

Predicting Ensemble Location and Width in Binaural Recordings of Music with Convolutional Neural Networks

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Abstract

Binaural audio technology has been in existence for many years, but its popularity has significantly increased over the past decade as a consequence of advancements in virtual reality and streaming technologies. Along with its growing popularity, the quantity of publicly accessible binaural audio materials has also expanded. Consequently, there is now a need for automated and objective measurements of spatial content information, with ensemble location and width being the most prominent. This study presents a novel method for predicting ensemble location and width in binaural recordings. To this end, 30 head-related transfer functions and 192 binaural music recordings from publicly accessible multi-track recording repositories were used to synthesize 23,040 binaural recordings. The synthesized recordings were then used to train a multi-task convolutional neural network model, the aim of which was to predict the location and width of the ensemble for unseen recordings. The results indicate that models of ensemble location and width can be successfully constructed with low prediction errors — $4.76^\circ (\pm 0.10^\circ)$ for ensemble location and $8.57^\circ (\pm 0.19^\circ)$ for ensemble width. The method developed in this study outperforms previous spatiogram-based methods recently published in the literature and holds promise for future development as a part of a novel tool for audio engineers to assess binaural audio.

1 Introduction

The human auditory system demonstrates exceptional proficiency in segregating, localizing, and interpreting diverse auditory signals, despite being limited to two ears. This capability arises from the intricate analysis of temporal, amplitude, and spectral disparities, a process termed binaural hearing (Blauert, 1996), which enables precise localization of sound sources in complex auditory environments. An important advantage of binaural hearing is demonstrated by the ‘cocktail party effect’, which showcases the system’s capacity to concentrate on individual sounds while suppressing background noise (Cherry, 1953). An understanding of the auditory system is essential for comprehending its limits and creating more immersive binaural experiences for entertainment purposes (W. Zhang et al., 2017). It also helps to improve hearing aid devices by enhancing auditory signal reception and improving spatial awareness (Hirsh, 1950; Thiemann et al., 2016).

The advancement of sophisticated machine learning techniques, particularly deep learning networks, has prompted an intriguing exploration into the extent to which these tools can emulate the human auditory system. This exploration proceeds without reliance on the advanced spatial audio feature engineering traditionally used in audio source localization, as evidenced by some prominent recent examples (Pang et al., 2019; Vera-Diaz et al., 2018; Yang & Zheng, 2022). While the application of convolutional neural networks (CNNs) (LeCun et al., 1989) — traditionally employed in the visual domain — to audio signals, particularly in conjunction with spectrograms (Espi et al., 2015; Thomas et al., 2014) or other feature engineering techniques (Abdel-Hamid et al., 2012; Sainath et al., 2013), is not novel. However, these approaches are continually being refined and adapted to the audio realm. Building on these foundations, this study developed an audio localization method by constructing a spectrogram-based multi-task CNN model.

Inspired by the fact, that humans tend to localize sound sources in groups rather than individually (Bregman, 1990; Rumsey, 2002), the objective of the proposed model is to predict ensemble location and width instead of positions of individual sources. This study is unique as it not only conceptualized the method but also tested it on a vast, real-life music corpus of 23,040 binaural excerpts that were synthesized using 192 multi-track music recordings (Senior, 2023) and 30 pub-

licly available head-related transfer functions (HRTFs) from various sources (see Table 1 in 5). The music recordings encompassed various genres, including rock, jazz, pop, and classical music.

The findings demonstrate that this method is effective in accurately predicting the spatial characteristics of sound sources in near-real-world scenarios. Furthermore, this paper demonstrates an experimental framework that facilitates the objective measurement of a binaural localization technique, employing a large-scale dataset synthesized from real-world music signal (for applications of similar frameworks, see: Antoniuk and Zieliński, 2023; Zieliński et al., 2020, 2022a, 2022b). One of the key advantages of the proposed method is that it does not assume the number of audio sources. However, significant limitations of this study include the absence of reverberation in the synthesized recordings and the method’s inapplicability to real-time scenarios — both are critical areas for future research.

The developed method has the potential to be highly beneficial in automated assessment tasks, where a significant number of binaural recordings must be evaluated and labeled in terms of their spatial content information. This may assist audio engineers in objectively assessing and segregating binaural audio recordings with regard to their spatial content. Furthermore, it could facilitate the development of an autonomous web-crawler bot that will collect binaural recordings from publicly accessible repositories and label them according to the spatial properties of the sound sources, such as the location of the music ensemble or the sparsity of audio source positions.

