A Signal Detection Theory Model of Binaural Cue Reweighting

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BACKGROUND

- When determining the sound source azimuth, humans rely on the binaural cues: interaural time difference (ITD) and interaural level difference (ILD).
- A specific relative weight is applied to each cue when the cues are combined, typically estimated as the "trading ratio" (Moore at el., 2020).
- Normal-hearing (NH) listeners primarily use ITDs at low frequencies and ILDs at high frequencies (Macpherson & Middlebrooks, 2002). However, the weighting is not always optimal (Ihlefeld & Shinn-Cunningham, 2011), as many other factors influence binaural cue weighting (overall level of the sound, active manipulation of one of the cues, and room acoustics). Hearing-impaired (HI) listeners often use a different weighting (e.g., Cochlear-Implant (CI), users only use ILD at all frequencies).
- Therefore, **if it is possible to train people to use the best weighting under specific conditions, that might improve spatial hearing in both NH and HI listeners.**
- Previous studies of binaural reweighting produced mixed results:
  - No reweighting effect in discrimination training around 0 values of ITD/ILD (Jeffress & McFadden, 1971)
  - ILD (but not ITD) weights increased during task performance with no feedback (Kumpik et al., 2019)
  - Reweighting induced in both directions by audiovisual (AV) training (Klingel et al., 2021)
  - Reweighting of spectral components generalized always to an increase of ILD weight (Spisak et al., 2021)

Klingel et al. (2020) proposed **an adaptive discrimination training protocol** that **worked** for **ILD** reweighting**. Singhal et al. (2023)** showed that the **training** also **works** for **ITD** reweighting**.** The training has several **advantages** (re. the AV training of Klingel et al. 2021)**:** 1) it is **simple** (no AV virtual environment needed), 2) it is **not expected** to result in **compression of space**, and 3) it is **individualized.** However, the **performance measure** used in those studies has several **disadvantages** (see below) and the **temporal profile** of the **training** has not been analyzed.

CURRENT STUDY

Following up on the Klingel/Singhal studies, the current study has 2 goals:

1. Propose a **Signal Detection Theory** based model (using the 2I-2AFC model of Durlach., 1968) that provides a robust estimate of the relative binaural cue weight related to the trading ratio.
2. Perform **analysis of the training-session** data to examine the time course of training within and between training sessions & its dependence on other training parameters.

EXPERIMENT OF KLINGEL/SINGHAL

Experimental procedure and results from Klingel et al. (2020) and Singhal et al. (2023).
Three subject groups:

ITD target group: Trained to increase ITD weight (14 subjects)
ILD target group: Trained to increase ILD weight (11 subjects)
Control group: No training (11 subjects)

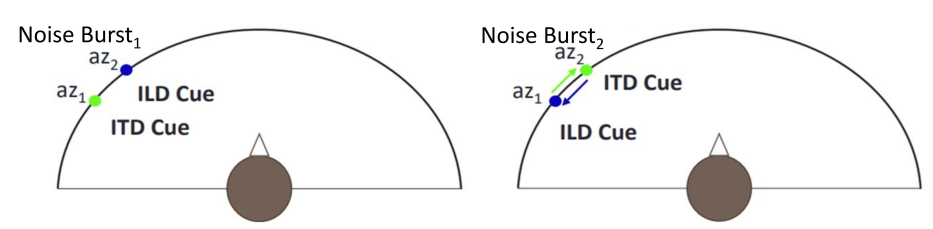
Design: Day 1: **Pretest** (all groups) + **1st Training Session** (training groups only)
Day 2: **2nd Training Session** (training groups only)
Day 3: **3rd Training Session** (training groups only) + **Posttest** (all groups)

Stimuli: 500-ms narrow-band noise bursts (2-4 kHz) with 50-ms on/off ramps
Each stimulus consisted of two noise bursts separated by a 0-ms gap
Train/Test trials: incongruent combinations of ITDs and ILDs in each noise burst
Catch trials: ITD/ILD congruent but different between the noise bursts

Task: Each trial consisted of
- stimulus presentation (2 consecutive noise bursts),
- subject's response (Did the stimulus move to the "left" or "right"?),
- in training: 1. feedback. 2. after wrong response, stimulus presented again.

