

# SEMANTIC-VAE: SEMANTIC-ALIGNMENT LATENT REPRESENTATION FOR BETTER SPEECH SYNTHESIS

Zhikang Niu<sup>1,2</sup>, Shujie Hu<sup>3</sup>, Jeongsoo Choi<sup>4</sup>, Yushen Chen<sup>1,2</sup>, Peining Chen<sup>1</sup>, Pengcheng Zhu<sup>5</sup>, Yunting Yang<sup>5</sup>, Bowen Zhang<sup>5</sup>, Jian Zhao<sup>5</sup>, Chunhui Wang<sup>5</sup>, Xie Chen<sup>1,2,†</sup>

<sup>1</sup>MoE Key Lab of Artificial Intelligence, X-LANCE Lab, School of Computer Science, Shanghai Jiao Tong University, China <sup>2</sup>Shanghai Innovation Institute, China,

<sup>3</sup>The Chinese University of Hong Kong, China,

<sup>4</sup>Korea Advanced Institute of Science and Technology, South Korea, <sup>5</sup>Geely, China

## ABSTRACT

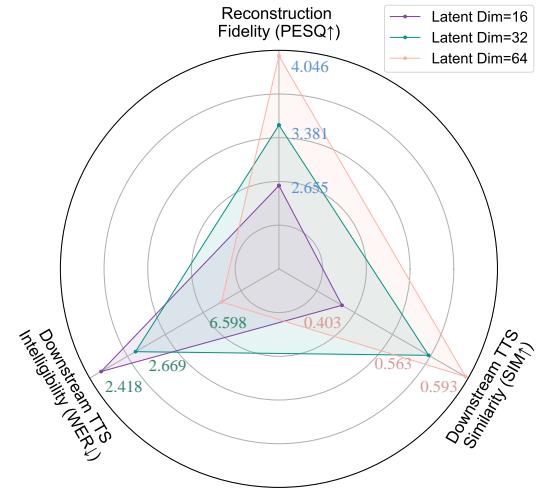
While mel-spectrograms have been widely utilized as intermediate representations in zero-shot text-to-speech (TTS), their inherent redundancy leads to inefficiency in learning text-speech alignment. Compact VAE-based latent representations have recently emerged as a stronger alternative, but they also face a fundamental optimization dilemma: higher-dimensional latent spaces improve reconstruction quality and speaker similarity, but degrade intelligibility, while lower-dimensional spaces improve intelligibility at the expense of reconstruction fidelity. To overcome this dilemma, we propose Semantic-VAE, a novel VAE framework that utilizes semantic alignment regularization in the latent space. This design alleviates the reconstruction-generation trade-off by capturing semantic structure in high-dimensional latent representations. Extensive experiments demonstrate that Semantic-VAE significantly improves synthesis quality and training efficiency. When integrated into F5-TTS, our method achieves 2.10% WER and 0.64 speaker similarity on LibriSpeech-PC, outperforming mel-based systems (2.23%, 0.60) and vanilla acoustic VAE baselines (2.65%, 0.59). We also release the code and models to facilitate further research.

**Index Terms**— text-to-speech, latent diffusion model, semantic alignment, variational autoencoder

## 1. INTRODUCTION

Zero-shot Text-to-Speech (TTS) aims to synthesize natural human speech from text inputs, conditioned on a reference speech prompt to closely mimic the speaker’s timbre. In recent years, zero-shot TTS models have achieved remarkable progress by scaling up both data and model size. Existing methods for zero-shot TTS can be broadly categorized into two approaches: Autoregressive (AR) [1, 2, 3, 4, 5] and Non-Autoregressive (NAR) [6, 7, 8, 9, 10, 11] models.