The remainder of this paper is organized as follows: Section 2 presents related studies. The description of the method developed for this study is provided in Section 3, which also includes detailed definitions of ensemble location and width, along with a description of the experiments used to evaluate this method. Section 4 discusses the results of the method-evaluation experiments conducted in this study. Finally, the paper concludes in Section 5.

2 Related studies

The majority of existing literature on the subject of sound source localization employs techniques that leverage the advantages of microphone arrays with more than two channels (Chung et al., 2022; Hahmann et al., 2022; Kaveh & Barabell, 1986; M. Liu et al., 2022; Pan et al., 2021; Pavlidi et al., 2012). In the context of sound source localization in binaural signals, the predominant focus of research is on the identification of individual sound sources, rather than groups of sounds (Benaroya et al., 2018; Dietz et al., 2011; Ma & Brown, 2016; Ma et al., 2017; May et al., 2011, 2012, 2015; Woodruff & Wang, 2012). In terms of source direction of arrival (DOA) methods, the majority of research assumes a fixed number of sound sources (Arthi & Sreenivas, 2021; Ma et al., 2017; Pang et al., 2019; Vera-Diaz et al., 2018; Woodruff & Wang, 2012), which limits its practical applications as this information is rarely known in real-life binaural recordings. Moreover, the majority of studies have focused on relatively homogeneous signals, namely speech (Benaroya et al., 2018; Dietz et al., 2011; Q. Liu et al., 2018; Ma & Brown, 2016; Ma et al., 2017, 2018; May et al., 2011, 2012, 2015; Wang et al., 2020; Woodruff & Wang, 2012; Yang & Zheng, 2022).

In contrast to the aforementioned studies, the proposed method is not constrained by the number of sources. Furthermore, the approach is not limited to speech and has been applied to a wide range of musical datasets, including instruments and vocals. In contrast to previous studies that primarily focused on individual sources, the proposed method does not aim to separate them, but rather considers them as a group, or in this case, a musical ensemble. This approach is similar to how the real musical ensembles are arranged on stage, thereby emphasizing practical applications in live settings. To the authors’ knowledge, this is one of the first methods to localize ensemble width (see Antoniuk and Zieliński, 2023 for the previous ensemble-width-related study), and the first to localize both ensemble position and width simultaneously using a multi-task model.

Sound localization methods can be classified into two categories based on the implementation of their underlying algorithms: glass-box (e.g., (Dietz et al., 2011; Ma & Brown, 2016; Ma et al., 2017, 2018; May et al., 2011, 2012, 2015; Woodruff & Wang, 2012)) and black-box (e.g., (Vera-Diaz et al., 2018; Yang & Zheng, 2022)). Glass-box methods, more traditional in the literature, rely on manually designed algorithms that mimic the auditory system to explicitly extract key features for location prediction, such as interaural level differences, interaural time differences, interaural coherence, or interaural phase differences (see Blauert, 1996 for feature descriptions). An example of one of the most advanced auditory models that is able to extract such features was developed by the Two!Ears project (Raake, n.d.).

In contrast, black-box methods generally employ minimal feature engineering, relying instead on advanced machine learning techniques to autonomously extract features and make predictions. These methods, while effective, do not explicitly reveal the features they extract nor necessarily

mimic the human auditory system. This opacity and the unpredictable nature of the outcomes, coupled with their dependency on deep neural networks that have extensive learning parameters, require the use of very large datasets for development and evaluation. Such datasets often include thousands of examples, as seen in the TIMIT corpus with 6300 examples (Garofolo et al., 1993) used in multiple studies (Benaroya et al., 2018; Ma et al., 2017, 2018; May et al., 2015; Pang et al., 2019; Vera-Diaz et al., 2018; Wang et al., 2020; Yang & Zheng, 2022), or custom corpora comprising hundreds of thousands of recordings (Antoniuk & Zieliński, 2023; Zieliński et al., 2020, 2022a, 2022b). This poses a significant challenge in assembling a sufficiently large and diverse collection of labeled binaural recordings. However, this challenge can be addressed through the synthesis of binaural sounds, as demonstrated in various studies (Antoniuk & Zieliński, 2023; Ma et al., 2018; Yang & Zheng, 2022; Zieliński et al., 2020, 2022a, 2022b) and further elaborated upon in Section 3.2 of this paper.

3 Methodology

This section presents a detailed description of the main objective of the model developed as part of this study, as outlined in Section 3.1. It also describes the audio dataset used for training and evaluating the model, as detailed in Section 3.2. In Section 3.3, the feature extraction procedure is presented. Section 3.4 describes the model topology, whereas Section 3.5 address model training and evaluation.

