Zhang et al., 2023) $\langle\text{BOS}\rangle$ and $\langle\text{EOS}\rangle$ indicate the start and end of the entire input sequence $\mathcal{Q}$, respectively, while $\langle\text{SPS}\rangle$ and $\langle\text{SPE}\rangle$ mark the beginning and end of the empathetic captions U_n^d.

To better represent the different modal information in the input sequence, we encode the textual content as T_n^t and the empathetic caption as T_n^d using Byte Pair Encoding (BPE) (Gage, 1994). Following CosyVoice, we extract the speaker vectors as T_n^p using a pre-trained voice-print model [1]. Additionally, we employ a supervised automatic speech recognition model with an inserted vector quantizer (VQ) (Gao et al., 2023) to encode the speech as T_n^a.

4.2 Emotion Understanding

In the "①" part of Fig. 2, we utilize the dialogue context $\mathcal{Q}$ ($\mathcal{H}$ and $\mathcal{C}$) as a prompt and apply the autoregressive EmGPT to comprehend the interactions between the user and the agent, as well as the changes in emotional states within the context. Simultaneously, EmGPT predicts the empathetic caption tokens T_N^d of the target utterance until the $\langle SPE \rangle$ token is predicted:

$$\begin{aligned} & p(T^d_{N,:}|\Re_{1\to N-1}, T^p_{N,:}, T^t_{N,:}; \Theta) \\ &= \prod_{j=0}^{D} p(T^d_{N,j}|T^d_{N,<j}, \Re_{1\to N-1}, T^p_{N,:}, T^t_{N,:}; \Theta) \end{aligned} \tag{2}$$

where, Θ represents EmGPT, $\Re_{1\to N-1}$ is the set $\{\,(T_n^p, T_n^a, T_n^t, T_n^d)\,\}_{1\to N-1}$, j denotes the value of the j-th token of T_N^d, and D is the length of T_N^d.

4.3 Semantic Understanding

In the "②" part of Fig. 2, once EmGPT comprehends the context and predicts an appropriate empathetic caption U_N^d, it utilizes this information in conjunction with the contextual content $\mathcal{Q}$ to further predict the speech codes T_N^a that contain the semantic information of the target utterance:

$$\begin{aligned} & p(T^a_{N,:}|\Re_{1\to N-1}, T^p_N, T^t_N, T^d_N; \Theta) \\ & \quad = p(T^d_{N,:}|\Re_{1\to N-1}, T^p_N, T^t_N; \Theta) \\ & \cdot \prod_{i=0}^{A} p(T^a_{N,i}|T^a_{N,<i}, \Re_{1\to N-1}, T^p_N, T^t_N; \Theta) \end{aligned} \tag{3}$$

where i denotes the value of the i-th token of T_N^a, and A is the length of T_N^a.

During the training EmGPT phase, we use a teacher forcing approach where the left-shifted sequence serves as the input pattern and the original sequence acts as the target output. We divide the loss function into two components: $\mathcal{L}_{\text{caption}}$ and $\mathcal{L}_{\text{speech}}$. They compute the cross-entropy loss between the true and predicted values for empathetic caption tokens and semantic codes, respectively.

4.4 Empathetic Rendering

In the "③" part of Fig. 2, unlike traditional models that directly decode speech tokens into speech responses, our approach uses previously predicted empathetic captions to guide emotion and style rendering during decoding. Specifically, the Synthesizer employs an optimal-transport conditional flow matching model (OT-CFM) (Du et al., 2024) as its backbone to predict Mel spectrograms and uses HIFI-GAN vocoder (Kong et al., 2020) to synthesize the waveform.

To enhance the quality and consistency of the generated speech, OT-CFM relies not only on the Mel spectrogram X and time step t, but also incorporates empathetic captions U_N^d, agent's speaker information U_{agent}^p, semantic codes T_N^a, and agent's masked Mel spectrograms U_{agent}^m into the prediction of the vector field. This process is specifically

[1] https://github.com/alibaba-damo-academy/3D-Speaker/tree/main/egs/3dspeaker/sv-cam++

represented by the following differential equation:

$$\frac{d\phi_t(X)}{dt} = \nu_t(\phi_t(X), t \mid U^p_{agent}, U^d_N, T^a_N, U^m_{agent}) \quad (4)$$

where $t \in [0, 1]$, empathetic captions are encoded using a pre-trained sentence-level BERT model [2] and integrated with each semantic code. Other settings follow CosyVoice.

To ensure that the model learns the correct vector field $v_t(X)$, OT-CFM introduces Optimal Transport (OT) flows and trains the model by minimizing the difference between the predicted vector field and the theoretical OT vector field. The loss function is defined as:

$$\begin{aligned} \mathcal{L}_{\text{OT-CFM}} = \mathbb{E}_{t,X_0,X_1} \big[\| \omega_t \left(\phi_t^{\text{OT}}(X_0, X_1) \mid X_1 \right) \\ - \nu_t \left(\phi_t^{\text{OT}}(X_0, X_1) \mid \theta \right) \| \big] \end{aligned} \quad (5)$$

where $\phi_t^{\text{OT}}(X_0, X_1)$ represents the optimal transport flow, i.e., the path from X_0 to X_1. $\omega_t(\phi_t^{\text{OT}}(X_0, X_1)|X_1) = X_1 - (1-\sigma)X_0$. θ is the parameter of the neural network, used to predict the vector field ν_t.

4.5 Multi-Stage Training

In the Chain-Talker framework, the training of EmGPT is divided into two stages: 1) **First-Stage**: The model is trained using single-sentence text-to-speech pair data, which equips the model with the basic capability to generate speech from text. In this work, we use "CosyVoice-300M-25Hz" [3] as the base model for fine-tuning, which is trained on about 170,000 hours of single-sentence speech data. 2) **Second-Stage**: The model is trained with dialogue data to infer appropriate empathetic captions based on the dialogue context and to continue predicting the corresponding semantic codes. Additionally, the Synthesizer can be trained separately in a single-sentence mode using empathetic captions and semantic codes, thereby enhancing the naturalness and robustness of the synthetic speech.

5 CSS-EmCap Pipeline

In this section, we provide a detailed description of CSS-EmCap, which includes two components: 1) *Multi-level Attribute Extraction.* 2) *Empathetic Captions Generation.* Through this LLM-driven automatic dialog-aware pipeline, empathetic captions can be annotated for any CSS datasets.

