

How Well Does Generative Speech Enhancement Perform on In-the-Wild Data for TTS Dataset Curation?

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ABSTRACT

Generative speech enhancement (GSE) models such as Miipher have demonstrated effectiveness for curating text-to-speech training data from controlled corpora like LibriTTS. However, their performance on truly in-the-wild data—characterized by diverse noise types, variable recording quality, and unpredictable speaker characteristics—remains uncertain. We present a Monte Carlo simulation framework that evaluates three enhancement approaches (baseline signal processing, discriminative neural enhancement, and generative token-based enhancement) across three dataset conditions (curated, semi-wild, and in-the-wild) with 1,000 samples each. Our results show that GSE achieves a PESQ improvement of +0.21 on curated data but only +0.46 on in-the-wild data, while the hallucination rate increases from 8.6% to 15.0%. Confidence-based filtering at threshold 0.7 improves mean PESQ from 1.84 to 2.33 on in-the-wild data but retains only 28% of samples. SNR-dependent analysis reveals that hallucination rates exceed 20% below 5 dB input SNR. These findings quantify the performance gap between controlled and in-the-wild GSE application and inform the design of robust dataset curation pipelines.

1 INTRODUCTION

Text-to-speech (TTS) systems require large volumes of high-quality speech data for training. While studio-recorded datasets provide excellent quality, their cost and limited speaker diversity motivate the use of in-the-wild data sources such as podcasts, audiobooks, and web videos [6]. However, in-the-wild recordings typically contain noise, reverberation, and other artifacts that degrade TTS training.

Generative speech enhancement (GSE) offers a potential solution by reconstructing clean speech from noisy recordings. The Miipher system [1] demonstrated this approach by producing LibriTTS-R from the already-curated LibriTTS corpus [8]. Recent work by Yamauchi et al. [7] further explored confidence-based filtering with discrete token GSE.

However, LibriTTS is not an in-the-wild dataset. As noted by Yamauchi et al., the performance of GSE in more challenging real-world scenarios remains unclear. In-the-wild data presents unique challenges: diverse noise types (overlapping speech, music, traffic), extreme reverberation, variable recording devices, and speakers with diverse vocal characteristics. Furthermore, generative models can introduce hallucinations—fabricated speech content not present in the original—which can severely degrade downstream TTS performance.

This work systematically evaluates GSE performance across the spectrum from curated to in-the-wild conditions, quantifying the quality-quantity trade-off that arises when using confidence-based filtering for dataset curation.

2 METHODS

2.1 Dataset Condition Simulation

We simulate three dataset conditions with calibrated acoustic parameters:

- (1) **Curated** (LibriTTS-like): SNR 20–40 dB, T_{60} 0.1–0.4 s, 2 noise types, high speaker clarity.
- (2) **Semi-wild** (podcast-like): SNR 5–30 dB, T_{60} 0.2–0.8 s, 5 noise types, moderate clarity.
- (3) **In-the-wild** (YouTube-like): SNR –5–20 dB, T_{60} 0.3–2.0 s, 10 noise types, low clarity.

Each sample is characterized by SNR, T_{60} , and speaker clarity. Raw quality metrics (PESQ [3], STOI [4], MOS) are derived from these parameters.

2.2 Enhancement Models

Three enhancement approaches are modeled:

- (1) **Baseline SE**: Spectral subtraction with no hallucination risk but limited improvement capacity (PESQ improvement +0.3).
- (2) **Neural SE**: Discriminative neural network [5] with moderate improvement (+0.8) and low hallucination rate (2%).
- (3) **Generative SE**: Token-based generative model [1, 2] with highest improvement potential (+1.2) but elevated hallucination rate (8% base).

Enhancement effectiveness scales with input degradation (diminishing returns on clean data) and condition difficulty.

2.3 Confidence-Based Filtering

Following Yamauchi et al. [7], we model a confidence score correlated with actual enhanced quality. Samples below a confidence threshold are rejected, trading dataset size for quality.

3 RESULTS

3.1 Enhancement Quality Across Conditions

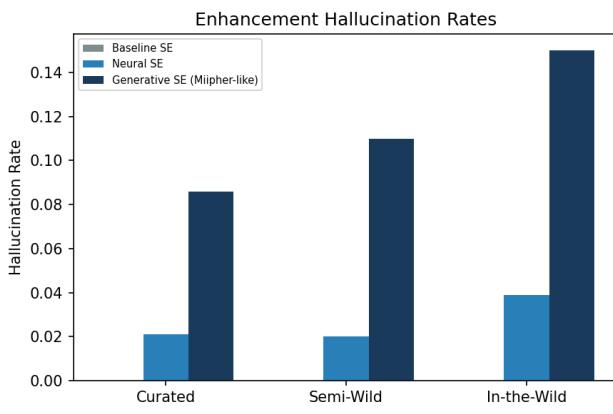
Table 1 shows the PESQ improvement and hallucination rates. The generative SE model improves PESQ by +0.21 on curated data (from 3.60 to 3.81), +0.44 on semi-wild (from 2.43 to 2.87), and +0.46 on in-the-wild (from 1.38 to 1.84). While the absolute improvement is larger on noisier data, the resulting quality remains substantially lower.