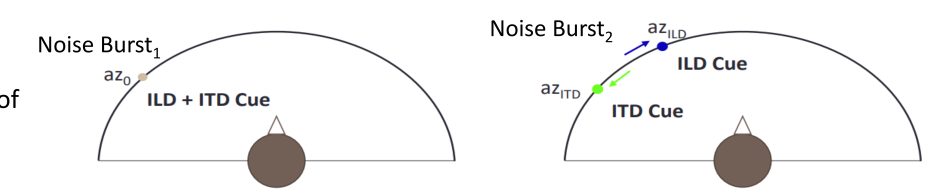
One test trial (Fig. 1):
Two azimuths az_1 and az_2 were randomly selected (range ±70.2°, disparity up to 25.2°). Noise Burst$_1$ had ITD corresponding to az_1 and ILD corresponding to az_2. For Noise Burst 2 the ITD and ILD was swapped.

Figure1: Design of a test trial



One training trial (Fig. 2):
Noise Burst$_1$ was presented from randomly selected az_0. Noise Burst$_2$ had the az offset of the trained cue (eg az_{ITD}-az_0) set adaptively using 2-down-1-up procedure. Direction of trained cue shift was random; non-trained cue always shifted in opposite direction. 3 adaptive tracks run in parallel. Disparity az_{ILD}-az_{ITD} (18, 21.6 and 25.2°) was fixed within adaptive track.

Figure2: Design of a training trial.



Results (Fig. 3):
Pre vs. posttest: Proportion of trials in which responses followed ILD (P_{ILD}) was used as the estimate of the weight of the ILD vs. ITD cues. (P_{ILD} = 1 means subjects only used ILD).

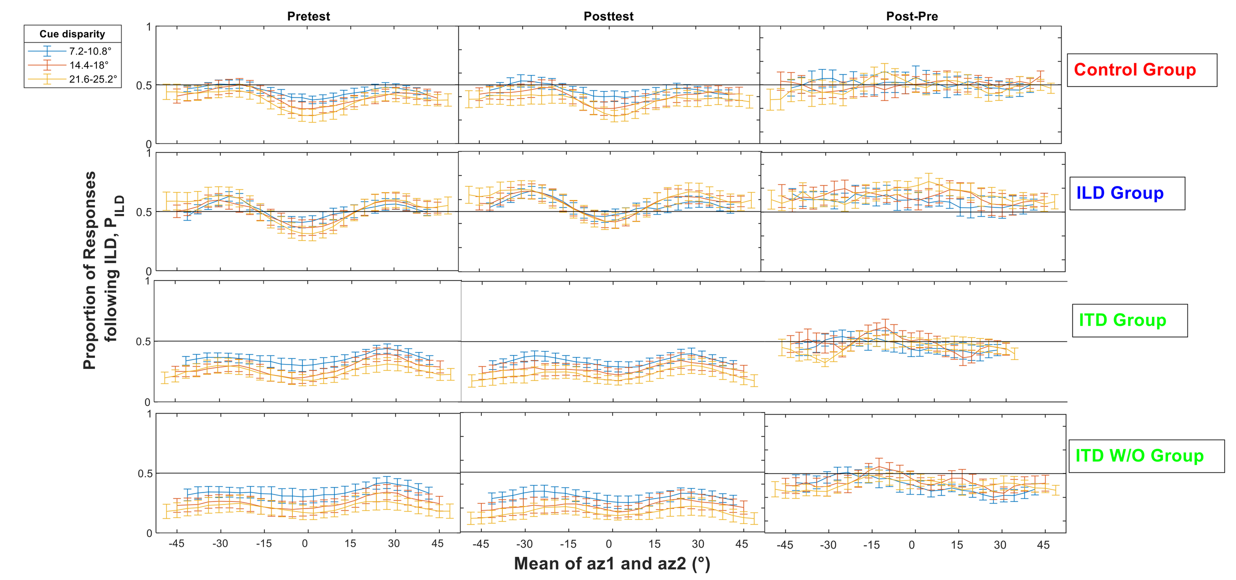


Figure 3 : Across-subject mean (±SEM) P_{ILD} as a function of the mean of az_1 and az_2 plotted separately for different az_1-az_2 cue disparities. Results for ITD group shown separately with and without outliers.

