

Are Deep Speech Denoising Models Robust to Adversarial Noise?

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Abstract

Deep noise suppression (DNS) models enjoy widespread use throughout a variety of high-stakes speech applications. However, in this paper, we show that four recent DNS models can each be reduced to outputting unintelligible gibberish through the addition of imperceptible adversarial noise. Furthermore, our results show the near-term plausibility of targeted attacks, which could induce models to output arbitrary utterances, and over-the-air attacks. While the success of these attacks varies by model and setting, and attacks appear to be strongest when model-specific (i.e., white-box and non-transferable), our results highlight a pressing need for practical countermeasures in DNS systems.

1 Introduction

Deep neural networks (DNNs) have found widespread use in speech denoising tasks (herein considered synonymous with *speech enhancement* and *noise suppression*). With existing usage in videoconferencing software [1] and speech recognition systems [2], and potential future usage in hearing aids [3], the robustness of such deep noise suppression (DNS) models is clearly of paramount concern.

However, it is well-documented that DNNs are often susceptible to adversarial perturbations—slight modifications to the input data that are subtle or imperceptible to humans, but which can lead to dramatically incorrect outputs from DNNs [4]. This vulnerability has been extensively studied in domains such as automatic speech recognition (ASR) [5, 6, 7] and speaker recognition [8, 9], where adversaries can induce the models to mistranscribe speech or misclassify speakers. Similarly, deep visual denoising models have been shown to be vulnerable to adversarial perturbations [10, 11], wherein

the addition of imperceptible visual noise causes them to output images that are noisier than the input.

Given their ubiquity and the vulnerability of similar models, we therefore posit that DNS models might also be appealing targets for adversarial attacks. The consequences of such attacks could be severe, particularly if the attack is capable of inducing a DNS model to output arbitrary target speech.

Despite these concerns, to our knowledge, there has been minimal research into the susceptibility of DNS models to adversarial noise. Dong et al. [12] attacked speech enhancement models from a privacy perspective; however, though groundbreaking, their research leaves open many critical questions. Among others: Are imperceptible adversarial attacks possible? Are attacks possible even when background noise is minimal? Are targeted attacks possible, in which the model is induced to output audio similar to a target utterance? What is the role of acoustic characteristics such as reverb in enabling attacks? And finally, are these attacks likely to work in over-the-air scenarios, where the adversarial perturbation is subjected to the same acoustic distortions as the original audio?

To address these questions, we evaluate the robustness of four recent DNS models of varying sizes and architectures [13, 14, 15, 16], given both white-box and black-box (model transfer) threat models. Using a variety of speech quality metrics, we find that with white-box access all four models can be induced to output unintelligible gibberish by imperceptible noise, hidden in the original audio by auditory masking [17, 6, 7]; moreover, the success of attacks varies little by setting, such as the presence or absence of non-adversarial background noise, and attacks are even possible in simulated over-the-air settings. Furthermore, models appear susceptible to targeted attacks, where their output is closer to a target utterance than the ground-truth clean utterance, though progress in this direction is limited by the quality of speech similarity metrics available.¹

Despite our concerning central result, we also find some areas for optimism. First, attacks appear to work best when designed for only a single utterance from the speaker; similar

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¹Samples are available online.

to other audio tasks [18, 19, 20, 21], imperceptible universal perturbations [22] are not yet possible in this domain. Second, while we do not evaluate any gradient-free black-box attacks, we find that attacks appear to be entirely model-specific and do not transfer to other models, even of the same architecture. Finally, simple Gaussian perturbation appears to be a moderately effective baseline defense; nevertheless, the possibility of adaptive attacks [23] highlights that real world DNS systems may need more sophisticated defenses.

2 Related Work

Adversarial perturbations for audio models. Adversarial perturbations were first discovered in convolutional neural networks for image classification tasks [4], and have since been discovered in DNN models for a wide variety of audio tasks. Similar to their visual counterparts, audio adversarial perturbations are both most straightforward and most frequently studied in classification tasks, including speaker recognition [8, 24, 9, 25, 26, 27, 28, 29, 30], speaker verification [31, 20], environmental sound classification [19, 27, 32], and speech command recognition [33, 27], among many others.

Attacks have also been successful on audio models that generate discrete outputs, such as ASR models [34, 35, 5, 6, 7, 18, 21, 36]. In particular, such work has shown the feasibility in some cases of imperceptible targeted perturbations, where the ASR system is induced to output a target transcription desired by the attacker.

The success of attacks on models for increasingly complex tasks such as ASR naturally raises the question of whether models with audio input and high-dimensional continuous output, such as audio, are equally vulnerable. However, to our knowledge, prior work on attacking generative audio models has been limited. Takahashi et al. [37] and Trinh [38] showed speech separation models to be vulnerable to attack, but it is unclear what level of perceptibility is required for these attacks to succeed.

Dong et al. [12] conducted the work which is closest to our present research, showing that speech enhancement models can be induced to output damaged speech (as measured by mean-squared error and ASR word accuracy) through the addition of adversarial noise. Their pioneering work nevertheless has several crucial limitations, which we attempt to expand upon in this paper. First, the attacks that their method produces appear to be perceptible, as judged both by the use of the infinity norm as a perceptibility constraint (see the discussion on imperceptibility below) and by the single sample they include online. Second, their attacks are only untargeted, meaning their goal is to destroy speech enhancement performance rather than induce a target output. Finally, their experiments test a highly limited set of environmental settings, using only signal-to-noise ratios of -8 to 8 (representing extremely noisy speech); 18 distinct non-compositional background noise samples; and, perhaps most importantly, no reverberation or other acoustic distortions, thus greatly limiting applicability to attacks in real-world situations. We

therefore expand on this work by crafting targeted and untargeted examples in a wide range of environmental settings using perceptibility constraints that previous work has shown to closely match human perceptibility [17, 6, 7].