3.1 Ensemble location and width definition

The objective of the model developed in this study is to predict the ensemble location (θ) and width (ω), as illustrated in Figure 1. An ensemble is defined as a group of audio point sources positioned on a circle around the listener on a virtual acoustic scene with equal distance to the listener. The location of source i is denoted by θ_i . The ensemble width (ω) is defined as the angular width between two extreme point sources ($\max_i(\theta_i) - \min_i(\theta_i)$), while the ensemble location, designated by θ , represents the middle angle between two extreme sound sources ($(\max_i(\theta_i) + \min_i(\theta_i))/2$). For the purposes of this study, the locations of the sources were limited to the frontal hemisphere only, i.e. $\theta \in [-45^\circ, 45^\circ]$, $\omega \in [0^\circ, 90^\circ]$, as this range encompasses the majority of real-world recording scenarios. It should be noted that although humans possess some limited abilities to localize sound sources in the vertical plane, in this study all sources are placed in the horizontal plane, at the height of the listener. This covers the majority of cases for real-world recordings (see Ma et al., 2018; Zieliński et al., 2022a for related studies that cover top-down discrimination).

3.2 Synthesis of binaural music recordings

The experiments conducted in this study involved 23,040 binaural recordings of music. The binaural recordings were synthesized using 192 multi-track publicly-available music recordings (Senior, 2023) and 30 HRTF databases (see Table 1 in Appendix A for a detailed list of HRTF databases used in this study). The number of tracks in multi-track recording ranged from 5 to 62, with median of 9. For each pair of a multi-track recording and an HRTF database, four binaural recordings were synthesized with different random ensemble parameters, namely location θ and width ω , as defined in Section 3.1. Both parameters were drawn from a uniform random distribution. Furthermore, the tracks of the input multi-track recordings were randomly assigned to sound source positions (θ_i) to enhance the diversity of the final binaural corpora. Before the synthesis, the tracks were equalized to -23 LUFS, in accordance with the ("ITU-R BS.1770-5", 2023) recommendation.

The binaural recordings were obtained in this study using the binaural synthesis procedure, known as binauralization, whose aim was to simulate the positions of sound sources within a virtual acoustic environment (Blauert, 1996). This was achieved by convolving multi-track signals with head-related impulse responses from a specified head-related transfer function (HRTF) database. The resulting binaural output signal $y_c[n]$ for each stereo channel c (left or right) at sample n is given by the following equation:

$$y_c[n] = \sum_{i=1}^N \sum_{k=0}^{K-1} x_i[k] \times h_{c,\theta_i}[n-k], \quad (1)$$

where x_i represents the signal of an individual sound source i from the input music recording and h_{c,θ_i} denotes the head-related impulse response for channel c at location θ_i of source track i .

