SAQAM: Spatial Audio Quality Assessment Metric

Pranay Manocha1∗, Anurag Kumar,2 Buye Xu,2 Anjali Menon,2 Israel D. Gebru,2 Vamsi K. Ithapu,2 Paul Calamia2

1Department of Computer Science, Princeton University, Princeton, NJ, USA
2Meta Reality Labs Research, Redmond, WA, USA
pmanocha@cs.princeton.edu, {anuragkr90, xub, aimenon, idgebru, ithapu, pcalamia}@fb.com

Abstract
Audio quality assessment is critical for assessing the perceptual realism of sounds. However, the time and expense of obtaining “gold standard” human judgments limit the availability of such data. For AR&VR, good perceived sound quality and localizability of sources are among the key elements to ensure complete immersion of the user. Our work introduces SAQAM which uses a multi-task learning framework to assess listening quality (LQ) and spatialization quality (SQ) between any given pair of binaural signals without using any subjective data. We model LQ by training on a simulated dataset of triplet human judgments, and SQ by utilizing activation-level distances from networks trained for direction of arrival (DOA) estimation. We show that SAQAM correlates well with human responses across four diverse datasets. Since it is a deep network, the metric is differentiable, making it suitable as a loss function for other tasks. For example, simply replacing an existing loss with our metric yields improvement in a speech-enhancement network.

Index Terms: spatial audio quality, listening quality, spatialization metric, binaural audio, speech enhancement

1. Introduction
Audio quality plays a fundamental role in many applications affecting the quality of listening experiences like AR&VR. To create an immersive AR&VR experience, both graphics and spatial audio need to be of high quality and synchronized to the user’s head movements in real time. In addition, audio sources must be accurately positioned such that they are localized at the targeted location. It is well-known that a mismatch between the stored auditory schemata of the expected listening scene and the perceived schemata of a simulation yields a significant decrease in presence and immersion in these multi-sensory systems [1]. Therefore, sound-quality evaluation tests are critical since they provide the necessary user feedback that drives improvements in these technologies. Listening tests in AR&VR via user studies demand more time and effort than conventional audio tasks as they require assessment across many attributes [2] (e.g. listening quality, spatial localization etc.). Thus, automatic (objective) SQA methods are more practical.

Recent research has focused on learning a spatial audio metric from known binaural auditory cues like Interaural Level Differences (ILD), Interaural Time Differences (ITD) and Cross-Correlation (IACC) between signals entering the left and the right ear [3–6]. However, these methods suffer from various general drawbacks. First, these methods are designed to only assess spatialization quality (SQ) that ensures how accurately the test sources are positioned as compared to the reference, but cannot assess effects of audio fidelity degradation’s, also referred to as listening quality (LQ). It includes undesired sounds and distortions that add artifacts to the audio signal and cause a loss in immersiveness. Second, these methods are full-reference and always require a clean signal for comparison (that share the same ‘content’ - matched reference), and thus cannot be applied in scenarios where the paired clean reference is unavailable. Third, they work well under anechoic conditions but are inaccurate under reverberant conditions. Fourth, they assume that the audio signal is created in relation to the reference, meaning that the two signals are time-aligned and of equal length which may not be valid. Finally, none of the metrics are differentiable, and thus cannot be directly leveraged as a training objective in downstream tasks. Addressing a few concerns, researchers have proposed AMBIQUAL [7] that compares multi-channel ambisonic recordings across LQ and SQ. However, it does not account for head listening direction, and the influence of Head Related Transfer Functions (HRTFs) in the resulting recording. Moreover, it also requires access to a clean, matched reference, and is also non-differentiable.

Manocha et al. [8] proposed a full-reference deep perceptual spatialization metric (DPLM) that evaluates the similarity of binaural presentation in terms of localization under realistic, echoic conditions. DPLM computes deep-feature distances between the full-feature activation stacks of direction-of-arrival (DOA) models to assess SQ and correlates well with human perceptual judgments. Moreover, the metric is differentiable and does not demand access to a clean reference or time-aligned signals. However, it does not assess LQ.