Imperceptible audio perturbations. Prior work paints a complex picture of how to ensure that audio perturbations are imperceptible. The standard approach for image perturbations is to limit the p -norm of the perturbation – originally taken to be the 2-norm [4, 39], but recently often the ∞ -norm [40, 22]. Some user studies have suggested that such norm constraints in the audio domain produce imperceptible perturbations in classification settings such as speaker verification [31], as well as weaker attacks on ASR models such as untargeted attacks [34] and single-word attacks [35].

On the other hand, more recent work has suggested that perturbations which are rendered imperceptible using such norms may offer insufficient attack capacity for more powerful sentence-level targeted attacks on ASR systems [6, 7], and has instead suggested the use of psychoacoustic models of hearing to mask the perturbations. Nevertheless, perturbations generated using such models were still demonstrated by user studies to be perceptible in many cases, suggesting that the difficulty of creating effective yet imperceptible perturbations may be determined more by the difficulty of the attack than by the quality of the perceptual model used.² For that reason, for our attacks on denoising models, we find it necessary to leverage several enhancements to existing psychoacoustic models, which we describe in Section 4.2.

Attacks on image denoising models. Image denoising models analogous to the DNS models we study have been demonstrated to be moderately vulnerable to imperceptible adversarial perturbations [10, 11]. However, this prior work suggests that attacks on image denoising models can at best cause the models to output slightly noisy images, implying a similar baseline assumption for speech denoising models. In contrast, we demonstrate that speech denoising models can be incapacitated by imperceptible perturbations, implying that audio models may in some cases be *easier* to attack than their image counterparts, contrary to prior findings [34].

3 Background

We study the existence of *adversarial perturbations* for DNS models. As background, we first review the standard behavior of DNS models and important characteristics of the models we study. We then formally state the definition of adversarial perturbations for DNS models, and finally review auditory masking, the standard perceptibility constraint for audio attacks [6, 7].

3.1 Speech Denoising

The primary goal of speech denoising models is to remove background noise from a speech signal [13, 14, 15, 41, 16].

²In some limited cases, imperceptible attacks may also be enabled by more creative perceptual constraints, such as hiding in >20 kHz audio [33].

In some cases [13], but not all [14, 15, 41], the model is also trained to dereverberate signals that have been distorted by the acoustic characteristics of the environment and possibly the microphone.³

Concretely, in this paper, speech denoising models are functions $f : \mathbb{R}^n \rightarrow \mathbb{R}^n$ which map to and from the space of audio waveforms. We model the denoising model’s input as some clean speech $y \in \mathbb{R}^n$, mixed additively with some (possibly zero) background noise $b \in \mathbb{R}^n$, and (optionally) convolved with some room impulse response (RIR) $r \in \mathbb{R}^m$: $x = r * (y + b)$. (Note that some work only convolves the speech with r [15]; in this paper, we convolve both speech and background noise.) Given this input, the model produces $f(x) = \hat{y}$, where \hat{y} is as close to either y or $r * y$ as possible. For simplicity and consistency with past benchmarks [42], and because this paper is not intended to evaluate the quality of each model’s default behavior, we assume that the model attempts to infer y .

3.1.1 Models

We test the robustness of four recent open-source DNS models with publicly available checkpoints: Demucs, published online as Denoiser [13]; Full-SubNet+ [14]; FRCRN [15]; and MP-SENet [41, 16]. The models we study either take waveforms as direct input, which we refer to as time-domain, or take short-time Fourier transform (STFT) spectrograms as input, which we refer to as time-frequency-domain (TF-domain) [41].

Demucs. The earliest of the models we study, Demucs – specifically, the “master64” Demucs checkpoint provided in the Denoiser library – is a time-domain denoising model with 33.5M (trainable) parameters. Uniquely among the models we study, Demucs operates end-to-end on waveforms, rather than spectrograms: it processes the input waveform using several convolutional layers, then encodes temporal dependencies with an LSTM, before decoding again with convolutional layers. Unlike the other models we study, Demucs is designed to have dereverberation capabilities as well as denoising.

Full-SubNet+. Full-SubNet+ (FSN+) is a TF-domain denoising model with 8.67M parameters. Full-SubNet+ takes magnitude, real, and imaginary spectra as input, and passes them through a variety of modules, including attention, convolution, and LSTMs. Like all TF-domain models we study, rather than directly outputting a waveform or spectrogram, Full-SubNet+ outputs a *ratio mask*, a complex-valued spectrogram q such that \hat{y} equals the element-wise complex product of x and q [44].

FRCRN. FRCRN is a TF-domain model with 10.3M parameters. Similar to FSN+, FRCRN uses a mixture of convolutional, attentional and recurrent structures in its architecture.

MP-SENet. MP-SENet (MPSE) – specifically, the ‘DNS’

³Prior work is inconsistent on whether dereverberation is considered part of speech denoising [42] or only speech enhancement more generally [43]; however, all of the models we study are called speech enhancement models by their authors.

checkpoint provided in the official GitHub repository – is a TF-domain model with only 2.26M parameters. Similar to FSN+ and FRCRN, MP-SENet also uses convolution, attention and recurrence for temporal modeling.

Note that FSN+, FRCRN and MP-SENet do not attempt to dereverberate, i.e., they infer $r * y$ instead of y . Therefore, their un-attacked results are slightly worse than they should be in our experiments with reverb (see Section 5.1).

3.2 Adversarial Perturbations

Given the definition of speech denoising given in the previous section, an adversarial perturbation for some input $x = r * (y + b)$ is any $\delta \in \mathbb{R}^n$ such that $x + \delta \mapsto y'$, where (a) y' is somehow undesirable and (b) $x + \delta$ sounds identical to x . To make these notions concrete, we distinguish untargeted and targeted attacks.