5.1 Multi-level Attribute Extraction

To improve the stability of LLMs in generating emotion- and style-related descriptions, we pre-extract two types of key expressive attributes (style factors and emotion) from conversational speech before generation. First, we use speech analysis tools to extract sentence-level style factors (including gender, pitch, energy, and tempo). Then we categorize the speech into different classes based on factor values and unified thresholds. Next, we use multimodal information such as speech, text, and speaker data to prompt LLM [4] to accurately distinguish the emotional category of each sentence within the dialogue context.

5.2 Empathetic Captions Generation

After extracting style factors at the sentence level and emotions at the dialog level, we employ Gemini [4] to generate diverse natural language descriptions for each speech. Unlike previous methods that rely solely on large language models to combine expressive attributes, we leverage Gemini's speech understanding capabilities to create empathetic captions by integrating the original speech. The prompting process is divided into two main steps as follows: 1) **Step-1**: we generate basic descriptions based on the dialogue context and the two levels of extracted expressive attributes. 2) **Step-2**: we apply rules such as synonym replacement and varying emotional intensity descriptions to prompt Gemini to expand and enrich the captions. Additionally, we add a verification process to ensure that the descriptions accurately reflect the speech's expressiveness. Consequently, CSS-EmCap produces empathetic captions that more accurately convey the emotions and expressive styles present in the dialogue.

6 Experiments and Results

In this section, we introduce the NCSSD-EmCap dataset used in this work, followed by a discussion of *Baselines* and *Metrics*. We then provide a comprehensive experimental analysis, including *CSS-EmCap Evaluation*, *Chain-Talker Evaluation*, *Ablation Results*, *Visualization Results*, and *Hyper-parameter Selection*. Further details on the *Experimental Setup* and *Case Study* are available in the Appendix.

[2] https://huggingface.co/sentence-transformers/distiluse-base-multilingual-cased-v1

[3] https://www.modelscope.cn/models/iic/CosyVoice-300M-25Hz

[4] https://deepmind.google/technologies/gemini/pro/

6.1 Datasets

We employ the open-source DailyTalk (Lee et al., 2023), MultiDialog (Park et al., 2024) and NCSSD (Liu et al., 2024b) datasets to develop the NCSSD-EmCap dataset via the CSS-EmCap pipeline. For detailed statistical information on these datasets, please refer to the Appendix.

6.2 Baselines

To validate the effectiveness of the CSS-EmCap and the capabilities of Chain-Talker, we compare two categories of baseline models:

To validate the LLM-driven automatic dialog-aware empathetic captioning pipeline, we compare the following caption generation schemes: 1) ***w/o SF***: Direct use of the LLM [4] to extract speech expressive attributes. 2) ***w/o SL-SF***: Removal of sentence-level style factors, followed by caption generation using the LLM. 3) ***w/o DL-SF***: Removal of dialog-level emotion, then using the LLM for caption generation. 4) ***Qwen2-Audio***: LLM with speech style capture capabilities (Chu et al., 2024). 5) ***SECap***: LLM with speech emotion captions capture capabilities (Xu et al., 2024).

We evaluate the effectiveness of Chain-Talker, trained based on NCSSD-EmCap, within dialogue scenarios by comparing it against state-of-the-art CSS systems: 1) ***CCATTS*** (Guo et al., 2021), 2) ***M^2-CTTS*** (Xue et al., 2023), 3) ***ECSS*** (Liu et al., 2024a), 4) ***GPT-Talker*** (Liu et al., 2024b), 5) ***GPT-Talker$_c$*** (GPT-Talker adds Emotion Understanding), 6) ***Chain-Talker$_e$*** (Using emotion labels to replace empathetic captions), 7) ***Chain-Talker$_s$*** (Using style labels to replace empathetic captions). Additionally, we also assess the importance of various modules and loss functions in Chain-Talker: 8) ***w/o context***: A Chain-Talker variant without dialog history $\mathcal{H}$. 9) ***w/o captions***: A Chain-Talker variant without emotion understanding, only semantic understanding. 10) ***w/o $\mathcal{L}^{caption}$***: Removing the loss function about emotion understanding. 11) ***w/o First-Stage***: Training Chain-Talker directly on the NCSSD-EmCap dataset.

For details of the baseline models, please refer to the Appendix.

6.3 Metrics

Objective Evaluation Metrics: 1) *Semantic Similarity (SIM$_*$):* We utilize RoBERTa (Liu et al., 2019) and mGTE (Zhang et al., 2024) to encode captions generated with different methods and descriptions composed of all Ground Truth style factors (e.g., "gender is female, pitch is high..."). The semantic similarity is then calculated using cosine similarity. Higher values mean that the captions more accurately reflect the real style. 2) *Caption Diversity (DIS-1/DIS-2)*: We use distinct-1/-2 (Li et al., 2015) to evaluate the diversity of generated captions. 3) *Emotion Accuracy (ACC$_m$):* We calculate the emotion accuracy of synthesized speech using Gemini. 4) *Speaker Similarity (SSIM):* Following Jiang et al. (2023), we use embeddings extracted from a fine-tuned WavLM [5] model to assess speaker similarity of synthesized speech. 5) *Dynamic Time Warping Distance (DDTW):* We use the method from Müller (2007) to measure expressiveness in speech by calculating the average Dynamic Time Warping distance of pitch distributions between real and synthesized speech, where lower values suggest higher similarity to Ground Truth.

Table 1: Subjective (with 95% confidence interval) and objective experimental results on the quality and diversity of empathetic captions. "*-w/o*" indicates the removal of sub-steps within CSS-EmCap, where: "*SF*" represents multi-level attribute extraction, "*SL-SF*" denotes sentence-level style attribute extraction, and "*DL-SF*" signifies dialogue-level emotion extraction.