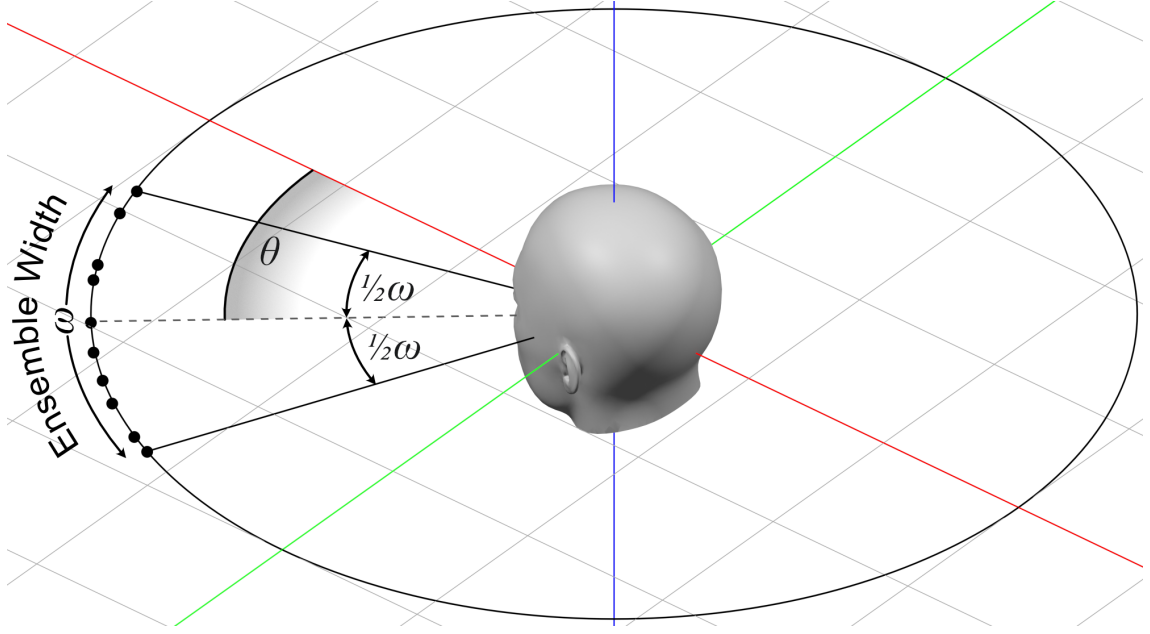


Figure 1: Illustration of ensemble width (ω) and ensemble location (θ) that are relative to the direction of the head. Black dots represent the positions of audio sources θ_i . The ensemble location (θ) is defined as the angular position of the center of the ensemble relative to the direction the head is turned. The ensemble width (ω) is defined as angular distance between two extreme audio sources.

Due to copyright restrictions, the music corpus utilized in this study was not published and can be provided upon request to the authors of this paper.

3.3 Feature extraction

Prior to input into the model, the binaural recordings of music were transformed into magnitude spectrograms. Although spectrograms do not directly provide information that can be translated into ensemble features, especially ensemble width, the goal of this task was to reduce the number of independent variables compared to the raw audio signal by extracting more compressed and informative data in the frequency domain. This step was necessary to decrease the likelihood of overfitting, reduce the number of examples needed to train the model, and thereby lower the overall computational power requirements. It is worth mentioning, however, that recent methods have shown that CNNs can be suitable for end-to-end audio localization without the spectrogram extraction step (Vecchiotti et al., 2019; Vera-Diaz et al., 2018).

On the computational side, the spectrograms were treated as three-dimensional floating-point precision feature matrices. The spectrograms were calculated using the Fast Fourier Transform (FFT) algorithm, with a limitation of 150 bands spaced linearly from 100 Hz to 16 kHz. Additionally, a Hamming window of 40 ms was applied to each frame of the signal, resulting in a total of 349 time frames. This procedure was conducted for both the left and right channels, yielding two spectrograms for each binaural sample. Each sample was represented by a matrix of dimensions $2 \times 349 \times 150$. This method parallels the procedure presented by Zieliński et al., 2022b.

3.4 Network topology

The network topology employed in this study, depicted in Figure 2, was significantly influenced by the AlexNet convolutional neural network demonstrated by Krizhevsky et al., 2012. Although AlexNet was originally designed for image classification, this study adapted it for the audio prediction task by converting binaural recordings into magnitude spectrograms, as described in Section 3.3. This conversion allowed the spectrograms to be treated as images, enabling their use in a standard image-prediction-like task.

The network accepts two spectrograms as inputs, and its architecture consists of a series of convolutional units followed by classification units, culminating in two output heads for predicting ensemble width and location. The architecture was designed in a multi-task fashion, enabling a single network to predict both ensemble parameters simultaneously. This multi-task capability is