Untargeted attacks. Here, we assume that the attacker has a loss function $\mathcal{L} : \mathbb{R}^n \times \mathbb{R}^n \rightarrow \mathbb{R}$, and they wish to *maximize* the value of $\mathcal{L}(y', y)$. They do so by selecting δ from a set of perturbations which are imperceptible when added to x , a feasible set which we refer to as $D(x)$. Thus, the adversary in an untargeted attack wishes to find

$$\delta^* \in \arg \max_{\delta \in D(x)} \mathcal{L}(f(x + \delta), y). \quad (1)$$

Targeted attacks. In this case, the attacker has a target output y' that they wish to cause f to output. We model this as the attacker wishing to *minimize* the loss $\mathcal{L}(f(x + \delta), y')$. Thus, the adversary wants to find

$$\delta^* \in \arg \min_{\delta \in D(x)} \mathcal{L}(f(x + \delta), y'). \quad (2)$$

Over-the-air attacks. In an over-the-air attack, the adversarial perturbation is distorted by the room’s acoustic characteristics and received through a microphone. As these distortions are assumed to be applied equally to all audio, this is generally simulated by applying the given RIR to the perturbation δ as well as speech y and background noise b [7, 45]. For example, the untargeted attack becomes the problem of finding

$$\delta^* \in \arg \max_{\delta \in D^*(x)} \mathcal{L}(f(r * (y + b + \delta)), y), \quad (3)$$

where D^* is all perturbations that are imperceptible after *all* audio, including the perturbation, is convolved with r .

3.3 Auditory Masking

We use a perceptibility constraint based on auditory masking, also known as psychoacoustic hiding: [17, 6, 7]: by varying the loudness constraint on the perturbation according to how loud the original signal is across different time segments and frequency bands, the perturbation can be effectively hidden in the original signal. This is accomplished through the computation of masking thresholds $\theta_{\tau, \omega}$ on the power spectral

density (PSD) matrix of the perturbation, such that any audio whose PSD is upper-bounded by these masking thresholds is, in principle, imperceptible by humans.

Our method for auditory masking is nearly identical to prior work [17, 6, 7]. However, we apply several enhancements to the threshold calculation to maximize attack power and minimize perceptibility; see Section 4.2.

4 Method

Most of the perturbations we study can be characterized as instantiations of the attacks shown in (1) and (2), given varying settings of (a) f , (b) y , (c) b , (d) r , (e) \mathcal{L} , (f) D , and (g) y' . In this section, we discuss \mathcal{L} , D , and optimization.

4.1 Optimization Objective

In this work, we used Short-Term Objective Intelligibility (STOI) [46] as the loss function \mathcal{L} for both targeted and untargeted attacks. STOI is open-source and differentiable, and hewed closely to our perceptions of intelligibility in untargeted experiments.

While mean-squared error (MSE) is widely used in comparable image tasks and has been successfully employed in prior attacks on generative audio models [37, 12], it remains an unreliable metric for intelligibility. It suffers from a lack of several detailed desiderata; for example, it is strongly phase-dependent, meaning that simply delaying the audio by a few milliseconds can cause very large MSE but almost no loss in intelligibility. Nevertheless, the central issue with MSE is that it is simply not designed to be an intelligibility metric; in our experiments, attacks would often achieve a large (untargeted) MSE by simply inducing the DNS model to fail to remove noise, rather than rendering the speech unintelligible.

We could not use Perceptual Evaluation of Speech Quality (PESQ) [47], a notable intelligibility metric, as its license owners did not grant us an academic license for this project. However, real adversaries would of course face no such ethical or legal concerns.

Finally, we also considered DNN-based intelligibility metrics such as DNSMOS [48], NISQA [49], and the word error rate (WER) of Whisper [50]. While such metrics were reasonably effective as unoptimized metrics for attack success, we found empirically that they work poorly as objectives, as the attack simply learns to induce the model to output adversarial noise against the metric network.

4.2 Perceptibility Constraint Enhancements

Our precise procedure for computing the masking thresholds is almost identical to the MP3 psychoacoustic model as described by Lin and Abdulla [17] and used by Schönher et al. [6] and Qin et al. [7], with the following changes: **(a)** for simplicity, we calculate the PSD of the input audio by normalizing to $[-1, 1]$ and converting to dB SPL explicitly, rather than setting the maximum bin to equal 96; **(b)** we enhance the

psychoacoustic model with temporal pre- and post-masking, as described by Lin and Abdulla [17] (see Appendix A for details); **(c)** because prior studies have found even attacks generated according to these masking thresholds to still be detectable by humans [6, 7], we restrict our attacks further by shifting all masking thresholds down by 12 dB. We combine thresholds from contemporaneous masking and pre- and post-masking by taking the maximum between each. See Appendices A and B for details on this and Section 4.3.

4.3 Optimization Algorithm

We use projected gradient descent (PGD; Madry et al. 51) to find δ^* in (1) and (2):

$$\delta_{t+1} = \Pi_{D(x)} (\delta_t + \alpha \nabla_{\delta_t} \mathcal{L}(x + \delta_t)), \quad (4)$$

where Π is the projection operator. Fortunately, the projection step is straightforward when using auditory masking on unreverberated perturbations (see Section 4.4 for details on reverberated perturbation optimization). If $\tilde{\delta}_{\tau,\omega}$ is the STFT spectrogram of δ at frame τ and frequency bin ω , then we clip the magnitude of $\tilde{\delta}_{\tau,\omega}$ such that $\text{PSD}(\tilde{\delta})_{\tau,\omega} \leq \theta_{\tau,\omega}$ while preserving its phase. See Appendix B for details. We also tested Lagrangian dual descent, a variant of which was used by Qin et al. [7], and the fast gradient sign method [40], but these did not perform as well.