Methods	**DMOS-C** (↑)	**SIM$_R$** (↑)	**SIM$_G$** (↑)	**DIS-1** (↑)	**DIS-2** (↑)
Ground Truth	4.327 ± 0.013	-	-	-	-
Qwen2-Audio	4.212 ± 0.018	0.431	0.534	$\underline{0.086}$	0.174
SECap	$\underline{4.268 \pm 0.022}$	$\underline{0.475}$	$\underline{0.617}$	0.081	$\underline{0.186}$
CSS-EmCap	**4.462 ± 0.019**	**0.568**	**0.694**	**0.106**	**0.296**
-w/o SF	3.819 ± 0.023	0.425	0.584	0.078	0.157
-w/o SL-SF	4.021 ± 0.017	0.335	0.384	0.024	0.049
-w/o DL-SF	4.113 ± 0.031	0.394	0.541	0.051	0.135

Subjective Evaluation Metrics: 1) *Dialog-level Mean Opinion Score for Naturalness (DMOS-N):* Participants are asked to judge the naturalness and quality of synthesized speech based on the dialogue context. 2) *Dialog-level Mean Opinion Score for Expressiveness (DMOS-E):* Participants are asked to evaluate whether the emotion and style of the synthesized speech match the current dialogue context. 3) *Dialog-level Mean Opinion Score for Captions (DMOS-C):* Participants are asked to evaluate whether the generated empathetic captions match the given speech and dialogue context.

6.4 CSS-EmCap Evaluation

We conduct a comprehensive analysis and evaluation of the annotated NCSSD-EmCap dataset, including the quality of the captions and the diversity of the generated descriptive styles.

[5] https://huggingface.co/microsoft/wavlm-base-plus-sv

Table 2: Subjective (with 95% confidence interval) and objective results using different dialogue speech synthesis models. "*-w/o*" indicates the removal of sub-modules within Chain-Talker, where: "*context*" refers to dialogue context, "*captions*" denotes empathetic captions, "$\mathcal{L}^{caption}$" signifies the loss for the captions, and "*First-Stage*" refers to the pre-training process using large-scale single-sentence data.

Methods	**DMOS-N** (↑)	**DMOS-E** (↑)	**ACC**$_m$ (↑)	**DDTW** (↓)	**SSIM** (↑)
Ground Truth	4.467 ± 0.020	4.571 ± 0.015	-	-	-
CCATTS	3.423 ± 0.033	3.469 ± 0.024	0.462	67.851	0.765
M^2-CTTS	3.461 ± 0.018	3.479 ± 0.021	0.471	66.184	0.769
ECSS	3.655 ± 0.035	3.672 ± 0.029	0.495	59.749	0.785
GPT-Talker	3.962 ± 0.011	3.913 ± 0.028	0.562	44.625	0.814
GPT-Talker$_c$	4.045 ± 0.021	4.102 ± 0.013	0.589	40.374	0.829
Chain-Talker$_s$	4.036 ± 0.027	4.015 ± 0.026	0.578	42.876	0.851
Chain-Talker$_e$	4.022 ± 0.019	4.127 ± 0.021	0.601	40.763	0.849
Chain-Talker	**4.147 ± 0.024**	**4.239 ± 0.011**	**0.612**	**38.784**	**0.862**
-w/o context	3.982 ± 0.038	3.984 ± 0.014	0.564	43.589	0.847
-w/o captions	4.037 ± 0.021	4.084 ± 0.032	0.571	43.479	0.836
-w/o $\mathcal{L}^{caption}$	3.947 ± 0.015	3.956 ± 0.025	0.568	45.764	0.829
-w/o First-Stage	3.756 ± 0.024	3.789 ± 0.018	0.517	52.640	0.793

Quality Evaluation: To evaluate whether captions generated by different methods accurately capture the emotions and styles of conversational speech, we randomly select 40 dialogue sets (comprising a total of 240 utterances) from the NCSSD-EmCap dataset. Subsequently, we employ the Category I baseline models described earlier to generate captions for the 240 utterances. Finally, we compare these captions with the Ground Truth to compute *SIM*$_*$ and conduct *DMOS-C* evaluations. Particularly, this *DMOS-C* evaluation involves 30 university students who are proficient in English as a second language and have strong dialogue and reading skills. As shown in the second to fourth columns of Table 1, by comparing *DMOS-C* and *SIM*$_*$, it is evident that our data annotation scheme exhibits clear advantages over other methods. Furthermore, the observation that *DMOS-C* values surpass those of the Ground Truth demonstrates that empathetic captions described in natural language are superior to style and emotion labels.

Diversity Evaluation: To evaluate the diversity of annotated empathetic captions, within the NCSSD-EmCap dataset, we identify 10 different style combinations based on various style factors and emotions. For each combination, we select 50 corresponding captions. We compute the *distinct-1* and *distinct-2* values for the 50 captions of each style, and the average values across all 10 styles are calculated as the experimental results. As shown in the fifth and sixth columns of Table 1, our scheme outperforms others with scores of 0.106 and 0.296, respectively. This demonstrates that our designed pipeline, leveraging LLMs, can generate diverse and appropriate natural language descriptions.

6.5 Chain-Talker Evaluation

We compare Chain-Talker with seven advanced CSS models using the NCSSD-EmCap dataset. For subjective evaluation, 30 university students rate 50 randomly selected synthesized sentences from the test set. The ratings are given in a quiet environment based on the context and using the criteria *DMOS-N* and *DMOS-E*. For objective evaluation, we measure the *ACC*$_m$, *DDTW*, and *SSIM* for each model's synthesized speech. The results are presented in rows two through ten of Table 2. The results show that Chain-Talker achieves significantly lower *DDTW* scores compared to other CSS models, indicating that its combination of GPT-based context modeling and CFM-based acoustic modeling excels in capturing pitch-related expressiveness. Additionally, the *SSIM* scores suggest that Chain-Talker's synthesized speech closely resembles the Ground Truth, effectively preserving the agent's timbre. The *ACC*$_m$ metric demonstrates that Chain-Talker is able to empathize by understanding and rendering generated speech emotions that are more appropriate for the entire conversation. In subjective evaluations, Chain-Talker ranks higher than its closest competitor by 0.102 in naturalness MOS and leads by at least 0.112 in expressiveness MOS. Overall, these results confirm Chain-Talker's ability to both understand dialogue context and produce empathetic, context-aligned speech.