In this paper, we introduce a novel metric that addresses some of the above concerns. We propose SAQAM that evaluates the LQ and SQ between any pair of binaural signals. The inspiration for the approach comes from human’s ability to do the same. Given two completely random audio (“non-matched”) recordings, it is highly likely that a human would be able to compare them across quality attributes irrespective of the audio content [9]. We first design a LQ assessment model that assesses the audio fidelity degradations, and is trained on a carefully simulated dataset of perturbations that mimic realistic environments. Next, these recordings are presented to the model as triplets, and the model is trained using triplet metric learning [10, 11], by carefully selecting triplets to have different audio content(s) which ensures content invariance. Next, to assess SQ, we build on top of the DPLM [8] approach that addressed the perceptual characteristics of localizing sounds. We combine these two tasks using a multi-task learning framework [12] to leverage the useful information contained in related tasks to improve generalization performance on both tasks. We show that, even in the absence of explicit perceptual training, these distances correlate well with human perceptual judgments (both via objective and subjective evaluations). We also show that the resulting metric generalizes well even for distinct (yet related) tasks such as audio codecs, and binaural reproduction from mono or multi-channel signals. Finally, we show that adding SAQAM to the loss function yields improvements to the existing state-of-the-art model for binaural speech enhancement.

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Listening Quality
Task Head
Feature
Extraction
Temporal
Aggregation
Spatialization
Task Head
Listening Quality $D_1(x_1, x_2)$ (LQ)
Spatialization Quality $D_2(x_1, x_2)$ (SQ)
Overall Quality $D_3(x_1, x_2)$ (OVRL)

2. The SAQAM Framework

Our framework SAQAM is designed to assess the quality of a given pair of binaural signals across various attributes. In this paper, we consider two such attributes: listening quality (LQ) and spatialization quality (SQ), but the framework can be easily extended to include more such attributes. Additionally, the SAQAM framework can also estimate a combined, overall attribute (OVRL) that implicitly combines all individual attributes. Refer to Fig. 1. Given two binaural signals $(x_1, x_2)$, our goal is to compute distance functions $D_1(x_1, x_2)$, $D_2(x_1, x_2)$ and $D_3(x_1, x_2)$ that characterize LQ, SQ, and OVRL between the signals. The distance function is designed to be non-negative and monotonic, thereby making it a pseudo-metric (we do not impose triangle or associative properties).

2.1. Multi-task learning

Multi-task learning (MTL) [12] has been beneficial to many speech applications [13, 14]. MTL aims to leverage useful information contained in multiple related tasks to help improve the generalization performance on all tasks. In our case, we consider LQ and SQ prediction as the two tasks. MTL makes the model easier to use - in the sense that if only the spatialization task is required, then we can simply use an appropriate task-head to learn the model easier to use - in the sense that if only the spatialization task is required, then we can simply use an appropriate task-head to learn.

LQ head: is trained using a triplet comparison dataset where we simulate human judgments on a simple question: “Is A or B closer to reference C?”. We algorithmically modify clean recordings under various real-life degradation commonly found in audio processing tasks including compression, additive noise, speech distortions and binaural recorded noises across sources.

SQ head: is re-purposed from training a sound source-localization model that predicts the direction-of-arrival (DOA) of a given sound source, similar to DPLM [8]. We train DOA models with carefully designed input perturbations as data augmentations that mimic realistic environments.

2.2. Architecture

Refer to Fig 2. The architecture of both tasks consists of 3 components: feature-extraction block, temporal aggregation block, and task specific heads for LQ and SQ. In the MTL framework, the first two blocks are shared between tasks.