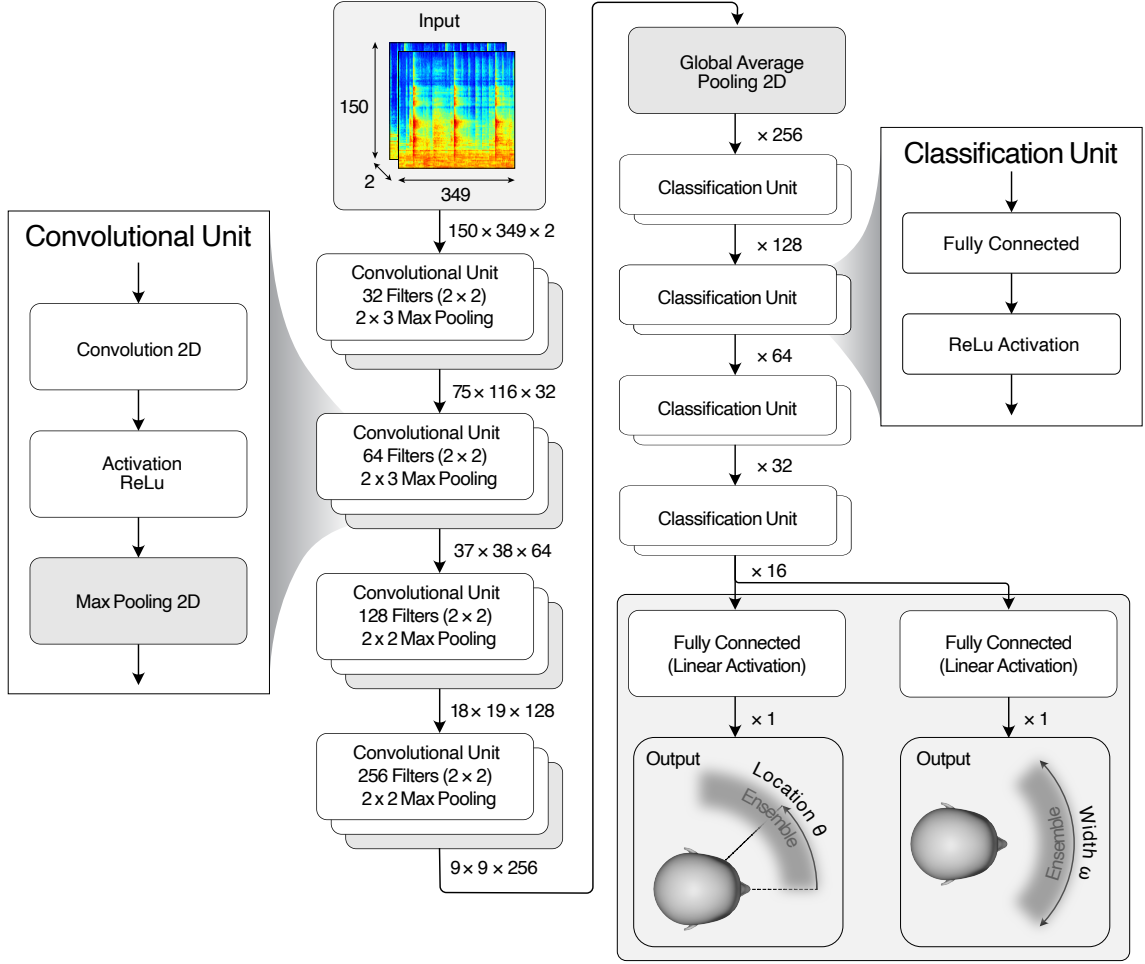


Figure 2: Topology of the Convolutional Neural Network (CNN) used for identifying ensemble location and width

achieved by connecting the output of the final classification unit to two separate outputs, one for each ensemble parameter.

The topology finalized in this study was selected based on the highest prediction quality observed on the validation dataset. Despite the existence of numerous algorithms for automatic topology selection (Branke, 1995; Miikkulainen et al., 2017; Shafiee et al., 2016; Stanley & Miikkulainen, 2002; H. Zhang et al., 2018), the final topology selected in this study was determined manually, based on its superior prediction quality observed on the validation dataset. This approach was necessitated primarily by the high computational demands compared to the available resources.

Various architectural configurations were assessed, varying key parameters such as the number of convolutional layers (from 1 to 5), the number of classification units (from 1 to 5), the inclusion or exclusion of Max Pooling Layers after each Convolution Layer, the number of filters within the Convolution Layers, the dimensions of these filters (2×2 , 2×3 , or 3×3), the stride size, and the dimensions of the Max Pooling Layers (2×2 , 2×3 , or 3×3). Although a detailed account of the selection process for the topology is beyond the primary scope of this study — particularly considering the task’s complexity — it was concluded that the Convolutional Neural Network (CNN) model is robust against variations in the assessed topologies. The differences in mean prediction error among the configurations were minimal, typically less than 1° for most configurations. Among the many tested topologies that yielded almost identical errors, the simplest one was chosen to optimize both performance efficiency and model simplicity.

Despite the availability of widely used techniques for addressing overfitting, such as the Dropout Layer (Srivastava et al., 2014), and for accelerating training, such as Batch Normalization (Ioffe & Szegedy, 2015), neither technique was employed in this study due to their observed ineffectiveness for the specific prediction task at hand. Instead, a Global Average Pooling Layer (Lin et al., 2013) was utilized, known for its proven capabilities in reducing overfitting. In this particular task, the inclusion of this layer significantly reduced overfitting, lowering the final mean absolute error score

by 0.83° (average across 10 trials) compared to configurations using a Flattening Layer.

3.5 Model training and evaluation

The topology described previously resulted in a model with 216,562 learning parameters. This model was trained 10 times from scratch, employing the Monte Carlo cross-validation method (Kuhn & Johnson, 2013). For each iteration, the entire dataset was randomly divided into two parts: a development set containing two-thirds of the dataset (15,360 recordings) for model construction, and a test set comprising the remaining one-third (7,680 recordings) for evaluation. The development set was further subdivided into training and validation subsets at a 7:1 ratio, with 13,440 recordings allocated to the training subset and 1,920 recordings to the validation subset.