Furthermore, GPT-Talker$_c$'s results show that adding emotional understanding and expression effectively enhances the model's empathy. How-

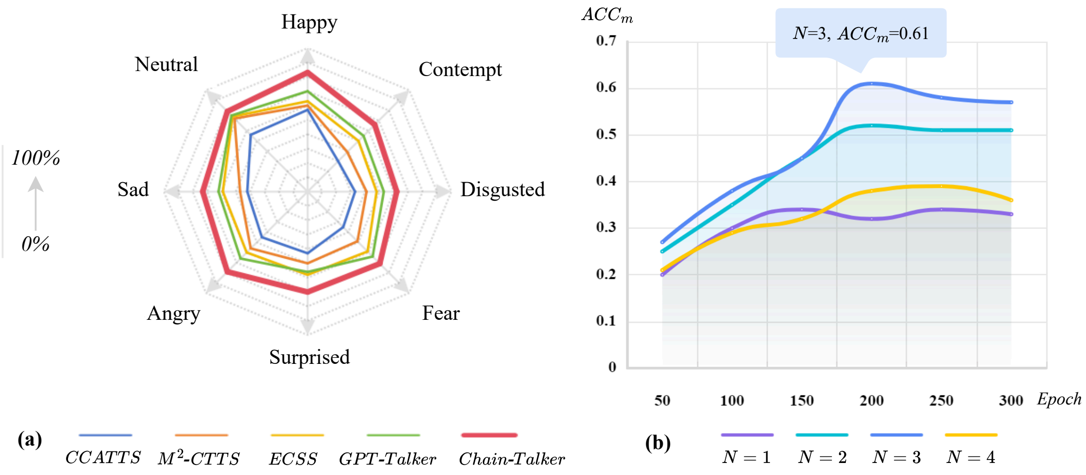

Figure 3: (a) The ability of Chain-Talker and various baseline models to synthesize target speech with different emotional categories based on dialogue context. (b) Experimental results on the selection of the hyperparameter N for dialogue turns.

ever, its speech encoding, derived from HuBERT, includes some acoustic information alongside semantics, which impacts emotional and semantic comprehension. This further highlights the importance of using speech encoding with purely semantic information in our work.

6.6 Ablation Results

To verify the effectiveness of our model components, we conduct ablation experiments by removing specific modules and training methods, with results shown in rows eleven to fourteen of Table 2. The "w/o context" condition, which excludes the dialogue history, shows significant difficulty in context-aware speech synthesis compared to Chain-Talker, indicating the importance of context modeling. "w/o captions" further shows that our Emotion Understanding and Empathetic Rendering are more effective than merely predicting and decoding speech token sequences. Under the "w/o $\mathcal{L}^{caption}$" condition, omitting the caption loss leads to a performance drop (*DMOS-N* decreases by 0.2 and *DMOS-E* by 0.283), highlighting its impact on inference stability and empathetic captions' accuracy. Comparing Chain-Talker with the results of "w/o First-Stage" indicates that pretraining the model on large-scale single-sentence data and then fine-tuning it on small-scale dialogue data can achieve better performance.

6.7 Visualization Results

To clearly demonstrate Chain-Talker's ability to comprehend and convey emotions in dialogue-based speech synthesis, we select 240 target sentences from various emotional categories. Based on the dialogue context, we identify and calculate the emotional categories of the synthesized speech for different models and present their accuracy rates in Fig. 3. In this figure, the arrows indicate each model's strength in understanding and rendering the corresponding emotion. The results show that Chain-Talker generally outperforms other baseline models in emotional expression, further confirming the superiority of chain modeling.

6.8 Hyperparameter Selection

To clearly demonstrate the impact of dialogue context length N on the model's empathy, we randomly select 100 dialogue pairs from the NCSSD-EmCap dataset. We assess the emotion accuracy of the synthesized speech produced by the model across different training epochs, setting N to $1 \rightarrow 3$ during training and $1 \rightarrow 4$ during inference. Fig. 3 illustrates that Chain-Talker's ability to understand and express emotions improves significantly with more training epochs, achieving peak performance around 200 epochs. The best results occur when N=3 at approximately 200 epochs. Although performance slightly declines at N=4, comparisons with N=1 demonstrate that the model can still manage dialogue lengths not encountered during training. Consequently, it is reasonable to hypothesize that increasing the number of dialogue turns during training could potentially enhance the Chain-Talker's performance.

7 Conclusion

In this work, we introduce a novel chain modeling-based CSS model named Chain-Talker, designed for spoken interaction in user-agent communications. This model comprises three primary processes: “Emotion Understanding”, “Semantic Understanding”, and “Empathetic Rendering”. This step-by-step modeling of the conversational process significantly reduces the difficulty of responding to empathetic speech. Additionally, we also develop an LLM-driven automated dialog-aware empathetic caption generation pipeline called CSS-EmCap. This pipeline has been utilized to annotate three open-source CSS datasets, DailyTalk, NCSSD, and MultiDialog. These datasets provide strong support for the training of Chain-Talker. The annotation pipeline will be made openly available, fostering community development.

Limitations

Inference Latency: We conduct inference tests using an NVIDIA GeForce RTX 4080 GPU with 32 GB of VRAM and a 12th Gen Intel® Core™ i7-12700K CPU with 32 GB of system RAM. The average duration of empathetic speech responses generated by Chain-Talker is 2.5 seconds, which we consider acceptable. However, there remains a gap compared to real-time interactions. In future work, we continue to explore faster dialogue modeling methods that incorporate empathetic capabilities, such as the integration of streaming inference.

Robustness: We employ “CosyVoice-300M-25Hz” as the foundational model, which is pre-trained on approximately 170,000 hours of speech data and demonstrates exceptionally high naturalness in synthesized speech. However, the conversational data used for fine-tuning comprises only 384 hours, predominantly featuring young speakers. As a result, Chain-Talker may not accurately capture the conversational styles of children and the elderly. In the future, we plan to construct larger-scale speech dialogue datasets to further enhance the model’s robustness.

Ethics Statement

Safety Risks: Chain-Talker possesses zero-shot speech synthesis capabilities, facilitating the creation of personalized conversational speech. In most cases, individuals are likely to utilize this technology to enhance movie dubbing, podcasts, and other services. However, it may also present potential risks for model misuse, such as spoofing voice. To address this, we plan to incorporate restrictions into the open-source license of the Chain-Talker project to prevent the misuse of the model.

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Technical Appendix

In this technical appendix, we will supplement the description of the proposed CSS model: ChainTalker, the implementation details of the LLM-driven automatic dialog-aware empathetic caption generation pipeline: CSS-EmCap, and additional experimental results.