For the feature-extraction block, we used an Inception [15] styled architecture. The 6-block Inception network consists of 1x1, 3x3 and 5x5 filters, leading to 3x3 max-pooling, and a 1x2 maxpool along the frequency dimension. For the temporal aggregation block, we use Temporal Convolutional Networks (TCNs) consisting of 4 temporal blocks, with each block consisting of 2 convolutional layers with a kernel size of 1x3. We use weight normalization [16] along with dilated convolutions to increase the effective receptive field of our model.

For the LQ task, we use 2 conv. layers to transform the embedding size to 64 per frame. These are then mean-pooled in the temporal dimension, the resulting embedding representing the LQ of the signal. For the SQ task, we divide azimuth ($\in (-180^\circ, 180^\circ)$) into 50 equally spaced bins, and the elevation ($\in (-90^\circ, 90^\circ)$) into 25 equal bins. The resulting embedding from the aggregation stage is then mapped to a one-hot vector, representing the location of the sound source. Note that both task-heads output a framework estimate.

2.3. Loss Functions

We use different losses to train the LQ and SQ heads. For LQ, we use deep metric learning with a triplet-loss as the basis to train the LQ head. Formally, we define the triplets as a set $T = \{(t_i)\}_{i=1}^N$, where each triplet $t_i = \{x_a, x_p, x_n\}$ with $x_a$ the anchor sample, $x_p$ the positive sample, and $x_n$ the negative sample. Then, we define the triplet loss as:

$$L(t) = \max\{0, D_1(x_a, x_p) - D_1(x_a, x_n) + \delta\}.$$ 

Here $\delta$ is the margin value to prevent trivial solutions, and $D_1(x_1, x_2)$ is the deep-feature distance [17] between the full-feature activation stacks between the two audio inputs.

For the SO metric, we use the same classification formulation as Manocha et al. [8]. However, instead of the conventional cross-entropy loss, we use the earth mover’s distance (EMD) as a loss function for training. It focuses on inter-class relationships, whereas plain cross-entropy loss ignores any relationship between classes. This is especially useful if the classes are ordered since that leads to a closed form solution, which is:

$$\text{EMD}^2(p, \hat{p}) = \sum_{n=1}^N (\hat{p}_n - p_n)^2$$

where $p_n$ is the $n$-th element of the cumulative density function of $p$, and $\hat{p}$ is the predicted output after softmax at the final layer. We follow a normal label distribution around the correct class, and use a discrete soft label distribution compared to one-hot:

$$p_n = \begin{cases} 
0.4 & n = v \\
0.2 & n = v \pm 1 \\
0.1 & n = v \pm 2 \\
0 & \text{otherwise}
\end{cases}$$

where $v$ is the index corresponding to the ground truth localization. Note that we also enforce continuity between the first and the last bins for the azimuth space.

2.4. Usage

Given a test input $x_1$, and a reference signal $x_2$, the LQ score is obtained from the LQ task head of the network by computing the deep-feature distances across activation maps $D_1(x_1, x_2)$. Similarly, the SQ score is obtained from the SQ task head of the network by computing the deep-feature distances across activation maps $D_2(x_1, x_2)$. Finally, the OVRL score is obtained from the shared head (temporal aggregation block) of the network by computing the deep-feature distances across activation maps $D_3(x_1, x_2)$.

Note that the reference signal does not need to contain the same speech (or content - hence ‘non-matching’) as the test signal.
3. Experimental Setup

3.1. Datasets and training

Speech recordings from the TIMIT [18] dataset are used as the source for anechoic recordings ($D_e$). We used a pool of 11 publicly available Binaural Room Impulse Response (BRIR) databases including ADREAM [19], AIR-LR [20], BRAS [21], Huddersfield [22], Ilmenau [23], IoSR [24], Oldenburg_IE-BTE [25], Rostock [26], TU Berlin [27], and Salford [28]. The resulting pool contained approximately 125k BRIR pairs from 36 different rooms ($RT_{60}$ ranging from 0.08 to 0.97 sec). All single channel additive noises are sampled randomly from the DNS Challenge [29].