The training subset was employed to update the model’s learning parameters, while the validation subset was utilized for implementing the early stopping technique (Morgan & Bourlard, 1989; Pocock & Hughes, 1989) in conjunction with model checkpointing (Eisenman et al., 2020). These methods played a crucial role in selecting the model that demonstrated the best generalization capabilities. The test subset, containing data not previously encountered in the training or validation phases, was used exclusively for performance assessment once per iteration. This process was repeated to collect 10 mean absolute errors, from which the final model error was determined. The quantified mean absolute error and its standard deviation illustrated the model’s prediction quality, generalization capabilities, and reproducibility.

For each sample, the model received two spectrograms as input: one for the left channel and one for the right channel. The rationale behind the application of Convolutional Neural Networks (CNNs) to this task was to automatically extract local features from the spectrograms and use these features to predict two contiguous ensemble parameters: ensemble location and width, both measured in degrees. The prediction errors, calculated as the difference between the actual ensemble parameters (known from the binaural synthesis described in Section 3.2) and the predicted values, were utilized in the Adam learning algorithm (Kingma & Ba, 2014). During training, the losses for both outputs were combined by summing them, thereby treating both ensemble features with equal importance.

All computations in this study were conducted on a workstation equipped with an RTX Nvidia GeForce 4090 GPU and a 48-core AMD Ryzen ThreadRipper processor. The binaural recordings were synthesized using the MATLAB (Inc., 2022b) environment with the Audio Toolbox (Inc., 2022a). Feature extraction and model training were performed in the Python (Van Rossum & Drake, 2009), utilizing the SciPy (Virtanen et al., 2020) library for feature extraction and Keras for training the CNN model. The complete source code for all stages of the process has been made available by the authors and is accessible to the public at GitHub (Antoniuk, 2024). The feature extraction phase required 21 minutes, data partitioning took 34 minutes, and the total training time for all iterations was 40 minutes. In total, the entire training and evaluation process required 95 minutes.

4 Results

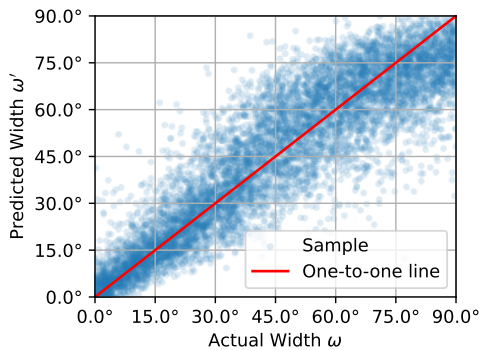


Figure 3: A comparison between the actual ensemble width ω and the predicted ensemble width ω' for a single iteration (of the total five)

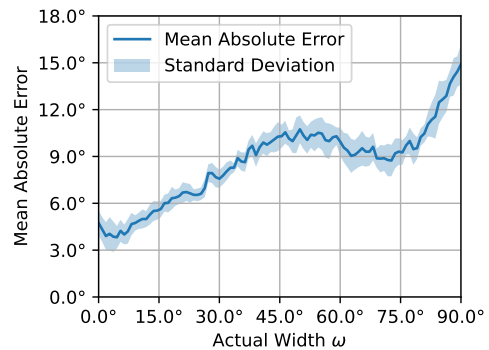


Figure 4: The impact of the actual ensemble width ω on the mean absolute prediction error, averaged across all five iterations, with indicated standard deviation.

Figure 3 illustrates the comparison between the actual and predicted ensemble widths. The results demonstrate that the model exhibits better prediction quality for narrower ensemble widths (5.65° for $\omega < 30^\circ$) and that its performance deteriorates with an increase in ensemble width (12.44° for $\omega > 80^\circ$). This suggests that the actual ensemble width significantly impacts the accuracy of ensemble width estimation, leading to worse predictions as width increases. Figure 4 further demonstrates that the relationship between the error and the width is not linear, exhibiting an interesting depression between 60° and 75° .

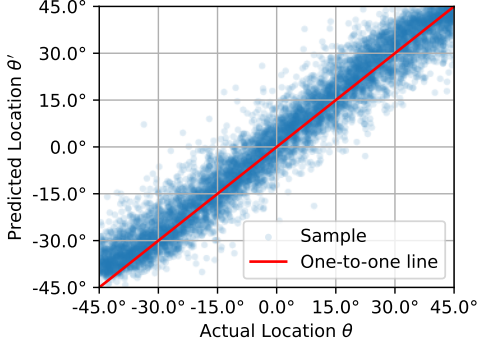


Figure 5: A comparison between the actual ensemble location θ and the predicted ensemble location θ' for a single iteration (of the total five)

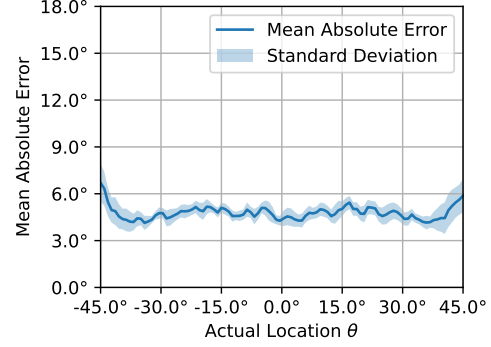


Figure 6: The impact of the actual ensemble width ω on the mean absolute prediction error, averaged across all five iterations, with indicated standard deviation.