Training worked for ILD Group. For ITD group, training worked only after catch-trial-based outliers were excluded.

MODELING

P_{ILD} measure is problematic as:

- it depends on the stimulus azimuth and disparity (see Fig. 3),
- its susceptibility to noise grows with decreasing disparity, reducing the reliability of the estimated P_{ILD}, and
- it is difficult to use it to derive one generalizable measure of relative the ITD/ILD weight, like the trading ratio.

Using the 2I-2AFC discrimination model of Durlach (1968) and using the assumptions similar in Kopčo et al. (2012), we propose a model that predicts P_{ILD} as a function of w_{LT}, the estimated relative weight of the ILD vs. ITD cues, using the equation:

$$P_{ILD} = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\frac{d}{2}} e^{\frac{-t^2}{2}} dt \quad \text{where} \quad d = w_{LT} * |az_2 - az_1|.$$

- d is a d'-like measure that represents the sensitivity to ILD vs. ITD (however, it can be both positive, when responses follow ILD, and negative, when responses follow ITD).
- d is proportional to w_{LT} scaled by the disparity between the two stimuli.
- w_{LT} is the relative ILD/ITD weight for azimuthal disparity of 1° and is in units of deg^{-1}
- w_{LT} is 0 when the cues are weighted equally, positive when ILD is weighted more and negative when ITD is more.
- w_{LT} characterizes all the data with a single number, independent of azimuth, disparity.

The model's w_{LT} was fitted on P_{ILD} data averaged across azimuths since the difference in P_{ILD}'s is approximately independent of azimuth (Fig. 3). Nonlinear fitting was used, optimizing the weighted RMS error between the predicted vs. measured P_{ILD} to obtain the fits that mostly rely on the large disparity, given that the small-disparity P_{ILD}'s are noisier.

Model visualization (Figs. 4, 5):
Based on Durlach (1968), the model uses a real random variable X (the "decision axis") which has the property that each noise presentation determines a value of X (Fig. 4).

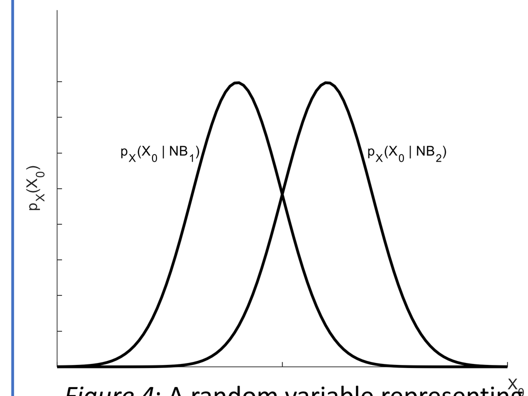


Figure 4: A random variable representing the two stimuli NB1 and NB2.

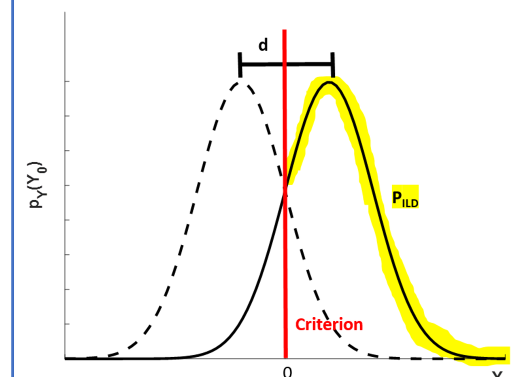


Figure 5: A random variable representing the shift of percept from NB_1 and NB_2 and the decision model.

In our experiment, two noise bursts are presented, NB_1 and NB_2, and the conditional probabilities p() represent the distributions of values of X for the two noises. Note that in this illustration, NB_1 is to the left of NB_2. If az_1 and az_2 are swapped, then the two distributions get reversed.

In *Fig.5*, each stimulus determines a value along the random variable Y, representing the internal percept's shift magnitude (i.e., difference between percepts NB_2 - NB_1). Assuming ILD moved to the right and that ILD is weighted more than ITD (i.e., w_{LT} is positive), the differential shift percept is most likely to be positive (i.e., right of the criterion). This is represented by the solid Gaussian distribution, while the dashed-line Gaussian distribution represents the situation if the stimulus order is reversed (i.e., az_1 and az_2 are swapped). The red line represents the optimally placed criterion. Then P_{ILD} is the integral of this distribution over the area where the shift percepts (random variable Y) followed ILD (highlighted area). Note that this distribution will shift to the right when the disparity $|az_2$-$az_1|$ increases, and it will move to the other side of the criterion if w_{LT} is negative.

