

# TOWARDS ROBUST DATA-DRIVEN UNDERWATER ACOUSTIC LOCALIZATION: A DEEP CNN SOLUTION WITH PERFORMANCE GUARANTEES FOR MODEL MISMATCH

## SUPPLEMENTARY MATERIALS

*Amir Weiss<sup>\*</sup>, Andrew C. Singer<sup>†</sup>, and Gregory W. Wornell<sup>\*</sup>*

<sup>\*</sup>Research Laboratory of Electronics  
Massachusetts Institute of Technology  
{amirwei,gww}@mit.edu

<sup>†</sup>Dept. of Electrical and Computer Engineering  
University of Illinois Urbana-Champaign  
acsinger@illinois.edu

### 1. THE ACCOMPANYING CODE PACKAGE

The supplementary materials of this paper contain a code package with the implementation of the proposed data-driven CNN-based DLOC method, namely the neural network (NN) architecture to be trained, the training script, the script that generates the datasets (for training, validation and testing). To empirically compute the bound, and specifically for a code implementation of estimation of the chi-square divergence, see the code package associated with [1].

### 2. IMPLEMENTATION MODIFICATIONS

As mentioned in the paper, we consider the architecture proposed in [2], and introduce local, though still important, modifications to the code associated with [2]. Therefore, in the following, we point out and briefly explain these modifications relative to the original implementation.

#### 2.1. Fusion of the Global Model

The first modification was introduced based on the following observation. When the outputs of the three sub-models for estimation of range, azimuth and inclination are concatenated, simply by changing the loss function to the 3D squared-error in *spherical* coordinates, the gradients w.r.t. each coordinate depends on the other two coordinates as well. Therefore, when the global architecture is trained with this “global” loss, the set of weights of what was previously a sub-model for estimation of a single coordinate (e.g., range or azimuth) can no longer be associated exclusively with that coordinate. In other words, by using the aforementioned global loss function for training of the direct localization (DLOC) model, functional interrelations, induced by joint statistical properties, are being learned.

In particular, there is no need to introduce an additional “merging” layer of any kind (e.g., a dense layer) in order to enable such functional interrelations, that obviously exist, since one coordinate’s estimate is informative about the other (e.g., a range estimator can be statistically related to an azimuth estimator). Therefore, in the current implementation, and differently from the previously proposed architecture, the concatenated outputs of the three sub-models, which were previously and individually trained, are defined as the outputs of the global model. This modification appears in the file:

```
direct_localization_model_weights_spherical.py in  
the function:  
get_DLOC_model_weight_spherical
```

#### 2.2. Average Attenuation Magnitude Normalization

In [2], a relatively simple (3-ray) propagation model was considered. In this work, we consider a substantially more realistic propagation model, using Bellhop simulator [3], which was developed specifically to generate more advanced propagation models for the underwater acoustic domain.

Working with these richer, more challenging propagation models, based on our experimental experience we observed that the second modification (described below), which pertains to a numerical issue, was necessary for the successful training of the NN.

For a given set of environmental parameters (such as the soundspeed profile), and for a given (fixed) pair of source position and receiver position, the Bellhop simulator outputs an impulse response. This impulse response is the result of an approximated (not necessarily a straight line) ray propagation model in the form of time delays with associated attenuation coefficients. Thus, for a fixed volume of interest that defines (say, a uniform) a 3D prior over the source’s position, the physical propagation model induces a prior distribution over the attenuation coefficients. Naturally, the magnitudes, for example, may differ significantly with the source-receiver pair positions.

From a NN training perspective, we were able to successfully train the global NN DLOC model when a certain form of this prior, which is relatively reasonable to obtain, was incorporated into the training process. Specifically, based on all the impulse responses from the training dataset, we computed the average norm of all the attenuation coefficients, and normalize the unit-variance (i.i.d. complex normal) waveform of the source with this average. In this way, the model is able to learn the direct localization function approximation over a range of different signal-to-noise ratio (SNR) values. This modification appears in the files:

```
train_DLOC_model_script_bellhop_ID1.py  
and  
train_DLOC_model_notebook_bellhop_ID1.ipynb
```

### 3. THE BELLHOP SIMULATOR

As mentioned above, to go beyond the 3-ray isovelocity propagation model, in this work we use the Bellhop simulator [3]. Upon providing input that includes the source’s and receiver’s position, soundspeed as a function of depth, bathymetry, and other characterizing parameters that affect acoustic impulse response, Bellhop returns (among other possible outputs) a set of time of arrivals and corresponding attenuation coefficients, with which an impulse response, of the form used in our signal model (1), can be simulated.

The code for generating such an impulse response, with the specific values we have used for the various input parameters, is given in the file:  
generate\_impulse\_responses\_via\_Bellhop.py

The details in this file also define the two environments we considered in our simulation experiment, namely the set  $\mathcal{P}_{\text{env}}$  and  $\mathcal{Q}_{\text{env}}$ , denoting the “true” and “presume” environments, respectively.

The files:

`test_DLOC_model_bellhop_ID1_ICASSP2023.py`

that is also included in this package is for testing the trained NN.

More details about this part of the code, as well as the files for training the NNs, are given in the supplementary materials of [2].

#### 4. REFERENCES

- [1] J. J. Ryu, S. Ganguly, Y.-H. Kim, Y.-K. Noh, and D. D. Lee, “Nearest neighbor density functional estimation from inverse laplace transform,” *IEEE Trans. Inf. Theory*, 2022.
- [2] A. Weiss, T. Arikan, and G. W. Wornell, “Direct localization in underwater acoustics via convolutional neural networks: A data-driven approach,” in *Proc. 2022 IEEE 32nd Int. Workshop Mach. Learn. Signal Process.*, 2022, pp. 1–6.
- [3] M. B. Porter, “The BELLHOP manual and user’s guide: Preliminary draft,” *Heat, Light, and Sound Research, Inc., La Jolla, CA, USA, Tech. Rep*, vol. 260, 2011.