Towards Domain Independence in CNN-based Acoustic Localization using Deep Cross Correlations

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Abstract—Time delay estimation is essential in Acoustic Source Localization (ASL) systems. One of the most used techniques for this purpose is the Generalized Cross Correlation (GCC) between a pair of signals and its use in Steered Response Power (SRP) techniques, which estimate the acoustic power at a specific location. Nowadays, Deep Learning strategies may outperform these methods. However, they are generally dependent on the geometric and sensor configuration conditions that are available during the training phases, thus having limited generalization capabilities when facing new environments if no re-training nor adaptation is applied. In this work, we propose a method based on an encoder-decoder CNN architecture capable of outperforming the well known SRP-PHAT algorithm, and also other Deep Learning strategies when working in mismatched training-testing conditions without requiring a model re-training. Our proposal aims to estimate a smoothed version of the correlation signals, that is then used to generate a refined acoustic power map, which leads to better performance on the ASL task. Our experimental evaluation uses three publicly available realistic datasets and provides a comparison with the SRP-PHAT algorithm and other recent proposals based on Deep Learning.

Index Terms—Acoustic Source Localization, Generalized Cross Correlation, Steered Response Power, Convolutional Neural Networks, Deep Learning

I. INTRODUCTION

One of the critical tasks in Acoustic Source Localization (ASL) is the time delay estimation [1], [2] between signals recorded by a pair of acoustic sensors that are generated by an unknown acoustic source. With at least three of these pairs, it is possible to estimate the position of the acoustic source by using hyperbolic trilateration techniques. However, this process is not reliable in everyday scenarios with signals contaminated with noise and multipath effects. Other ASL methods are more robust to these effects such as those based on the Steered Response Power (SRP) techniques [3]–[7] or the Minimum Variance Distortionless Response (MVDR) techniques [8], [9]; all of them based on the Generalized Cross Correlation (GCC) technique [10].

In recent years, ASL methods based on Deep Learning techniques have appeared in the literature. In [11], they use raw acoustic signals to estimate the source position coordinates directly, and in [12], they use the signal spectra to estimate the Direction of Arrival (DoA) of the acoustic source. Their results are promising, reporting better accuracy than classical methods. However, they have significant limitations: 1) they require a large amount of labeled data for training, whereas there is limited availability of large and public datasets for ASL, and 2) learning techniques are highly dependent on the room and sensor geometry, and the training conditions. As a consequence, their accuracy dramatically degrades when used in other environments or outside the physical area used to generate training examples.

In this paper, we propose a method based on a Convolutional Neural Network (CNN). It takes the GCC of a pair of signals in its input and estimates a likelihood function where its maximum appears at the time-delay between the two signals. We then combine these likelihood functions in a 3D spatial grid, as proposed in classical SRP techniques. The target is similar to that described in [13], in which they propose a method to obtain the time-delay between two signals using the GCC and multilayer perceptrons with a single hidden layer. However, their system is only tested using artificial signals (chirps), so that it is not possible to assess its applicability in realistic scenarios.

Our contributions are the following: 1) our method is largely independent of the room and sensor geometry, 2) we can use small size datasets to train the neural network and 3) it is consistently more accurate than classical methods such as SRP-PHAT and also better than other Deep Learning methods in general conditions, where the testing room is physically different, or the source position significantly differs from those available in the training data.

II. PROBLEM STATEMENT

Let us consider an environment where we place $M$ microphones at known positions $\mathbf{m}_k = (m_{x_k}, m_{y_k}, m_{z_k})^T$ with $k = 0, \ldots, M - 1$. An acoustic source emits a signal $s(t)$
which is received and sampled by each microphone, obtaining a discrete-time signal $x_k[n]$ at the $k^{th}$ microphone.

In fully ideal conditions the signals received at microphones $k$ and $l$ from a source at position $\tilde{q} = (q_x, q_y, q_z)^T$ only differ in a time delay $\Delta \tau(\tilde{q}, \tilde{m}_k, \tilde{m}_l)$:

$$\Delta \tau(\tilde{q}, \tilde{m}_k, \tilde{m}_l) = \frac{\| \tilde{q} - \tilde{m}_k \| - \| \tilde{q} - \tilde{m}_l \|}{c},$$

(1)

where $\| \cdot \|$ represents the Euclidean norm and $c$ is the sound propagation velocity ($340 \text{ m/s at } 20 \, ^\circ\text{C}$). The GCC-PHAT between the two signals is defined as:

$$gcc(x_k[n], x_l[n]) = \mathcal{F}^{-1}\left( \frac{X_k \cdot X_l^*}{|X_k| \cdot |X_l|} \right),$$