A More Details of CSS-EmCap

A.1 Data Flow Diagram of CSS-EmCap

As shown in Fig. 4, the empathetic caption annotation process in CSS-EmCap comprises several steps. First, we extract sentence-level style factors—such as gender, pitch, energy, and tempo—along with dialog-level emotions:

- **Sentence-level Style Factors Extraction**,we employ the Qwen2-Audio large-scale model [6] for speaker gender recognition, which achieves superior accuracy by providing the speech path in the prompt and having the model return the corresponding result (male or female). Additionally, Librosa [7] is used to analyze energy levels, and the World Vocoder (Morise et al., 2016) extracts pitch information. Furthermore, MFA [8] aligns text and speech data to obtain duration information, which is then averaged. To ensure that datasets annotated using this pipeline adhere to the same hierarchical classification standards, a set of uniform thresholds [9] is established after calculating the factor values for all speech data. Pitch, energy, and tempo are categorized into three levels: low, normal, and high.

- **Dialog-level Emotion Extraction**, in order to identify the emotional category of each speech in the dialogue, we carefully design prompts to enable the state-of-the-art Gemini 1.5 pro model [4], which understands and analyzes both text and speech modalities, to return results accurately. The model receives the complete dialogue content, encapsulated within $\langle dialog \rangle ... \langle / dialog \rangle$, including dialogue turns, speaker, textual content, and corresponding speech paths. It then identifies the emotional category of each speech, leveraging the context provided by the entire dialogue. Compared to pure single-sentence emotion recognition models, this context-based approach improves the accuracy of emotion recognition.

Table 3: Statistical results for the NCSSD-EmCap dataset, includes DailyTalk, NCSSD, and MultiDialog subsets.

NCSSD-EmCap					
Factors	**Items**	**Sub-datasets**			**Total**
		DailyTalk	**NCSSD**	**MultiDialog**	
Gender	Male	11,866	33,672	79,061	124,599
	Female	11,906	38,964	70,515	121,385
Pitch	Low	4,594	18,444	35,787	58,825
	Normal	8,143	22,495	41,973	72,611
	High	11,035	31,697	71,816	114,548
Energy	Low	2	72,636	18,546	91,184
	Normal	52	0	33,650	33,702
	High	23,718	0	97,380	121,098
Tempo	Low	4,048	12,491	2,780	19,319
	Normal	15,980	25,262	76,282	117,524
	High	3,744	34,883	70,514	109,141
Emotion	Angry	378	8,048	716	9,142
	Contempt	24	390	0	414
	Disgusted	57	277	1,152	1,486
	Fear	86	781	760	1,627
	Happy	2,613	6,026	23,393	32,032
	Sad	848	7,007	1,975	9,830
	Neutral	19,240	47,281	97,708	164,229
	Surprised	526	2,826	23,872	27,224
Hours		20	92	272	384
Dialogs		2,541	8,229	7,810	18,580
Utterances		23,772	72,636	149,576	245,984

Next, we employ a LLM [4] to generate basic descriptions by integrating these extracted expressive attributes with the dialogue's speech. Subsequently, we utilize the same LLM to expand these descriptions using one of eight predefined rules. Simultaneously, it performs consistency checks to ensure that the descriptions accurately reflect the original speech, resulting in the final empathetic captions.

A.2 Statistical Information of NCSSD-EmCap

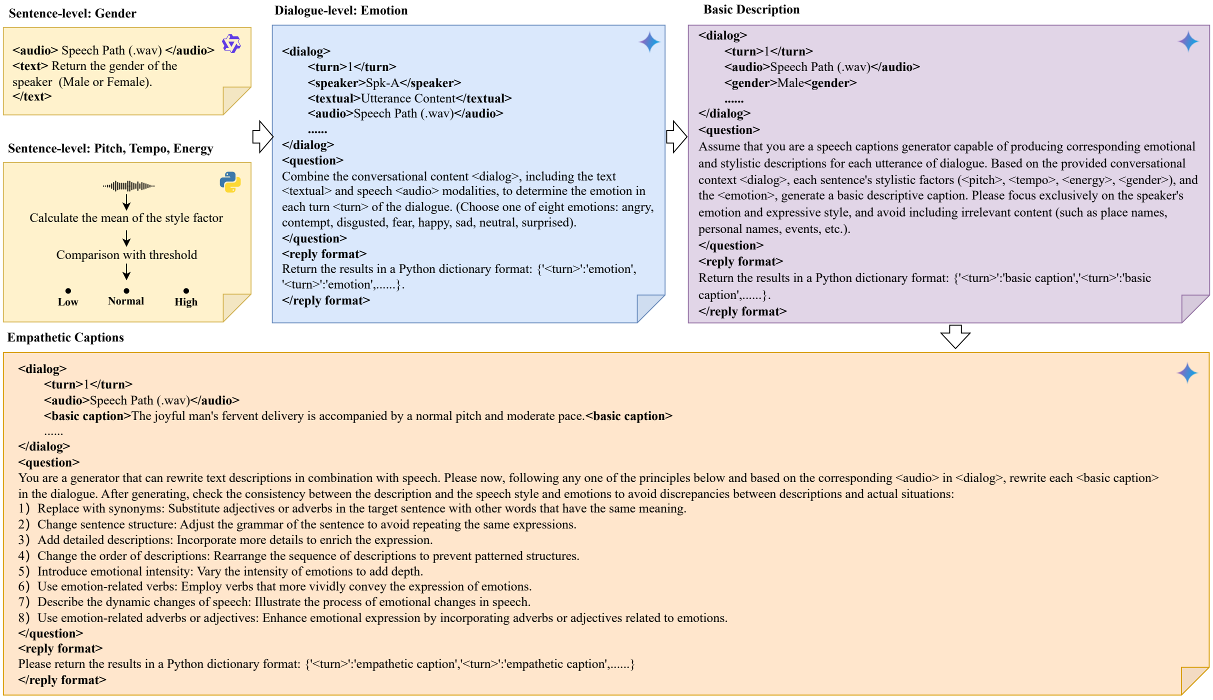
As shown in Table 3, the overall statistics for the NCSSD-EmCap dataset are presented. It consists of 384 hours of natural spoken dialogue, comprising 18,580 dialogs and 245,984 dialogue utterances. Each utterance includes speaker information, text, empathetic captions, and corresponding speech. DailyTalk, NCSSD, and MultiDialog offer a wide range of emotional categories along with varying levels of pitch, energy, and tempo, providing strong support for training highly expressive CSS models.