Most AR models directly quantize speech into discrete tokens and achieve exceptional performance in capturing and reproducing the acoustic characteristics of a reference speaker through in-context learning. However, they suffer from slow inference speed and error accumulation due to autoregressive generation of speech representation and information loss from quantization [12, 13, 14]. NAR models, primarily built on diffusion and flow matching models and using continuous speech representations, address the inherent limitations of AR models and overcome the information loss introduced by quantization, thereby improving both inference speed and output



**Fig. 1.** Reconstruction and Generation(TTS) dilemma on continuous representation. Higher-dimensional latents retain more acoustic information, improving reconstruction and speaker similarity; lower-dimensional latents focus on semantic information, boosting intelligibility while trading off reconstruction and similarity.

quality. NAR-based models can be grouped into two main categories based on their intermediate representation:

**1) Models conditioned on the mel-spectrogram**, which constitute the predominant paradigm in NAR-based TTS, utilize a pre-trained vocoder to reconstruct the waveform from the generated mel-spectrogram. Representative examples include VoiceBox [6], E2 TTS [15], and F5-TTS [9]. Despite the strong performance of mel-based systems, they still suffer from several inherent limitations [16, 17, 18], including loss of phase information, high dimensionality with substantial redundancy, and the absence of fine-grained high-frequency details, which limit high-fidelity speech synthesis.

**2) Models conditioned on latent representations** produced by a Variational Autoencoder (VAE) encoder and synthesize waveforms directly using the corresponding decoder. VAE-based systems mitigate the drawbacks mentioned above by learning compact latent representations that preserve essential acoustic information while eliminating redundancy. These compact representations not only accelerate training convergence but also yield improved synthesis quality [11]. For instance, SeedTTS<sub>DiT</sub> [2] is a large-scale state-of-the-

† Corresponding author

art industrial TTS model that leverages VAE latent representations, highlighting the effectiveness of compact representation for high-fidelity speech synthesis. Building on this idea, MegaTTS-3 [11] further introduces a novel sparse alignment strategy to guide a latent diffusion transformer over the VAE latent space, achieving performance gains.

Consistent with findings in the vision domain [19], latent diffusion models with vanilla acoustic VAE systems face an **optimization dilemma** between reconstruction and generation performance. The results of preliminary experiments are shown in Fig. 1. Specifically, increasing the latent dimension enhances reconstruction quality and speaker similarity but impairs intelligibility in zero-shot TTS, whereas reducing the latent dimension improves intelligibility at the expense of reconstruction quality and speaker similarity. This trade-off exemplifies the information bottleneck: lower-dimensional representations capture core semantic content, whereas higher-dimensional representations preserve richer acoustic details but introduce redundancy and complicate semantic modeling.

To address this challenge, we introduce **Semantic-VAE**, a novel variational autoencoder with semantic alignment regularization in the latent space to mitigate the difficulty of semantic modeling in zero-shot TTS tasks with unconstrained high-dimensional latent representations. Extensive experiments demonstrate that Semantic-VAE mitigates the generation–reconstruction dilemma in high-dimensional latent spaces, accelerates training convergence, and achieves state-of-the-art performance in zero-shot TTS tasks. Specifically, the F5-TTS model with the proposed Semantic-VAE features achieves **2.10%** WER and **0.64** speaker similarity on the LibriSpeech-PC test-clean dataset, outperforming the mel-based F5-TTS baseline (2.23%, 0.60) and the vanilla acoustic VAE baseline (2.65%, 0.59). Additional reconstruction experiments show that Semantic-VAE achieves reconstruction quality comparable to vanilla VAE and substantially better than the vocoder [20] with mel-spectrograms. This demonstrates that our proposed semantic alignment regularization enables more effective generative modeling without compromising the representational capacity of the latent features. We release the full Semantic-VAE framework with code and checkpoints at <https://github.com/ZhikangNiu/Semantic-VAE>.