4.4 Additional Experimental Methods

Optimization in Simulated Over-the-air Attacks. We simulate over-the-air attacks in a specific acoustic environment by applying the given RIR to the adversarial perturbation as well as to the clean speech and background noise (see (3)). Doing so dramatically increases the difficulty of the optimization problem we solve, as the projection step in (4) no longer has a closed-form solution: rather than directly clipping δ such that $\text{PSD}(\delta)_{\tau,\omega} \leq \theta_{\tau,\omega}$, we must instead solve for some δ such that $\text{PSD}(r * \delta)_{\tau,\omega} \leq \theta_{\tau,\omega}$.

We explore three methods to find such a δ : Wiener deconvolution, manual projection through gradient descent, and a combination of both. See Appendix C for details.

Targeted Attacks. We test three types of targets for targeted attacks: speech samples from the same speaker, speech samples from different speakers, and artificial targets generated using voice cloning systems such as MaskGCT [52]. For all target types, our attack objective is the STOI of the model’s output versus the clean speech minus the STOI of the model’s output versus the target speech, maximizing the relative intelligibility of the target speech.

Defenses. Prior work has investigated a wide range of defenses against adversarial audio perturbations, from pre-processing steps like randomized smoothing [53, 54], purification [55], and adversarial example detection [56, 57], to more involved defenses like adversarial training [58]. In this paper, we evaluate the simplest of these defenses: Gaussian noise applied to the attacked audio, normalized to various SNRs.

Universal Adversarial Perturbations. While most of our experiments focus on attacking a single known input, we also explore the existence of universal adversarial perturbations (UAPs): individual perturbations that lead one or more models to misbehave on multiple inputs [22, 19, 18, 27, 20, 21]. We design UAPs for DNS models under the assumption that the background noise b and RIR r remain the same for varying clean speech samples y_n , and calculate $D_U = \bigcap_n D(r * (y_n + b))$ (i.e., take the minimum of the different masking thresholds). To train the attack, we iteratively execute one step of PGD sequentially on each input $r * (y_n + b)$.

5 Experiments

In our experiments, we focused on answering the following questions: **a)** Are DNS models more or less susceptible to adversarial perturbations than image denoising models? **b)** In which use cases (amount of noise, reverb, etc.) are the models we study vulnerable to adversarial attacks? **c)** How does adversarial robustness vary by model, and which model characteristics seem to correlate with robustness? **d)** Can attackers induce the model to output a target utterance, as in the case of ASR transcriptions, or are they limited to untargeted attacks? **e)** Do imperceptible universal adversarial perturbations exist, or does the attacker need to know what the speaker will say? **f)** Do attackers need to have access to model gradients in order to successfully attack these models? **g)** Are sophisticated defenses (e.g., adversarial training) necessary, or is Gaussian perturbation good enough? **h)** Are real, over-the-air attacks possible in principle, or is this setting too difficult?

5.1 Experimental Details

Datasets. All audio samples – speech, noise, and RIRs – were taken from the main track of the ICASSP 2022 DNS Challenge 4 [59]. Ten-second clean speech samples were selected randomly from English read speech (as noted by Dubey et al. [59], collated from LibriVox.org) and VCTK Corpus [60]. Audio was clipped to five seconds for MP-SENet due to insufficient VRAM. We filtered speech to contain at least 15 words according to Whisper. See Appendix D for more details.

Metrics. In addition to STOI, we also evaluated our attacked audio and the model’s output using ViSQOL [61], another intrusive (i.e., binary with ground-truth) and unlearned metric; two non-intrusive deep metrics, NISQA [49] and DNS-MOS [48]; and word accuracy [62] using the ASR model Whisper [50]. See Figure 3.

Attacks. All combinations of environment setting (background SNR and reverb/no reverb) and model choice were run for 20 shared seeds. The attack lasted for a different number of iterations for each model, chosen to ensure that the entire attack (including metric computation) lasted for about one hour on an Nvidia L40S GPU. In particular, this allowed 20,000 iterations for Demucs and FSN+, 10,000 iterations for MP-SENet, and 5,000 iterations for FRCRN.

5.2 Results and Discussion

Figure 1 demonstrates our fundamental result: all DNS models we tested could be induced to output far worse-quality audio than the input through the addition of imperceptible adversarial noise, and indeed, all models could be reliably (or often, in the case of FSN+) reduced to outputting gibberish. Furthermore, the success of the attack was relatively invariant with respect to setting: all models could be successfully attacked in all settings, notably including a setting which has almost no attack vector: 70 dB SNR noise with no reverb. Thus, we can answer question **b**: three out of four tested models were completely susceptible in all settings, while FSNP was fairly susceptible in most settings. We can also answer question **a**: based on results so far [10, 11], DNS models appear substantially more susceptible to adversarial noise than image denoising models. The latter simply make images noisier when attacked, while the former can render audio unintelligible.

5.2.1 Targeted Attacks

Figure 2 demonstrates our results for the strongest targeted attack, where targets are real samples from the same speaker. At first glance, it appears to suggest that the answer to question **d** is resoundingly positive: DNS models are equally susceptible to targeted attacks as ASR models, and equally susceptible to adversarial perturbations in general. However, we found that, while STOI was an excellent minimization objective (low STOI implies low intelligibility), it broke down when used as a metric for maximization (high STOI does not imply high intelligibility). This issue is audible in our samples: even in attacked model outputs that are judged to have STOIs of more than 0.5 with respect to the target audio, a human listener can discern at most a faint robotic hint of the target speech. Thus, while future attackers may find ways to generate targeted attacks using more sophisticated objectives, the answer to question **d** is currently both positive and negative.