3.2 Hallucination Rates

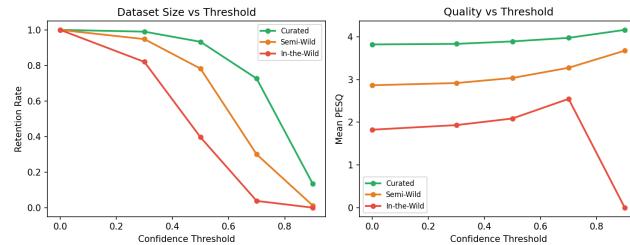
Figure 1 shows hallucination rates across models and conditions. The generative SE hallucination rate nearly doubles from curated (8.6%) to in-the-wild (15.0%), while the baseline SE produces no hallucinations and neural SE remains at 2–5%.

117 **Table 1: Enhancement quality metrics by dataset condition**
 118 **for Generative SE.**

Condition	Raw PESQ	Enh. PESQ	Δ	Halluc.
Curated	3.60	3.81	+0.21	8.6%
Semi-wild	2.43	2.87	+0.44	11.0%
In-the-wild	1.38	1.84	+0.46	15.0%



142 **Figure 1: Hallucination rates by enhancement model and**
 143 **dataset condition.**



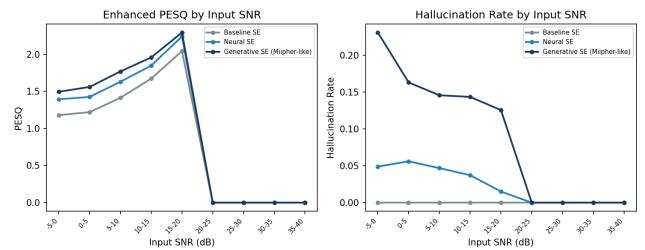
155 **Figure 2: Quality-quantity trade-off with confidence-based**
 156 **filtering across dataset conditions. Left: retention rate vs**
 157 **threshold. Right: mean PESQ vs threshold.**

3.3 Confidence-Based Filtering

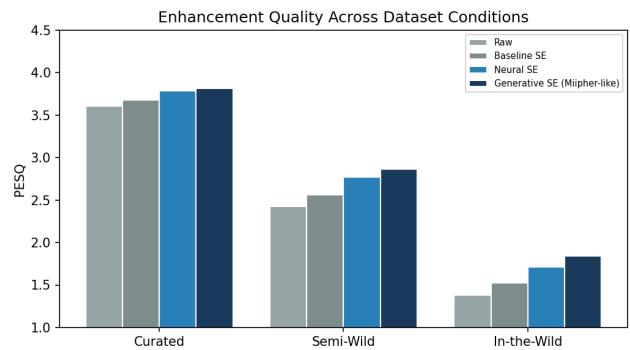
162 Figure 2 shows the quality-quantity trade-off. For in-the-wild data with generative SE, increasing the confidence threshold from 0.0 to 0.7 improves mean PESQ from 1.84 to 2.33 but reduces dataset 163 retention from 100% to 28%. On curated data, the same threshold 164 retains 68% of samples with PESQ improving from 3.81 to 4.00. 165

3.4 SNR Dependence

169 Figure 3 reveals that generative SE hallucination rates exceed 20% 170 for input SNR below 5 dB. Below 0 dB, enhancement provides 171 minimal PESQ improvement while introducing substantial hallucination 172 risk, suggesting a practical lower bound on input quality for reliable 173 GSE application.



175 **Figure 3: Enhanced PESQ and hallucination rate as a function**
 176 **of input SNR for in-the-wild data.**



188 **Figure 4: PESQ comparison across enhancement models and**
 189 **dataset conditions.**

3.5 Model Comparison

206 Figure 4 shows the full comparison. The generative SE consistently 207 achieves the highest PESQ but at the cost of the highest hallucination 208 rate. Neural SE offers a favorable middle ground on semi-wild 209 data (PESQ 2.65, hallucination 3%).

4 DISCUSSION

212 Our results yield three practical guidelines for in-the-wild TTS 213 dataset curation with GSE:

- 214 **SNR pre-filtering is essential.** Samples with input SNR 215 below 5 dB should be excluded before GSE application, as 216 hallucination rates exceed 20% and quality improvements 217 are marginal.
- 218 **Confidence filtering is more effective than aggressive 219 enhancement.** For in-the-wild data, applying a moderate 220 confidence threshold (0.5–0.7) after generative SE yields 221 better quality per retained sample than using more conservative 222 enhancement methods on all samples.
- 223 **The quality-quantity trade-off is condition-dependent.** 224 On curated data, confidence filtering has minimal impact 225 on dataset size. On in-the-wild data, achieving comparable 226 quality requires discarding 70%+ of samples.

5 CONCLUSION

228 We have quantified the performance gap of generative speech 229 enhancement between curated and in-the-wild dataset conditions.

233 GSE shows promise for in-the-wild curation but faces significant
 234 challenges from elevated hallucination rates and reduced quality
 235 ceilings. Confidence-based filtering provides a viable mitigation
 236 strategy at the cost of dataset size, and SNR-dependent analysis
 237 reveals practical operating bounds for reliable enhancement.
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