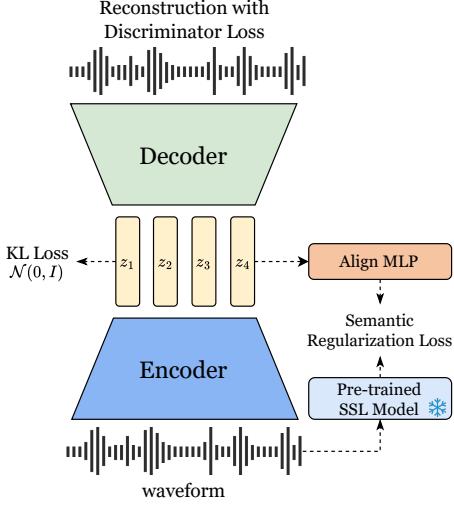
## 2. METHOD

As illustrated in Fig. 2, we propose an improved training paradigm for acoustic VAE systems that incorporates semantic regularization to mitigate the reconstruction and generation optimization dilemma. In this section, we provide a detailed introduction of our proposed method, highlighting its key components and underlying motivations. Section 2.1 introduces our baseline VAE architecture and objective. Section 2.2 presents our strategy for semantic regularizing latent representations using pre-trained self-supervised learning (SSL) speech models.

### 2.1. Variational Autoencoder

To obtain latent representations for speech generation, we employ a Variational Autoencoder (VAE) [21] that models speech waveforms. The VAE consists of an encoder that maps the input speech  $\mathbf{x}$  into a latent representation  $\mathbf{z}$ , and a decoder that reconstructs the signal  $\hat{\mathbf{x}}$  from  $\mathbf{z}$ . The standard training objective of a VAE maximizes the Evidence Lower Bound (ELBO):

$$\text{ELBO} := \mathbb{E}_{q_\phi(\mathbf{z}|\mathbf{x})} [\log p_\psi(\mathbf{x}|\mathbf{z})] - \mathcal{D}_{\text{KL}} [q_\phi(\mathbf{z}|\mathbf{x}) \| p(\mathbf{z})], \quad (1)$$



**Fig. 2.** Overall training framework. The encoder maps the input into latent representations, regularized by a KL loss. The decoder reconstructs the waveform guided by a discriminator loss, while a semantic regularization loss aligns the latent space with features from a frozen pre-trained SSL model.

where  $q_\phi(\mathbf{z}|\mathbf{x})$  denotes the variational posterior that approximates the true latent distribution,  $p_\psi(\mathbf{x}|\mathbf{z})$  models the conditional likelihood of the reconstructed speech  $\hat{\mathbf{x}}$  given  $\mathbf{z}$ , and the KL divergence term regularizes the latent space towards the standard Gaussian prior  $p(\mathbf{z}) = \mathcal{N}(0, \mathbf{I})$ .

Following the standard VAE objective, we express the generative loss as a weighted sum of the reconstruction loss  $\mathcal{L}_{\text{recon}}$  and the KL divergence loss  $\mathcal{L}_{\text{KL}}$ :

$$\mathcal{L}_{\text{gen}} = \lambda_{\text{recon}} \mathcal{L}_{\text{recon}} + \lambda_{\text{KL}} \mathcal{L}_{\text{KL}}, \quad (2)$$

where  $\lambda_{\text{KL}}$  balances the trade-off between reconstruction fidelity and latent space regularization. Following DAC [22], we use multi-scale frequency domain reconstruction loss  $\mathcal{L}_{\text{recon}}$ , defined as L1 distance between mel-spectrograms of the ground-truth and the reconstruction over multiple window lengths.

Moreover, to enhance the perceptual quality of the output, we adopt adversarial training with a multi-period discriminator [23] and a multi-band, multi-scale STFT discriminator [22]. We use a Hinge-GAN [24] adversarial objective with L1 feature-matching loss. The overall VAE training objective is then expressed as follows:

$$\mathcal{L}_{\text{VAE}} = \mathcal{L}_{\text{gen}} + \lambda_{\text{adv}} \mathcal{L}_{\text{adv}} + \lambda_{\text{feat}} \mathcal{L}_{\text{feat}}. \quad (3)$$

### 2.2. Semantic Representation Alignment

The reconstruction and generation dilemma is a widely discussed challenge in discrete audio codecs. Previous studies [25, 8] have demonstrated that aligning with pre-trained SSL speech models (e.g., HuBERT [26], WavLM [27], w2v-BERT [28], etc.), which capture rich phonetic and semantic representations, can provide more informative supervision for audio codec training and improve downstream AR model performance and convergence. Similarly, incorporating SSL alignment into Diffusion Transformers (DiT) training accelerates convergence and yields better performance in speech synthesis [29] and image generation [30].