Furthermore, for both untargeted and targeted attacks, we found that UAPs were unable to cause more than slight decreases in the quality of the model output while remaining imperceptible (question **e**); this is likely due to the difficulty of hiding relevant perturbations inside of background noise alone, rather than a single clean speech sample. This result is consistent with prior work showing that audio UAPs are generally perceptible [21].

5.2.2 Model Results

Figures 1 and 2 suggest that FSN+ is by far the most resilient, FRCRN and Demucs have comparable resilience, and MP-SENet is slightly more susceptible. Surprisingly, though, the resilience of FSN+ is not due to high-level architecture differences such as domain or parameter count (see Table 1). Instead, the large difference between FSN+’s susceptibility and others was due to the pseudo-robustness of exploding gradients [63]: during the course of the attack on FSN+, the

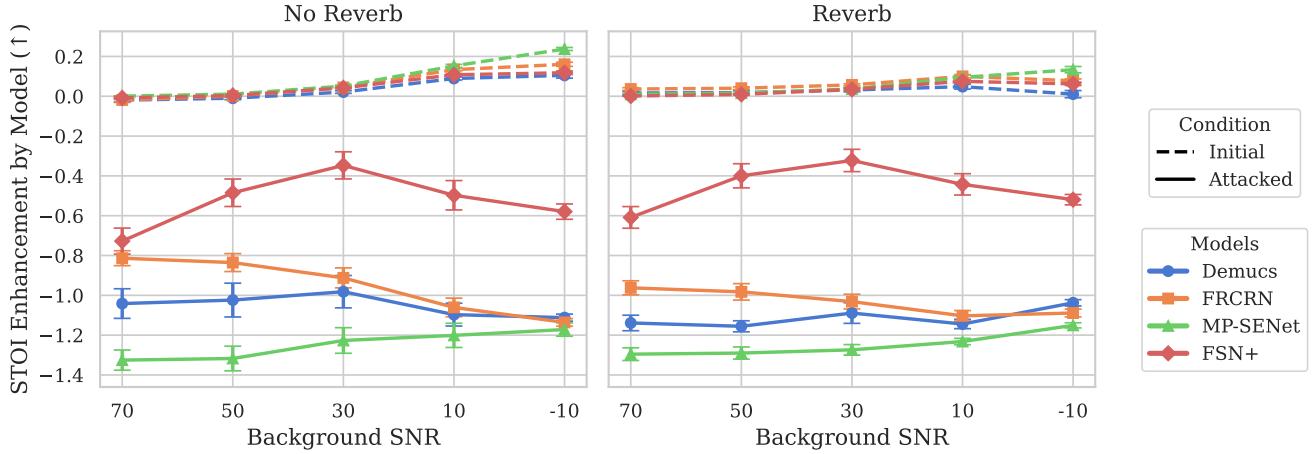


Figure 1: STOI provides a measure of the intelligibility of audio. The curves in these figures report how much DNS models have *enhanced* the intelligibility by reporting the difference in STOI between the inputs and outputs of the DNS models (i.e., the intelligibility of the speech prior to denoising, and the intelligibility of the speech after denoising). That is, $\text{STOI}(\text{clean}, \text{output}) - \text{STOI}(\text{clean}, \text{input})$. The dashed lines show the performance of the model for the initial input speech, which is typically greater than zero, indicating that the DNS model successfully enhanced the audio. The solid lines show the performance of the model for the input with the inclusion of the imperceptible adversarially generated perturbations. These values being negative indicates that the model not only made the speech less intelligible, but often did so to the point of rendering it unintelligible. Error bars show standard error across 20 seeds.