[6] https://huggingface.co/Qwen/Qwen2-Audio-7B

[7] https://librosa.org/

[8] https://montreal-forced-aligner.readthedocs.io/en/latest/

[9] The three sets of thresholds are: pitch [136.577, 196.098], tempo [0.252, 0.386], and energy [0.033, 0.0505]. Within each set, the first value distinguishes between low and normal, and the second between normal and high.


Sentence-level: Gender
Sentence-level: Pitch, Tempo, Energy
Calculate the mean of the style factor
Comparison with threshold
Low
Normal
High
Dialogue-level: Emotion
Basic Description
Empathetic Captions

```
<audio> Speech Path (.wav) </audio>
<text> Return the gender of the
speaker  (Male or Female).
</text>
```

```
<dialog>
      <turn>1</turn>
      <speaker>Spk-A</speaker>
      <textual>Utterance Content</textual>
      <audio>Speech Path (.wav)</audio>
      ......
</dialog>
<question>
Combine the conversational content <dialog>, including the text
<textual> and speech <audio> modalities, to determine the emotion in
each turn <turn> of the dialogue. (Choose one of eight emotions: angry,
contempt, disgusted, fear, happy, sad, neutral, surprised).
</question>
<reply format>
Return the results in a Python dictionary format: {'<turn>':'emotion',
'<turn>':'emotion',......}.
</reply format>
```

```
<dialog>
      <turn>1</turn>
      <audio>Speech Path (.wav)</audio>
      <gender>Male<gender>
      ......
</dialog>
<question>
Assume that you are a speech captions generator capable of producing corresponding emotional
and stylistic descriptions for each utterance of dialogue. Based on the provided conversational
context <dialog>, each sentence's stylistic factors (<pitch>, <tempo>, <energy>, <gender>), and
the <emotion>, generate a basic descriptive caption. Please focus exclusively on the speaker's
emotion and expressive style, and avoid including irrelevant content (such as place names,
personal names, events, etc.).
</question>
<reply format>
Return the results in a Python dictionary format: {'<turn>':'basic caption','<turn>':'basic
caption',......}.
</reply format>
```

```
<dialog>
      <turn>1</turn>
      <audio>Speech Path (.wav)</audio>
      <basic caption>The joyful man's fervent delivery is accompanied by a normal pitch and moderate pace.<basic caption>
      ......
</dialog>
<question>
You are a generator that can rewrite text descriptions in combination with speech. Please now, following any one of the principles below and based on the corresponding <audio> in <dialog>, rewrite each <basic caption>
in the dialogue. After generating, check the consistency between the description and the speech style and emotions to avoid discrepancies between descriptions and actual situations:
1)  Replace with synonyms: Substitute adjectives or adverbs in the target sentence with other words that have the same meaning.
2)  Change sentence structure: Adjust the grammar of the sentence to avoid repeating the same expressions.
3)  Add detailed descriptions: Incorporate more details to enrich the expression.
4)  Change the order of descriptions: Rearrange the sequence of descriptions to prevent patterned structures.
5)  Introduce emotional intensity: Vary the intensity of emotions to add depth.
6)  Use emotion-related verbs: Employ verbs that more vividly convey the expression of emotions.
7)  Describe the dynamic changes of speech: Illustrate the process of emotional changes in speech.
8)  Use emotion-related adverbs or adjectives: Enhance emotional expression by incorporating adverbs or adjectives related to emotions.
</question>
<reply format>
Please return the results in a Python dictionary format: {'<turn>':'empathetic caption','<turn>':'empathetic caption',......}
</reply format>
```

Figure 4: The overall process of CSS-EmCap, It includes extracting Sentence-level style factors and Dialog-level emoton, as well as prompting LLM to generate Basic Descriptions and final Empathetic Captions.

B More Details of Experiments and Results

B.1 Baseline Models

In this part, we will detail the baseline models compared in this work, still organized into two categories:

Category I: Evaluation of the LLM-driven Automatic Dialog-aware Empathetic Captioning Pipeline CSS-EmCap.

- ***w/o SF***: We directly use the LLM [4] to generate captions from given speech without extracting style factors and emotion.

- ***w/o SL-SF***: We remove the sentence-related style factors, and then generate captions using only emotional labels with the LLM.

- ***w/o DL-SF***: We remove the extraction process of Dialog-level emotion, and simply use gender, pitch, tempo, and energy as prompts for the LLM to generate style captions for speech.

- ***Qwen2-Audio***: A versatile multi-task LLM that accepts both audio (including human speech, natural sounds, and music) and text inputs, and outputs text. This model has the ability to understand speech content and style (Chu et al., 2024).

- ***SECap***: A LLM trained on a 41-hour emotional dataset, capable of returning speech emotions described in natural language (Xu et al., 2024).

Category II: Effectiveness of Chain-Talker in Dialogue Scenarios.

- ***CCATTS***: A context-aware CSS model, which employs a GRU-based network to model the sentence-level dependency among the dialogue context (Guo et al., 2021).

- ***M^2-CTTS***: It extracts context-dependent information at multiple granularities—both word-level and sentence-level—from the speech and text within the dialogue context (Xue et al., 2023).

- ***ECSS***: It considers different utterances in the dialogue context and modal information as individual graph nodes and uses a heterogeneous graph neural network to model the dialogue context (Liu et al., 2024a).

- ***GPT-Talker***: It takes the text and speech of the dialogue context as prompts and then utilizes a GPT-style autoregressive model to predict the discrete token sequence of the response speech, followed by synthesizing the

Table 4: Statistics of some model parameters.

EmGPT	speech sample_rate	22050
	spk_embed_dim	192
	text_token_size	60515
	speech_token_size	4096
	LLM	
	llm_input_size	1024
	llm_output_size	1024
	num_blocks	14
	dropout_rate	0.1
	Sampling	
	top_k	25
	win_size	10
	tau_r	0.1
Synthesizer	OT-CFM	
	input_size	512
	output_size	80
	output_type	mel
	vocab_size	4096
	input_frame_rate	25
	HiFiGAN	
	in_channels	80
	base_channels	512
	upsample_rates	[8, 8]
	upsample_kernel_sizes	[16, 16]

final speech waveform using VITS (Liu et al., 2024b; Kim et al., 2021).