Results (Figs. 6 and 7):

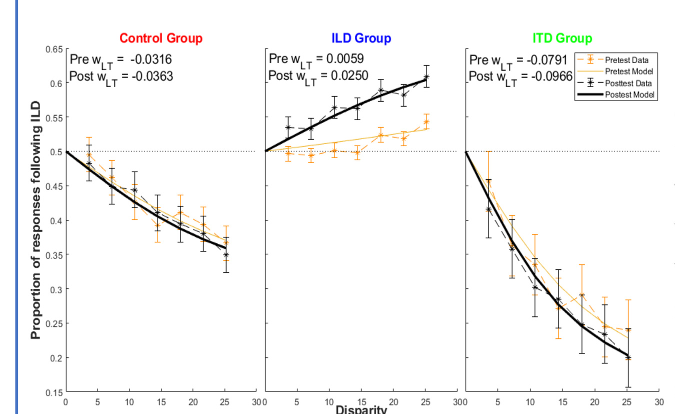


Figure 6: Across-subject average (±SEM) P_{ILD} and model fits as a function of disparity, averaged across azimuths

Fig. 6 shows the P_{ILD} data from top three rows of Fig. 3 averaged across azimuths and plotted as a function of disparity, along with the average predictions of the model fitted to each individual. The model fits are very accurate. The across-subject average values of the pretest and posttest w_{LT} are shown in the insets in Fig. 6 and the individual fits (along with the averages) are shown in Fig 7.

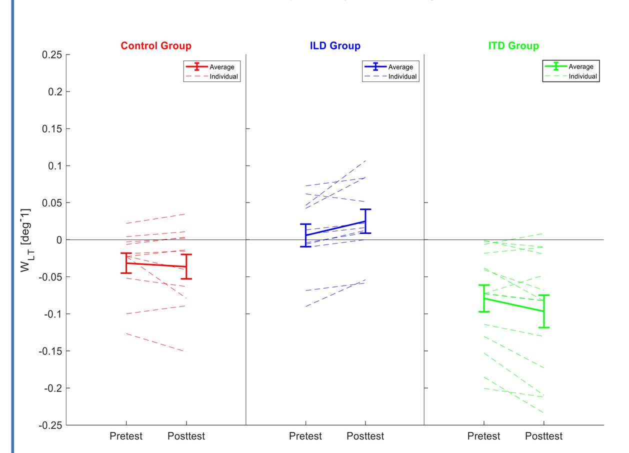


Figure 7: Pretest and posttest weights w_{LT} estimated for individual subjects and averaged (±SEM).

Fig. 7 shows that training worked for both **ILD** and **ITD** groups. RM ANOVA with factors of group and time found a significant group X time interaction ($F_{2,33}$ =8.54, p = 0.001) and post-hoc t-tests performed separately on both groups were significant (**ILD**: p = 0.009; **ITD**: p = 0.019). The average difference in weights were 0.02 deg^{-1} for **ILD** group and -0.017 deg^{-1} for **ITD** group.

There are also slight differences in absolute values of w_{LT} across the groups. While their source is unknown, they are unlikely to drive the effect, as they are in opposite direction to what would drive the effect randomly.

If evaluated using the model-based estimates of pretest vs. posttest weights, the training worked for both ILD and ITD groups with similar strength.

Weight w_{LT} vs. Trading Ratio

ILD/ITD weight w_{LT} is a difference in the effects of ILD/ITD for a unit angle in units deg^{-1}.
Trading ratio (TR) is a ratio of ILD vs. ITD at which they cancel each other, in units of [dB/μs].
Assuming a linear mapping between azimuth and ILD/ITD (ITD_{az} / ILD_{az}), the relationship is:

$$w_{LT} = k * \log(TR * ITD_{az} / ILD_{az})$$

where *k* is a scaling factor to be determined, e.g., by simulation.