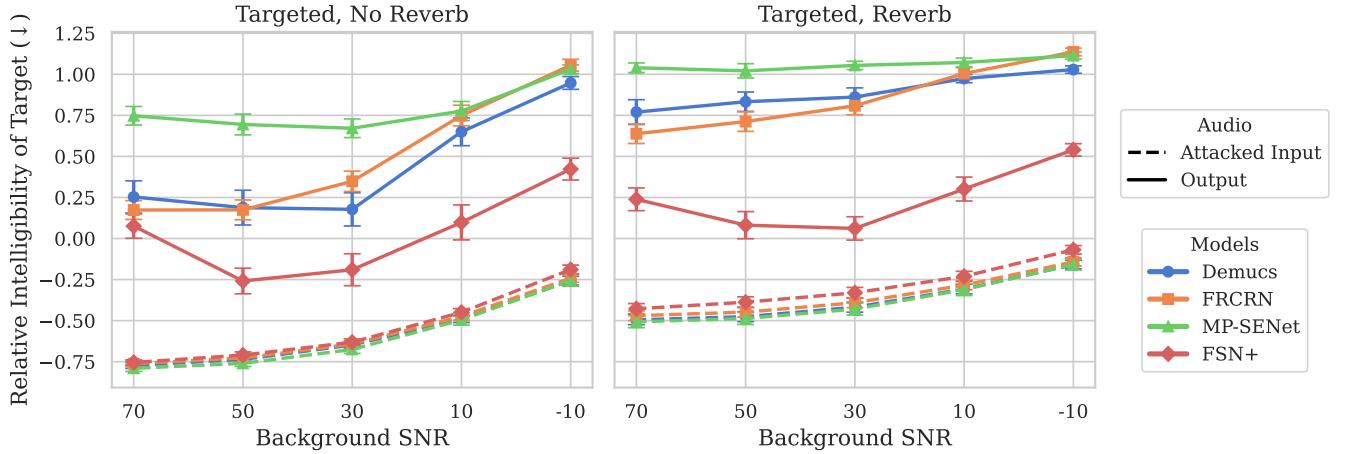


Figure 2: STOI provides a measure of the intelligibility of audio. The curves in this plot represent how intelligible the **target** speech (not actually present in the original input) is in the model’s inputs and outputs, relative to the **clean** speech (actually present). That is, $\text{STOI}(\text{target}, \text{audio}) - \text{STOI}(\text{clean}, \text{audio})$, where audio is either the attacked input to the model (dashed lines) or the model’s output (solid lines). The dashed lines show the relative intelligibility of the target and clean speech within the attacked input audio (clean speech plus background noise and adversarial perturbation). These values being negative indicates that the clean speech is more intelligible than the target speech, despite the perturbation. The solid lines show the relative intelligibility of the target and clean speech within the model’s output, given the attacked audio. These values generally being positive indicates that the model outputted audio in which the target speech (not present in its input) is more intelligible than the clean speech (its desired output). Error bars show standard error across 20 seeds. Attacks used target speech taken from the same speaker as the clean speech; synthesized targets were empirically ineffective.

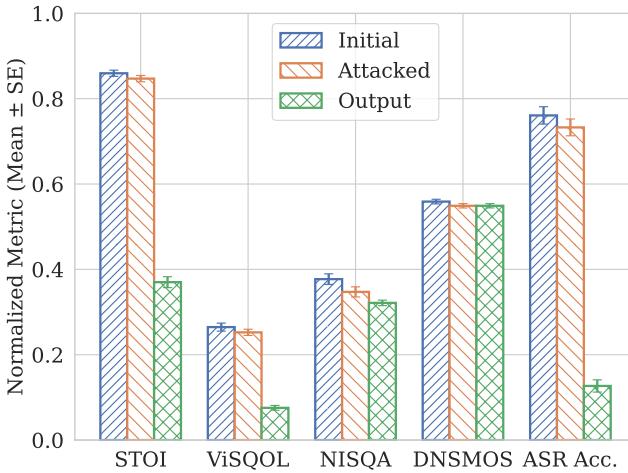


Figure 3: Normalized values of various speech intelligibility and quality metrics, averaged across all models and settings of Figure 1 and 20 seeds. “Output” refers to model output given the attacked input. ASR accuracy is computed as $1 - \min(\text{WER}, 1)$. Ranges used for normalization were: STOI: [-1, 1]. ViSQOL: [1, 5]. NISQA: [0, 5]. DNSMOS: [0, 5]. ASR accuracy: [0, 1]. ASR ground-truth is determined by the ASR model (Whisper) applied to the clean, unreverberated speech. Results suggest that attacked inputs are mostly indistinguishable from clean inputs, while attacked model outputs are far worse than either input. Results vary more for intrusive metrics (STOI, ViSQOL, ASR accuracy) than unintrusive; because the minimization target (STOI) is intrusive, this is consistent with prior results showing intrusive metrics to be poorly correlated with non-intrusive ones [62].

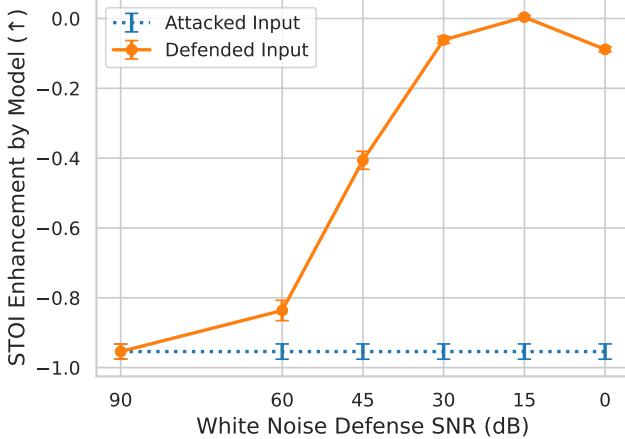


Figure 4: $\text{STOI}(\text{output, clean}) - \text{STOI}(\text{input, clean})$ on attacked inputs passed through Gaussian perturbation (referred to as “white noise defense” (WND)) of varying magnitudes, averaged across all models and settings of Figure 1 and 20 seeds. (See Figure 1 for an explanation of the metric.) Moderate Gaussian perturbation enhances model robustness by subsuming the adversarial perturbation, though does not recover the model’s original unattacked performance. Error bars are standard error (for $n = \text{number of seeds}$).

gradient of the STOI loss with respect to the adversarial waveform would often grow to have a norm of 10^{30} or greater (compared to single-digit norms for other models), causing numerical instability even with gradient clipping. Therefore, FSN+ might be more vulnerable to black-box attacks [63].

Table 1: Comparison of several model characteristics and final attacked performance: $\text{STOI}(\text{output, clean}) - \text{STOI}(\text{input, clean})$. MPSE stands for MP-SENet. The Demucs parameter count is not provided by Defossez et al. [13] and so was determined manually. Results show that FSN+’s resilience is unrelated to these high-level architectural details.

Model	Domain	#Params (M)	Attacked Perf.
Demucs	Time	33.5	-1.08
FRCRN	TF	10.3	-0.99
FSN+	TF	8.7	-0.49
MPSE	TF	2.26	-1.25

5.2.3 Model Transfer

Table 2: Denoising performance of various models (columns) on inputs designed to attack the same or other models (rows), as measured by $\text{STOI}(\text{clean, output}) - \text{STOI}(\text{clean, input})$, averaged across all settings and 20 seeds. FSN+ stands for Full-SubNet+, and MPSE stands for MP-SENet. Standard errors are omitted for space. Results show that naive attack transfer between models is generally not possible, so in the absence of more sophisticated transfer or black-box attacks, model gradients must be accessible to develop a successful attack.