For the perturbation set, we consider all degradations commonly found in various audio processing tasks including additive noise, speech distortions (e.g. clipping and frequency masking, frequency resampling, pitch shifting), compression (e.g., mu-law and MP3), and recorded binaural sounds [30,31]. We also use the data collected using the binaural multichannel wiener filter (MWF) [32] algorithm, and find that adding datasets (BRIR) databases including ADREAM [19], AIR-LR [20], BRAS [21], Huddersfield [22], Ilmenau [23], IoSR [24], Oldenburg_IE-BTE [25], Rostock [26], TU Berlin [27], and Salford [28]. The resulting pool contained approximately 125k BRIR pairs from 36 different rooms ($RT_{60}$ ranging from 0.08 to 0.97 sec). All single channel additive noises are sampled randomly from the DNS Challenge [29].

To obtain the simulated triplet set ($t_i = \{x_{a}^i, x_{p}^i, x_{n}^i\}$), we first sample three clean recordings ($s_a, s_p, s_n$) from $D_e$ and binauralize. Next, a perturbation is sampled from the above mentioned perturbation set, and applied to ($s_a, s_p, s_n$) at three different levels uniformly sampled from a range (-20dB to +30dB) to create ($x_{a}, x_{p}, x_{n}$). It is ensured that the perturbation levels of $x_{a}$ and $x_{p}$ are closer than those for $x_{a}$ and $x_{n}$ to satisfy our triplet formulation. Note here that the inputs to be model ($x_{a}, x_{p}, x_{n}$) are created by sampling different clean recordings, but adding the same noise at different levels. This encourages the model to be invariant to recording content. These findings can be treated as a pilot study for future work on a dataset of subjective quality preferences.

We use an adaptive margin ($\delta$) strategy that starts out with a low value ($\delta = 0.5$), and increases gradually ($\delta = 1.50$) to ensure robust training [33]. We use 3-sec excerpts for training. For both heads, phase and magnitude spectrogram are extracted from the 2 channels using a 512-point DFT with a hamming window of length 512, and 50% overlap. We use a learning rate of $10^{-4}$ with a batch size of 64 for training. As part of online data augmentation to make the model invariant to small delay, we randomly add a 0.25s silence to the audio at the beginning or the end to provide shift-invariance property to the model. For the localization model, we follow the same training methodology as in Manocha et al. [8].

### Table 1: Objective evaluations

| Name | Attribute | Common Area | $MP_{0.8}$ | $MP_{0.5}$ | Monotonicity |
|------|-----------|-------------|-------------|-------------|--------------|
| Proposed | SQ | 0.19 | 0.92 | 0.89 | 0.94 |
| LQ | 0.23 | 0.87 | 0.79 | 0.92 |

**Table 1: Objective evaluations.** See 4.1 describes common area, mean precision, and monotonicity (using Spearman correlations) across simulated datasets. $\uparrow$ or $\downarrow$ is better.

4. Results

4.1. Objective evaluations

Objectively, we compare various metrics on (i) robustness to content variations; (ii) clustering in learned space; and (iii) monotonic behavior with increasing perturbation levels. Refer to Table 1 for the results. Note that none of the above-mentioned baselines accepts non-matched inputs, except DPLM, which only assesses SQ.

**Robust to content variations** To evaluate robustness to non-matched recordings, we create a test dataset of two groups: first group consists of pairs of recordings with the same quality attributes (LQ and SQ) but different speech content; the other group consists of recordings with different quality attributes and speech content. We calculate the common area between these normalized distributions. Our SAQAM metric has the lowest common area suggesting that it is agnostic to speech content.

**Clustered Embed. Space:** To better understand the learnt representations, we evaluate the retrieval performance of our model using Precision@K to measure the quality of the top K items in the ranked list. This is done for both LQ and SQ task heads. We divide both attributes into 10 different perturbation-level groups, with each group consisting of 100 recordings with the same perturbation and level, but non-matched content. We randomly selected queries and calculate the number of correct class instances in the top K retrievals. We report the mean precision@K (MP$_K$) over all test queries which shows high precision retrievals that suggests that the embeddings indeed capture these quality attributes.