In contrast to the correlation between ensemble width and its prediction error, there is no significant relationship between the actual location and its prediction error, as illustrated in Figures 5 and 6. This finding indicates that the model's capabilities for localizing the center of the ensemble is robust, unaffected by the actual spatial positioning of the ensemble, including lateral locations.

The mean absolute prediction error for ensemble width was 8.57° ($\pm 0.19^\circ$), while the error for ensemble location prediction was 4.76° ($\pm 0.10^\circ$). Although both ensemble parameters were constrained within the same angular span of 90° , the ensemble location was predicted with significantly better precision — approximately 80% better. This shows that the model prediction quality is much better for ensemble location prediction than width prediction. This difference can be attributed to the fact that the model's performance on ensemble width deteriorates significantly for wider ensembles, whereas location prediction remains largely unaffected. For a visual comparison, please refer to Figures 6 and 4.

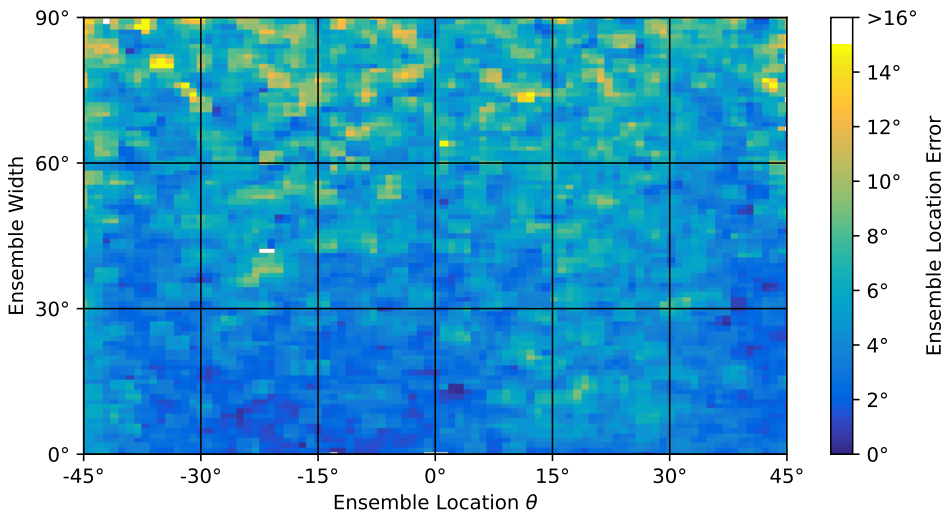


Figure 7: The heatmap that illustrates the mean absolute error (MAE) of ensemble location distribution across different ensemble locations (x-axis) and ensemble widths (y-axis). The color intensity corresponds to the MAE values, with lighter areas indicating higher errors.