Trained on	Evaluated on			
	Demucs	FSN+	FRCRN	MPSE
Demucs	-1.08	0.04	0.06	0.08
FSN+	0.05	-0.49	0.05	0.08
FRCRN	0.06	0.04	-0.99	0.08
MPSE	0.03	0.03	0.05	-1.25

To answer question f), we evaluated the possibility of model transfer attacks, where an attack is trained for one model but applied to another. Our results indicated that attacks generally do *not* transfer between different architectures (e.g., from Demucs to FSN+); see Table 2. We also tested whether attacks between three different available Demucs checkpoints transfer to each other. Surprisingly, we found that they did not.

Our results stand in contrast to those of Dong et al. [12], who found that perceptible adversarial examples can transfer between models. Thus, without more sophisticated transfer techniques [64], our results suggest an affirmative answer to question f), *as long as* the attacker is truly constrained to producing imperceptible attacks. However, further research is urgently required, particularly on pure black-box attacks [25].

5.2.4 Defenses

We discovered that simple Gaussian perturbation offers reasonable protection against adversarial perturbations, though only when applied at a low enough SNR to damage model performance (Figure 4; note that a STOI enhancement of 0 is slightly lower than the unattacked average of ~ 0.044). However, we do not assume adaptation by the attacker; knowledge of this defense would likely allow the attacker to train more noise-resistant perturbations (see, e.g., Tramer et al. [23] for an example of such adaptive attacks in image classifiers), emphasizing a need for more sophisticated defenses.

5.2.5 Simulated over-the-air attacks

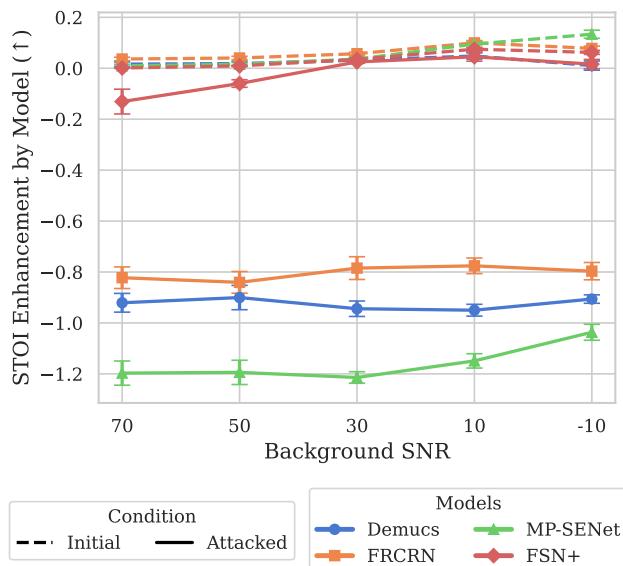


Figure 5: The simulated over-the-air experiment. Similar to Figure 1, we plot $\text{STOI}(\text{output}, \text{clean}) - \text{STOI}(\text{input}, \text{clean})$ for both normal model inputs (dashed lines) and model inputs combined with an untargeted adversarial perturbation (solid lines); however, in this experiment, the adversarial perturbation is subjected to the same acoustic conditions as the rest of the input, by convolving it with an RIR. Error bars show standard error across 20 seeds. Results show that attacks succeed at incapacitating all models except FSN+ even in this challenging threat model.

While the pseudo-protection of FSN+'s exploding gradients was amplified in our simulated over-the-air experiments, we discovered that all other models are highly vulnerable to untargeted reverberated perturbations, despite the additional optimization challenges in developing them (see Figure 5). However, the increased challenge of this attack did require that we slightly loosen our perceptibility constraint, reducing the masking thresholds by only 6 dB rather than 12 dB. While this loosening still implies a tighter perceptibility constraint than prior work, it did cause a slight crackling to sometimes be audible inside of speech, though it would be difficult to

distinguish from minor distortion in real settings.

6 Conclusion

In this paper, we show for the first time that DNS models are susceptible to imperceptible adversarial attacks in a wide variety of simulated settings. We demonstrate in the process that they are far more fragile than comparable image denoising models: through the addition of adversarial noise hidden in the original input signal, all of the models we study can be induced to output audio with almost no resemblance to either clean or noisy speech. Our attacks generalize to a wide variety of settings, including simulated over-the-air attacks and attacks with no background noise or reverb, and demonstrate that targeted attacks may soon be feasible.

Our results have several important limitations and caveats. First, the DNS model Full-SubNet+ (FSN+) is partially protected from gradient-based attacks due to its exploding gradients, though this pseudo-defense is generally easily overcome by determined adversaries [63]. Second, although we provide samples and use well-established methods for generating imperceptible noise, we do not run an ABX user study to prove the imperceptibility of the generated perturbations. Third, our attacks all rely on gradient access for now, as we showed model transfer to be ineffective for the adversarial perturbations that we found. Finally, we only attack fully differentiable DNS models; discrete token-based DNS models [65] will require different techniques to attack.

Nevertheless, we hope to convince the research community that DNS models are both an appealing and eminently feasible target for attack by real adversaries, with the potential to incapacitate live audio streams, speech recognition systems, users of hearing devices, and more. With simple defenses such as Gaussian perturbation only offering limited protection, we urge readers to evaluate further models in more lifelike settings and develop and apply better defenses before attackers exploit these critical weaknesses.

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A Auditory Masking

Temporal Masking. Let $\theta_{\tau,\omega}$ be the masking threshold in frame τ and frequency bin ω , as computed by the default approach [17, 7]. This computation already involves consideration of the effect of sound in one frame τ and frequency bin ω on the masking thresholds in the same frame, τ , but adjacent frequency bins, ω' . For example, the model already accounts for the fact that a 1 kHz sine tone would mask a 990 Hz tone as well.