**Monotonicity** To show our metric’s monotonicity with increasing angular distance and noise, we create a test dataset having non-matched audio recordings at increasing perturbation levels. To check for monotonicity in SQ, we evaluate SAQAM between a fixed reference, and a moving test source for three different source positions compared across recordings of non-matched content (see Fig 3). Manocha et al. [8] showed the trend for recordings having matched content, and here we see that the general trend is similar. To check for monotonicity in LQ, we calculate the Spearman rank order correlation (SC) between the distance from the metric and the perturbation levels. The absolute correlation is high suggesting that the score from the metric decreases with increasing noise levels.

4.2. Subjective evaluations

We use previously published diverse third-party studies to verify that our trained metric correlates well with subjective ratings related to their task. We compute the correlation between the model’s predicted distance with the publicly available subjective
Table 2: Subjective evaluation (1): Compared across overall ratings. Models include: Conventional model (e.g., PESQ), our proposed models (SQ and OVRL models), Baseline models including DPLM and BAMLQ, Spearman Correlation (SC). ↑ is better.

Table 3: Subjective evaluation (2): Compared across individual attribute ratings. Models include: Conventional model (e.g., PESQ), our proposed models (SQ and LQ models), and DPLM and BAMLQ, as baseline. Spearman Correlation (SC). ↑ is better.

Table 4: Ablations: Models include: Individual trained models for Spatialization and Listening Quality, as well as our Multi-task framework models. Spearman Correlation (SC). ↑ is better.

Table 5: Evaluation of enhancement models using a held out test set with objective measures.

often the improvement is of the order of 20 to 30% (see table 4).

Different input feature representations To evaluate how the metric correlates with different types of input representations, we train another set of models using either magnitude spectrum or phase spectrum, and compare performance with SAQAM which is based on both magnitude and phase spectrum features. We observe that phase features are better correlated with subjective ratings than magnitude features. We also observe that SAQAM scores the highest correlations, suggesting that it makes use of both sets of features.

4.4. Binaural speech enhancement

To further demonstrate the effectiveness of our metric, we design a binaural speech enhancement model that is based on a popular U-Net type convolutional neural network [39]. The input to the model is the real and imaginary components of the STFT of the binaural signal, and the outputs are the complex ratio masks.

The baseline enhancement model is trained using Log Mean Square Error (LogMSE) between the estimated and target real and imaginary STFT components for both channels. We supplement SAQAM in two different ways: (i) Scratch SAQAM - where we train using LogMSE and SAQAM from scratch; and (ii) Finetune SAQAM - where we first pretrain on LogMSE and finetune on SAQAM.

For evaluation, we randomly select 2000 unseen audio recordings from an unseen dataset [40, 41]. Following prior work, we evaluate the quality of enhanced binaural recordings using a variety of objective measures: i) PESQ (from 0.5 to 4.5); (ii) Short Time Objective Intelligibility (STOI) (from 0 to 100); (iii) L2 distance on the waveform; (iv) Scale invariant signal to distortion ratio (Si-SDR); and (v) Multi-resolution STFT at various FFT, hop, and window sizes, all evaluated over each channel separately, and then averaged to get one value.

As we see in Table 5, both of our models perform better than the baseline. We observe that our Finetune SAQAM model scores the best objective scores. This highlights the usefulness of using SAQAM in audio similarity tasks, especially in identifying and eliminating minor human perceptible artifacts that are not captured by traditional losses.

5. Conclusions and future work

We present SAQAM, a general purpose, differentiable, non-matching, non-clean-reference based objective metric to assess listening quality and spatial localization differences between any two binaural signals. We show the utility of MTL and deep-feature distances that guide the model to correlate well with human subjective ratings without any perceptual training or calibration. In the future, we would like to include more spatial quality attributes like perception of distance and coloration.
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