TRAINING SESSIONS

We analyzed how the performance changed in adaptive tracks within and between the three training sessions (days) among **ILD group** and **ITD Group**.

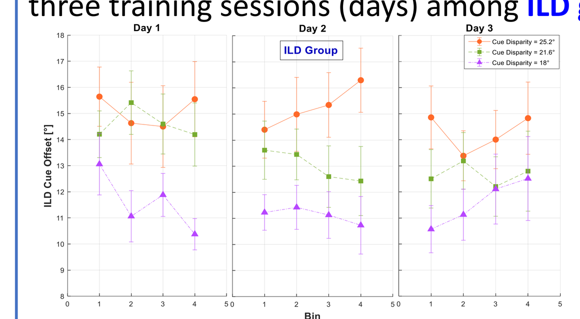


Figure 8: ILD (trained) Cue Offset at Reversals during adaptive training runs for **ILD Group**

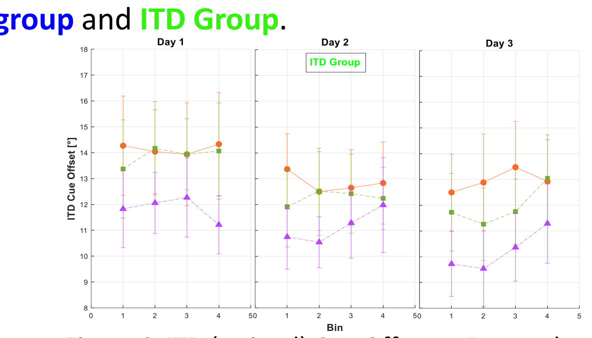


Figure 9: ITD (trained) Cue Offset at Reversals during adaptive training runs for **ITD Group**

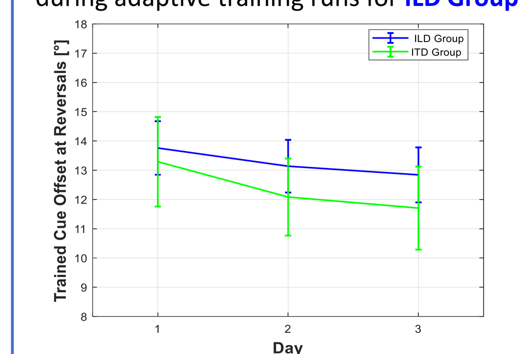


Figure 10: Trained cue offset from Figs. 8 and 9 averaged across bins and disparities.

Figs. 8 and 9: Reversals in the adaptive tracks were analyzed after the first 20 trials (approx. 2 reversals). Average trained cue offset in 10-reversal bins is plotted for the first 4 bins of each adaptive run, separately for each disparity (adaptive track), day and group. Fig. 10: Data from Figs. 8 & 9 averaged across bins and disparities. RM ANOVA found significant main effects of day ($F_{2,46}$ = 8.5, p = 0.0007) and disparity ($F_{2,46}$ = 44.7, p < 0.0001) .

In both groups, performance improved between and not within training sessions. → Adaptation is slow and/or needs consolidation during breaks.

CONCLUSIONS

- Using Signal Detection Theory modeling, we derived a relative weight estimate w_{LT}, related to the training ratio, that is independent of the stimulus azimuth/separation, and that appropriately weights the reliability of estimates when combining the data.
- Using w_{LT}, we observed the training effect was approximately equally effective for both ILD and ITD training groups (without excluding any outliers, as in Singhal et al., 2023).
- Discrimination training resulted in gradual improvement over 3 days. Thus, further training might have brought stronger effects. On the other hand, AV training only improved performance on training day 1 (out of 7) in Klingel et al. (2021).

FUTURE WORK

- Extend the model to make it applicable to the lateralization training results of Klingel et al., (2021) and Spisak et al. (2021) which used absolute localization responses instead of discrimination in testing. Thus, results of modeling will allow us to compare the effectiveness of the training methods.
- Perform an analysis of the cues to test the hypothesis that the variations in the rates of ILD and ITD change with azimuth are responsible for the azimuthal dependence of P_{ILD}.
- Integrate the discrimination training into existing brain training game "Listen" (developed by Brain Game Center at Northeastern University).
- Examine the neural basis of the reweighting by using neuroimaging (e.g., EEG).

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