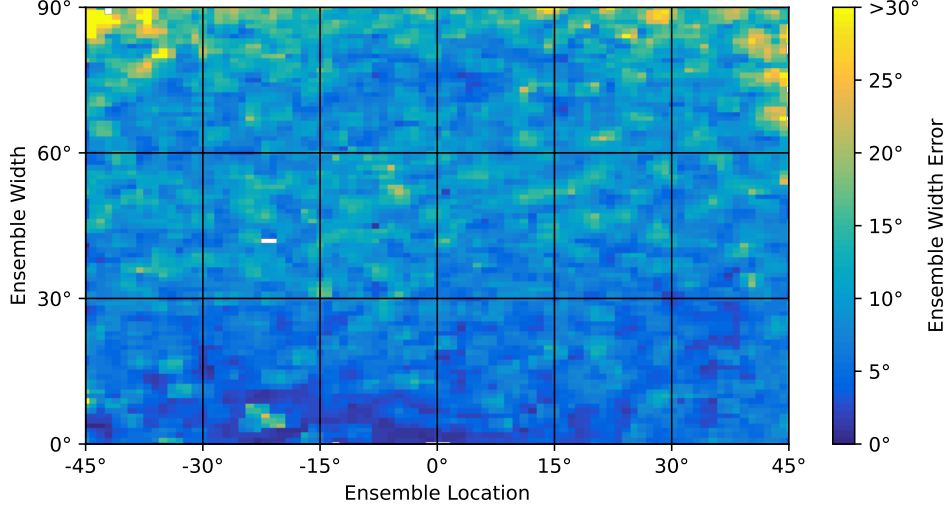


Figure 8: The heatmap that illustrates the mean absolute error (MAE) of ensemble width distribution across different ensemble locations (x-axis) and ensemble widths (y-axis). The color intensity corresponds to the MAE values, with lighter areas indicating higher errors. Notably, the values between 30° and 60° on the y-axis exhibit unexpectedly higher MAE values region — please see Figure 4 for comparison.

Figure 7 illustrates the influence of both ensemble location and width on the mean absolute error for ensemble location, offering a detailed view complementing the results presented in Figure 6. Some asymmetric anomalies are depicted in this figure, mostly within the $\theta \in [15^\circ, 30^\circ]$ region, which can be attributed to the sparsity of sample result data across this heatmap. Although this figure primarily shows that ensemble location does not significantly influence the model’s location prediction accuracy, it does demonstrate that ensemble width has a significant impact. Similarly, Figure 8 reveals a characteristic depression in $\omega \in [30^\circ, 60^\circ]$ previously shown from a different perspective in Figure 4. This heatmap highlights another interesting phenomenon in its upper corners — the error in these areas is considerably higher. This indicates that the model’s performance for estimating ensemble width is substantially worse at extreme widths and locations, i.e., when both the width and locations are at their maximum.

5 Conclusions

Appendix A

Table 1: List of HRTF sets used to synthesize binaural audio excerpts

No.	Type	Head	Radius [m]	Source	Acronym
1.	Human	Human subject	1.2	RWTH Aachen University (Braren & Fels, 2020)	AACHEN
2.	Artificial	GRAS 45BB-4 KEMAR	1		
3.	Human	Subject 2	1.2	Austrian Academy of Sciences (“HRTF-Database”, n.d.)	ARI
4.	Human	Subject 4	1.2		
5.	Human	Subject 10	1.2		
6.	Artificial	ARI Printed Head	1.2		
7.	Human	Subject 012	1	CIPIC Interface Laboratory, University of California (Algazi et al., 2001)	CIPIC
8.	Human	Subject 015	1		
9.	Human	Subject 020	1		
10.	Artificial	Neumann KU 100	0.9	NASA (2007) (Andreopoulou et al., 2015)	CLUBFRITZ
11.	Artificial	Neumann KU 100	1.5	Helsinki University of Technology (2009) (Andreopoulou et al., 2015)	
12.	Artificial	FABIAN	1.47	Technical University Berlin, Huawei Technologies, Munich Research Centre, Sennheiser Electronic (Brinkmann et al., 2019)	HUTUBS
13.	Human	Subject pp2	1.47		
14.	Human	Subject pp3	1.47		
15.	Human	Subject 1003	1.95	IRCAM, AKG (“LISTEN HRTF DATABASE”, 2023)	LISTEN
16.	Human	Subject 1002	1.95		
17.	Artificial	KEMAR DB-4004 (DB-061)	1.4	MIT (Gardne & Martin, 1994)	MIT
18.	Artificial	KEMAR DB-4004 (DB-065)	1.4		
19.	Human	Subject 001	1.5	Tohoku University (Watanabe et al., 2014)	RIEC
20.	Human	Subject 002	1.5		
21.	Artificial	Koken SAMRAI	1.5		
22.	Artificial	Neumann KU 100	1.2	University of York (Armstrong et al., 2018)	SADIE II
23.	Human	Subject H3	1.2		
24.	Human	Subject H4	1.2		
25.	Artificial	KEMAR	1	South China University of Technology (Yu et al., 2018)	SSCUT

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Table 1: List of HRTF sets used to synthesize binaural audio excerpts (Continued)

26.	Artificial	Neumann KU 100	1	TH Köln (Pörschmann et al., 2017)	STH Köln
27.	Artificial	FABIAN	1.7	TU Berlin (Brinkmann et al., 2017 ; Wierstorf et al., 2011)	TU Berlin
28.	Artificial	GRAS 45BA KEMAR	1		
29.	Artificial	GRAS 45BB-4 KEMAR - subject A attachment	1	Aalborg University; University of Iceland (Spagnol, 2019 ; Spagnol et al., 2020)	VIKING
30.	Artificial	GRAS 45BB-4 KEMAR - subject B attachments	1		

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