However, it is well known [17] that masking also occurs between frames, along the same frequency bin; this is known as pre-masking and post-masking. Combining results shown by Lin and Abdulla [17] with our own experimentation, we model this by first computing contemporaneous masking thresholds as before, then for each $\theta_{\tau,\omega}$ computing the post-masking threshold it causes on later frames $\tau' > \tau$ using exponential decay of 0.02 ms^{-1} , clipping to zero at a gap of 100 ms. Pre-masking, where $\tau' < \tau$, is modeled similarly but much more

sharply, with a decay of 0.16 ms^{-1} , clipping to zero after a gap of 20 ms.

Finally, each frame and frequency bin now has one contemporaneous masking threshold, a small number of masking thresholds due to pre-masking by future sounds, and a larger number of masking thresholds due to post-masking by previous sounds. To combine all of these thresholds, we set the final threshold to be their maximum, as we find this to empirically produce the best perceptibility constraint.

B Projected Gradient Descent with Masking

Given the TF masking thresholds $\theta_{\tau,\omega}$ calculated for the normalized input x , we seek an imperceptible perturbation δ whose reverberation-free STFT magnitude does not exceed $\theta_{\tau,\omega}$. Let

$$\tilde{\delta}_{\tau,\omega} = \text{STFT}(\delta)_{\tau,\omega}.$$

For the purposes of illustration, let

$$\text{PSD}(\delta)_{\tau,\omega} = 10 \log_{10}(|\tilde{\delta}_{\tau,\omega}|^2).$$

(In reality, there are subtleties around Hann window energy and length correction which we elide here; the full process is discussed by Lin and Abdulla [17] and Qin et al. [7].)

To enforce $\text{PSD}(\delta)_{\tau,\omega} \leq \theta_{\tau,\omega}$, we use a projection operator $\Pi_{D(x)}$ in each iteration of projected gradient descent (PGD). Specifically, after each gradient step, we adjust $\tilde{\delta}_{\tau,\omega}$ to satisfy

$$\text{PSD}(\delta)_{\tau,\omega} \leq \theta_{\tau,\omega}$$

by scaling its magnitude if necessary:

$$\tilde{\delta}_{\tau,\omega} \leftarrow \tilde{\delta}_{\tau,\omega} \times \min\left(1, 10^{\frac{\theta_{\tau,\omega} - \text{PSD}(\delta)_{\tau,\omega}}{20}}\right).$$

This enforces time-frequency masking constraints bin-by-bin while preserving the phase of $\tilde{\delta}_{\tau,\omega}$.

Note that this is not necessarily a projection operator in the strict sense of mapping to the nearest point in $D(x)$, particularly when δ is parameterized in the time domain, but it does ensure a feasible δ after each projection step.

C Over-the-air Attack Optimization

Given knowledge of an RIR r and a clipped, imperceptible reverberated perturbation $\delta^r = r * \delta$, Wiener deconvolution is the following process: if $\tilde{\delta}_\omega^r$ is the full frequency spectrogram of δ^r in bin ω , and similar for \tilde{r}_ω , we approximate

$$\tilde{\delta}_\omega \approx \frac{\tilde{\delta}_\omega^r \tilde{r}_\omega^*}{|\tilde{r}_\omega^*|^2 + \epsilon},$$

where ϵ is a small stability term (10^{-4}) and $*$ represents complex conjugation. Although a mathematically principled inversion, Wiener deconvolution is approximate for our use case, as convolution by RIRs is generally non-invertible.

One could attempt to apply Wiener deconvolution iteratively to find an exact δ such that $(r * \delta) \in D^*(x)$. However, a simpler iterative approach is gradient descent: we directly compute the total constraint violation $g(\delta)$ as

$$g(\delta) = \sum_{\tau,\omega} \max(\text{PSD}(r * \delta)_{\tau,\omega} - (\theta_{\tau,\omega} - d), 0),$$

where d is a small positive offset (1 dB) to ensure that gradient descent finds an exact feasible solution; we then find $\nabla g(\delta)$ using autodifferentiation and repeat until $\delta \in D^*(x)$, i.e., $g(\delta) = 0$. For over-the-air attacks, we parameterize δ in STFT spectrogram space, as this representation produces smoother gradient descent behavior. Because these attacks are harder, we gradually decrease the masking thresholds from a high starting point over time, similar to iterative constraint tightening in other works [7].

Finally, we also test applying one step of Wiener deconvolution and then finishing the projection with gradient descent.

D Additional Experimental Details

Dataset. Noise was selected randomly from the dataset and repeated up to ten seconds. All audio was sampled single-channel at 16 bits and 16 kHz. All settings had five sources of background noise added to them, with their post-RIR sum being set to various SNRs with respect to the post-RIR clean speech. (While five is a large number of sources, note that 70 dB SNR still represents an effectively zero-noise setting.)

Optimal perturbation selection. Within each trial, the final output was selected as the perturbation with the lowest final loss – i.e., STOI(output, clean) for untargeted attacks, and STOI(output, clean) - STOI(output, target) for targeted attacks. For over-the-air attacks where not every attack iteration converged to the feasible set, we instead selected the final output, as earlier outputs might not satisfy the final masking threshold (see Appendix C).

STFT. We use short-time Fourier transforms with Hann windows, 512 FFT points, a window length of 512, and a hop length of 256.

Optimization Details. In all experiments except the simulated over-the-air experiment, we parameterize δ in the time domain. We use Adam for all optimization, using an initial learning rate of 0.01, and clip gradients to a 2-norm of 10. We decrease the learning rate by a factor of 0.99 whenever the loss fails to decrease for 10 iterations in a row.