However, to the best of our knowledge, no prior work has explored applying semantic regularization to continuous latent spaces, nor examined its potential to improve downstream task performance. Motivated by these insights, we introduce a semantic regularization loss into the VAE training framework. This addition aims to investigate whether semantic-aligned VAEs can improve both the convergence speed and performance of NAR-based TTS models compared to vanilla acoustic VAEs. Specifically, we employ a pre-trained SSL speech model  $f(\cdot)$  to extract structured semantic representations from the same speech  $\mathbf{x}$ . The hidden states  $\mathbf{h}$  of the SSL model, aligned in both temporal and feature dimensions with the VAE latent representation, are obtained through an interpolation layer followed by a 1D convolution layer, formulated as

$$\mathbf{h} = \text{Conv1D}(\text{Interp}(f(\mathbf{x}))).$$

The semantic alignment regularization loss is then defined as

$$\mathcal{L}_{\text{Align}} = -\frac{1}{T} \sum_{t=1}^T \cos(\mathbf{h}^{[t]}, \mathbf{z}^{[t]}),$$

where  $T$  denotes the sequence length and  $\cos(\cdot, \cdot)$  computes the cosine similarity between the aligned VAE latent and the SSL feature at each time step  $t$ . This loss regularizes the VAE latent space, encouraging the VAE to learn a structured semantic representation from SSL models. To jointly optimize for high-fidelity speech reconstruction and semantically meaningful latent representations, we integrate the VAE training objective with the proposed semantic regularization loss. The overall training objective is formulated as

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{VAE}} + \lambda_{\text{Align}} \mathcal{L}_{\text{Align}}, \quad (4)$$

where  $\lambda_{\text{Align}}$  is a hyperparameter that controls the relative importance of the semantic alignment regularization.

### 3. EXPERIMENTAL SETUP

In this section, we describe implementation details, datasets, and the evaluation setup.

#### 3.1. Semantic-VAE Model Setup

Following DAC [22], Semantic-VAE adopts the same convolutional encoder, discriminator, and loss weights. To improve reconstruction performance, we replace the original convolutional decoder with an AMP Block-based decoder [31]. The encoder downsamples the 16 kHz input  $\mathbf{x}$  with factors of  $[4, 4, 5, 5]$ , producing a 64-dimensional latent representation  $\mathbf{z}$  at a frame rate of 40 Hz.

Semantic-VAE is trained for 1M iterations with a global batch size of 64, and the ablation experiments are trained for 600K iterations. Each sample is a 3-second segment and resampled to 16 kHz, totaling approximately 192 seconds per batch. We employ the Adam optimizer with a learning rate of  $1 \times 10^{-4}$  and apply exponential decay with a factor of  $\gamma = 0.9996$ . In our experiment, we set  $\lambda_{\text{Align}} = 1$ ,  $\lambda_{\text{KL}} = 0.01$ ,  $\lambda_{\text{adv}} = 1$ ,  $\lambda_{\text{feat}} = 2$ , and  $\lambda_{\text{recon}} = 15$ .

#### 3.2. Zero-shot TTS Model Setup

We use the F5-TTS [9] Small model as the baseline and adopt its training setup. In our approach, the mel-spectrograms are replaced with VAE latent representations. The model is optimized using the AdamW optimizer with  $7.5 \times 10^{-5}$ , following a warm-up schedule for the first 20,000 updates and linear decay thereafter. For inference, we follow the same setup as F5-TTS, applying the swav sampling strategy and using the Euler ODE solver.

**Table 1.** Zero-shot TTS results on the LibriSpeech-PC test-clean. The best results in the low-resource setting are marked in **bold**. High-resource results are quoted from the F5-TTS for comparison.