- ***GPT-Talker$_c$***: A variant of GPT-Talker adds empathetic captions during context modeling to help understand emotional changes in conversations.

- ***Chain-Talker$_s$* and *Chain-Talker$_e$***: They are two variants of Chain-Talker, the former replacing the empathetic captions with style factor labels and the latter with emotion labels.

- ***w/o context***: A Chain-Talker variant without dialog history $\mathcal{H}$, it predicts caption and renders speech directly from the given target utterance.

- ***w/o captions***: A CosyVoice variant, similar to GPT-Talker, where the input part includes various modal information from the dialogue history in addition to the target sentence, but without empathetic captions.

B.2 Experimental Setup

For some parameter settings of the two modules EmGPT and Synthesizer in the model Chain-Talker, please refer to Table 4. For additional details on the model configuration, please refer to our open-source repository on GitHub. Moreover, the Chain-Talker model was trained on four NVIDIA A800s. All datasets used are divided into training, validation, and test sets with a ratio of 8:1:1. During training, Chain-Talker's dialog turns are set to one to three. To ensure fairness in experimental results, during inference, the dialogue is also set to three turns for Chain-Talker and other CSS baseline models. For decoding strategy, EmGPT uses an auto-regressive decoding method, specifically employing the Top-K sampling strategy.

Table 5: Comparative results on emotion and style controllability.

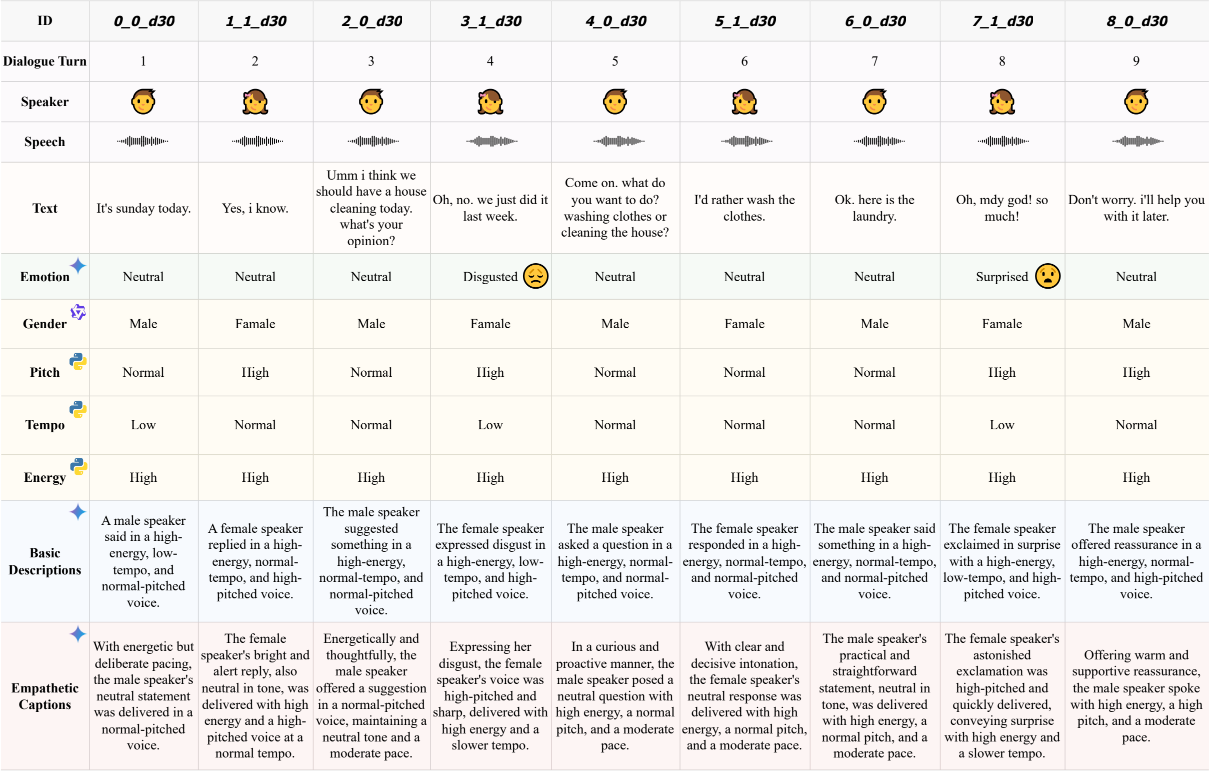
Dataset: NCSSD-EmCap					
Methods	**ACC$_g$** (↑)	**ACC$_e$** (↑)	**ACC$_p$** (↑)	**ACC$_t$** (↑)	**ACC$_m$** (↑)
PromptTTS	0.825	0.728	0.826	0.739	0.487
Salle	0.841	**0.766**	0.852	0.742	0.516
Chain-Talker	**0.854**	0.759	**0.861**	**0.747**	**0.623**
Dataset: TextrolSpeech					
Methods	**ACC$_g$** (↑)	**ACC$_e$** (↑)	**ACC$_p$** (↑)	**ACC$_t$** (↑)	**ACC$_m$** (↑)
PromptTTS	0.834	0.746	0.835	0.744	0.494
Salle	0.856	0.761	0.836	**0.751**	0.506
Chain-Talker	**0.864**	**0.765**	**0.857**	0.743	**0.598**

Table 6: A sample set of empathetic captions generated by Chain-Talker at different epochs.

Source	**Emapthetic Caption**
Ground Truth	The speaker, a wrathful man , speaks with a lively tone at a moderate pace , radiating high energy .
Epoch 50	In his speech, the tone is high and energetic .
Epoch 160	The wrathful male speaker addresses with lively speech, normal pitch .
Epoch 200	His voice, though at a normal pitch and speed , is filled with a palpable sense of fury.

B.3 Verifying Emotion and Style Controllability

In Chain-Talker, the consistency between empathetic captions and dialogue speech in terms of emotion and style is crucial, as it directly affects the context modeling and rendering processes. Therefore, in this part, we aim to evaluate whether Chain-Talker can synthesize speech with the corresponding style and emotion directly from a given caption in a single-sentence mode. We conduct comparative experiments with the two most advanced natural language-controlled style TTS models, PromptTTS (Guo et al., 2023) and Salle (Ji et al., 2024). The evaluation metrics are consistent with the previously used ACC_m (Emotion) and include ACC_p (Pitch), ACC_e (Energy), ACC_t (Tempo), and ACC_g (Gender). These metrics are used to determine the accuracy of the synthesized speech in conveying different expressive attributes. We evaluate three models using the constructed NCSSD-EmCap dataset, please refer to Table 5. Chain-Talker outperforms the other models in all metrics except energy. Additionally, we also evaluate them on the open-source style-controlled



ID	0_0_d30	1_1_d30	2_0_d30	3_1_d30	4_0_d30	5_1_d30	6_0_d30	7_1_d30	8_0_d30
Dialogue Turn	1	2	3	4	5	6	7	8	9
Speaker	👦	👧	👦	👧	👦	👧	👦	👧	👦
Speech									
Text	It's sunday today.	Yes, i know.	Umm i think we should have a house cleaning today. what's your opinion?	Oh, no. we just did it last week.	Come on. what do you want to do? washing clothes or cleaning the house?	I'd rather wash the clothes.	Ok. here is the laundry.	Oh, mdy god! so much!	Don't worry. i'll help you with it later.
Emotion	Neutral	Neutral	Neutral	Disgusted 😖	Neutral	Neutral	Neutral	Surprised 😮	Neutral
Gender	Male	Famale	Male	Famale	Male	Famale	Male	Famale	Male
Pitch	Normal	High	Normal	High	Normal	Normal	Normal	High	High
Tempo	Low	Normal	Normal	Low	Normal	Normal	Normal	Low	Normal
Energy	High	High	High	High	High	High	High	High	High
Basic Descriptions	A male speaker said in a high-energy, low-tempo, and normal-pitched voice.	A female speaker replied in a high-energy, normal-tempo, and high-pitched voice.	The male speaker suggested something in a high-energy, normal-tempo, and normal-pitched voice.	The female speaker expressed disgust in a high-energy, low-tempo, and high-pitched voice.	The male speaker asked a question in a high-energy, normal-tempo, and normal-pitched voice.	The female speaker responded in a high-energy, normal-tempo, and normal-pitched voice.	The male speaker said something in a high-energy, normal-tempo, and normal-pitched voice.	The female speaker exclaimed in surprise with a high-energy, low-tempo, and high-pitched voice.	The male speaker offered reassurance in a high-energy, normal-tempo, and high-pitched voice.
Empathetic Captions	With energetic but deliberate pacing, the male speaker's neutral statement was delivered in a normal-pitched voice.	The female speaker's bright and alert reply, also neutral in tone, was delivered with high energy and a high-pitched voice at a normal tempo.	Energetically and thoughtfully, the male speaker offered a suggestion in a normal-pitched voice, maintaining a neutral tone and a moderate pace.	Expressing her disgust, the female speaker's voice was high-pitched and sharp, delivered with high energy and a slower tempo.	In a curious and proactive manner, the male speaker posed a neutral question with high energy, a normal pitch, and a moderate pace.	With clear and decisive intonation, the female speaker's neutral response was delivered with high energy, a normal pitch, and a moderate pace.	The male speaker's practical and straightforward statement, neutral in tone, was delivered with high energy, a normal pitch, and a moderate pace.	The female speaker's astonished exclamation was high-pitched and quickly delivered, conveying surprise with high energy and a slower tempo.	Offering warm and supportive reassurance, the male speaker spoke with high energy, a high pitch, and a moderate pace.

Figure 5: A sample set of conversational data annotated using the CSS-EmCap pipeline.

dataset TextrolSpeech (Ji et al., 2024). The results demonstrate that Chain-Talker consistently achieves outstanding performance, particularly excelling in emotional expression by 0.092% compared to the second-best model. All experimental results demonstrate that Chain-Talker has effective style control capabilities. In other words, as long as an appropriate empathetic caption is predicted, it can generate speech with the corresponding emotion and style in conversational settings. This also provides additional evidence supporting our previous experiments that evaluated Chain-Talker's performance in CSS scenarios.

B.4 Details in Subjective Evaluation

In this study, we recruited 30 university students to participate in subjective evaluations, compensating them at a rate of $15 per experiment. This remuneration is fair and reasonable locally. For *DMOS-N*, *DMOS-E*, and *DMOS-C*, each participant rated on a scale from 1 to 5, where 1 is Bad, 2 is Poor, 3 is Fair, 4 is Good, and 5 is Excellent. In each subjective experiment, the results from different methods in each evaluation group were randomly ordered. This randomization ensured that participants did not know which model or method produced each result, enabling a fairer assessment.

B.5 Case Study

B.5.1 Examples of Understanding Empathetic Captions Using Chain-Talker

To clearly demonstrate Chain-Taker's ability to understand and generate empathetic captions, Table 6 shows the captions produced by the model at different training epochs (50, 160, and 200), with the number of dialogue turns N set to 3. Various stylistic attributes and their values are highlighted with colored rectangles for comparison. In the early stages of training, the model's understanding is inaccurate. For instance, at 50 epochs, the pitch is predicted incorrectly. As training epochs increase, the model gradually improves its ability to generate appropriate empathetic captions. By 200 epochs, the results are satisfactory. Compared to the Ground Truth, the model accurately predicts stylistic attributes such as pitch, speech rate, gender, and the emotion of anger. While it does not directly indicate the energy level, the phrase "is filled with a palpable sense of fury" also reflects the speaker's degree of anger.

B.5.2 Examples of Generating Empathetic Captions Using CSS-EmCap

In Fig. 5, we show a set of dialogue data annotated with CSS-EmCap, which includes nine utterances. First, we identify the emotional categories and style attributes of each utterance. Then, we use the designed prompts to guide the LLM to generate basic descriptions and later to generate more suitable empathetic captions. The example demonstrates that the pipeline successfully detected the female speaker's negative emotion towards household chores (in dialogue turns 4 and 8). Additionally, we can see that the empathetic captions are more accurate and natural compared to the basic descriptions.