Method	# Param.	Data	WER(%)↓	SIM↑
Ground Truth			2.23	0.69
<i>High-resource</i>				
CosyVoice [37]	300M	170kh	3.59	0.66
FireRedTTS [38]	580M	248kh	2.69	0.47
E2 TTS [15]	333M	100kh	2.95	0.69
F5-TTS [9]	336M	100kh	2.42	0.66
<i>Low-resource</i>				
USLM [25]	361M	0.6kh	6.11	0.43
E2 TTS [15]	157M	0.6kh	3.51	0.61
+ Semantic-VAE	157M	0.6kh	2.31	0.62
F5-TTS [9]	159M	0.6kh	2.23	0.60
+ Vanilla VAE	159M	0.6kh	2.65	0.60
+ Semantic-VAE	159M	0.6kh	<b>1.95</b>	<b>0.64</b>

### 3.3. Training Datasets

We use two large-scale English corpora: Libriheavy [32] and LibriTTS [33]. Libriheavy contains around 50k hours of re-segmented audiobook speech at 16 kHz, and LibriTTS contains approximately 585 hours of high-quality multi-speaker speech segments at 24 kHz. In our experiments, Semantic-VAE is trained on LibriTTS as well as the small and medium subsets of Libriheavy, over 6k hours in total, while the F5-TTS model is trained on LibriTTS.

### 3.4. Evaluation

To comprehensively evaluate Semantic-VAE regarding the optimization dilemma between reconstruction and generation, we consider two tasks: 1) reconstruction and 2) downstream zero-shot TTS.

For the reconstruction evaluation of Semantic-VAE, we utilize the LibriTTS test-other as our test set, and employ UTMOS [34], PESQ (Perceptual Evaluation of Speech Quality) [35], and STOI (Short-time Objective Intelligibility) as the evaluation metrics to quantify perceptual quality and intelligibility. For the zero-shot TTS evaluation, we follow the setup in F5-TTS<sup>1</sup> and evaluate on the LibriSpeech-PC [36] test-clean. We perform the cross-sentence generation and evaluate the performance using the Word Error Rate (WER), Speaker Similarity (SIM-o), and UTMOS, which respectively measure intelligibility, speaker consistency, and naturalness.

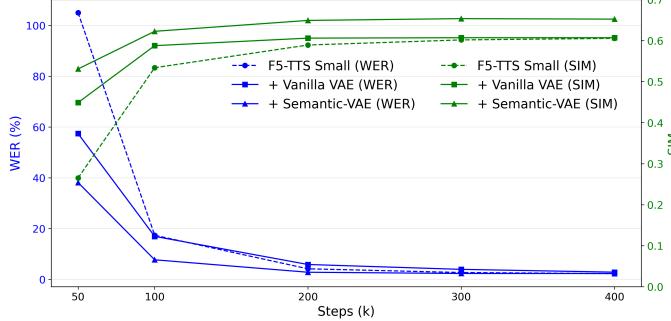
## 4. RESULTS

### 4.1. Downstream Zero-shot TTS Results

Table 1 reports zero-shot TTS results on the LibriSpeech-PC test-clean dataset, with results presented separately for high-resource and low-resource settings. In the high-resource scenario, NAR models (E2 TTS and F5-TTS) achieve performance comparable to AR models such as CosyVoice [37] and FireRedTTS [38].

For a fair comparison, we evaluated the models in the low-resource setting, which highlights the advantages of Semantic-VAE.

<sup>1</sup>[https://github.com/SWivid/F5-TTS/tree/main/src/f5\\_ts/eval](https://github.com/SWivid/F5-TTS/tree/main/src/f5_ts/eval)



**Fig. 3.** Comparison of WER and SIM on the LibriSpeech-PC test-clean dataset between the F5-TTS baseline, Vallina VAE, and Semantic-VAE across different training steps.

When integrated into F5-TTS, Semantic-VAE achieves state-of-the-art results, reducing WER to 2.10% and increasing speaker similarity (SIM) to 0.64 under the same inference setting, outperforming both F5-TTS Small baseline and its vanilla VAE variant. A similar trend is observed when applying Semantic-VAE to E2 TTS, yielding consistent gains over the baseline. To further assess convergence, we compare the proposed Semantic-VAE against the vanilla VAE and the mel-based F5-TTS baseline across different training steps. As shown in Fig. 3, Semantic-VAE converges faster and achieves better performance than both the vanilla VAE and the mel-based baseline at the same step. These results demonstrate that Semantic-VAE not only improves the final performance, especially speaker similarity, but also accelerates convergence and reduces training costs compared with the baseline F5-TTS.

#### 4.2. Reconstruction Results

Table 2 reports reconstruction results on LibriTTS test-other. Despite its aggressively compact representation in both temporal and latent dimensions, vanilla VAE outperforms Vocos in reconstruction. It indicates that end-to-end VAE training encourages the latent to retain essential information while discarding redundancy. Moreover, Semantic-VAE maintains reconstruction performance comparable to vanilla VAE, demonstrating that semantic alignment simplified generative modeling without sacrificing reconstruction performance.

**Table 2.** Reconstruction performance on LibriTTS test-other

Model	frame/s	dim	PESQ↑	STOI↑	UTMOS↑
ground truth	-	-	-	-	3.48
Vocos	93.75	100	3.57	0.96	3.24
Vanilla VAE	40	64	<b>3.75</b>	<b>0.97</b>	<b>3.57</b>
Semantic-VAE	40	64	3.74	0.96	3.56

#### 4.3. Ablation Study

Table 3 presents a comprehensive ablation study on semantic alignment methods and semantic guidance selection. The results indicate that negative cosine similarity loss provides a more effective alignment mechanism than the L1 or MSE losses. This can be intuitively explained that L1 and MSE overly constrain absolute numerical differences between the latent space and the semantic guidance,

**Table 3.** Effect of different SSL models, layer, and alignment methods on zero-shot TTS performance on LibriSpeech-PC test-clean. “Avg.” = average of all layers; “Last” = final layer output.

Align method	Layer	WER (%)↓	SIM↑	UTMOS↑
Baseline	-	2.65	0.59	4.42
$ \Phi_n - f(x) $	WavLM	3.12	0.47	3.29
$\ \Phi_n - f(x)\ _2$	23rd	4.37	0.48	4.16
$-\cos(\Phi_n, f(x))$		<b>2.10</b>	<b>0.64</b>	<b>4.39</b>
SSL Models	Layer	WER (%)↓	SIM↑	UTMOS↑
HuBERT	23	2.28	0.63	4.38
	Last	2.33	0.50	4.41
	Avg.	2.29	0.61	4.39
WavLM	23	<b>2.10</b>	<b>0.64</b>	4.39
	Last	2.62	0.58	4.34
	Avg.	2.31	0.63	<b>4.42</b>

whereas cosine loss focuses on directional alignment in the latent space, which better captures structured semantic representations.

Moreover, we explore *which semantic guidance is most effective for semantic alignment*. It observes that WavLM[27] generally outperforms HuBERT[26] on SIM and comparable performance on WER, which can be attributed to its speaker-aware training objectives. Moreover, we compare different SSL layers and find that while all SSL layers help reduce WER, their impact on SIM varies considerably. In particular, the final layer consistently leads to a substantial drop in SIM performance, likely due to distributional adjustments required for aligning with the SSL training target, thereby discarding speaker-specific cues. Averaging SSL features across all layers improves SIM compared to the last-layer feature, which suggests that averaging all layers introduces more information that can improve acoustic details. However, incorporating too much information may also introduce redundancy, which could degrade semantic modeling. To verify this hypothesis, we chose the 23rd layer of WavLM for supervision. In SUPERB[39], this layer has the highest weight for WER and provides richer semantic representations. Experimental results confirm that this layer offers an optimal trade-off between WER and SIM, providing practical guidance for selecting pre-trained SSL features for alignment.

## 5. CONCLUSION

In this paper, we investigate the optimization dilemma in high-dimensional latent spaces and propose Semantic-VAE, a speech variational autoencoder with semantic alignment regularization. By learning structured and semantically aligned latent representations, Semantic-VAE alleviates the reconstruction-generation dilemma and improves downstream zero-shot TTS performance. Experiments demonstrate that our approach accelerates convergence and achieves state-of-the-art results on the zero-shot TTS task. In addition, comprehensive analyses and ablation studies confirm the effectiveness of each proposed component. We believe that these promising findings pave the way for future research on advanced modality alignment techniques and further optimization of latent diffusion-based text-to-speech systems.

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