(2)

where $X_k$ is the DFT of signal $x_k[n]$, $\cdot$ is the element-wise product operator, $(\cdot)^*$ is the conjugate operator, $| \cdot |$ is the magnitude and $\mathcal{F}^{-1}$ denotes the inverse DFT. Under ideal propagation conditions, the GCC-PHAT is a Dirac's delta shifted according to the time-delay between the signals. In a real scenario, the microphone signals are affected by the distortion and reverberation introduced by the environment, and the GCC-PHAT signals do not easily allow for the recovery of accurate time delays. A common approach to overcome this issue is to compute the so-called Acoustic Power Map (APM), evaluated on a grid of possible source positions $\tilde{q}_0, \ldots, \tilde{q}_K$, by using the SRP-PHAT beamformer:

$$APM(\tilde{q}) = \sum_{k=0}^{M-1} \sum_{l=k+1}^{M-1} gcc(x_k[n], x_l[n])$$

(3)

The source position that maximizes $APM$ is an estimate of the true source position.

Our proposal is a encoder-decoder CNN, represented by the mathematical function $f_{net}$, that takes as input the GCC-PHAT between two signals and produce a Gaussian-like signal with variance $\sigma^2$ and mean equal to the time-delay shift (see Figure 1):

$$f_{net}(gcc(x_k[n], x_l[n])) = e^{-\frac{(D - \Delta \tau(\tilde{q}, \tilde{m}_k, \tilde{m}_l) f_s)^2}{2 \cdot \sigma^2}}$$

(4)

with $D = -L/2, \ldots, L/2$, and $L$ being the maximum possible sample delay according to the microphone topology. We can define the $APM$ based on our method by using equation (4) as an estimation of the $gcc$ function in equation (2). Our method produces a smoother $APM$ (see Figure 3), and yields better ASL performance than SRP-PHAT, as described in section IV.

III. PROPOSED CNN ARCHITECTURE

The proposed CNN model that implements equation (4), from now on DeepGCC, is shown in Figure 1. DeepGCC uses an encoder-decoder architecture with 36025 parameters. Both the encoder and the decoder use four blocks composed of a 1D convolual layer with kernels of size 4, Max-Pooling (encoder) or upsampling (decoder) layers with size of two samples, batch-normalization, and ReLU activations. Table 1 summarizes the input and output sizes of every block.

IV. EXPERIMENTAL SETUP

A. Datasets

In order to evaluate till what extent the proposed method works properly under different acoustic and geometric conditions, we used three different datasets for the training and testing phases (refer to Figure 2 for graphical details):

- The CAV3D dataset [14] was recorded at 96kHz in a rectangular room of 4.77m × 5.94m × 4.50m, with a circular array of 8 microphones and 10cm radius, placed on top of a 73cm height table. All acoustic frames include the speaker’s 3D mouth position coordinates. This dataset is composed of 10 single and moving speaker sequences, with varying user characteristics and moving patterns.

- The AV16.3 dataset [15] was recorded in a 3.6m × 8.2m × 2.4m rectangular room that includes two circular arrays with the same geometry as the CAV3D array, also placed on top a 73cm height table. This paper focuses on a subset of the dataset composed of 5 single speaker sequences recorded at 16kHz, comprising three static user and two moving user sequences. The recordings also include varying user characteristics and moving patterns. In our experimental work, we only use one circular array and upsample the signal to 96kHz, to provide the same array configuration and sampling rate as those of the CAV3D dataset.

- The CHIL-CLEAR dataset [16] contains sequences of “lecture seminars” with 3 to 8 participants (with no overlapped speech) recorded at five different rooms (AIT, IBM, ITC, UKA, and UPC). In each room, eight sequences of 5 minutes were recorded. In this work, we focus only on the 8 UPC sequences, which were recorded in a 3.97m × 5.25m × 4.00m room, using three inverted
T-shaped 4-microphone arrays located on the walls at the height of 2.38 m. Again, we upsampled the microphone signals up to 96 kHz.

Figure 2 shows the top view of the three rooms corresponding to the CAV3D (left), AV16.3 (center), and UPC (right), adequately scaled to provide the reader with a visual clue on the different geometrical and acoustical conditions for each database. It also shows the specific geometry of the microphone array configurations for each room.

![Top view of the rooms](image)

**Fig. 2. Top view of the rooms used: CAV3D room (left), AV16.3 (center) and UPC (right).**

Table II summarizes the characteristics of the used sequences. We selected the sequences from CAV3D for training, validation, and testing, and the sequences from AV16.3 and UPC for testing (see section IV-E for details). We code the characteristics of each sequence as follows: $S$ refers to static speakers, $M$ refers to moving speakers, 1 denotes noise present in the sequence, 2 denotes a speaker at two different heights, and 3 refers to the case of target positions not present in the rest of the sequences (thus not available in the training stages).

### Table II

| CAV3D | # | Charact. | AV16.3 | # | Charact. | UPC | # | Charact. |
|-------|---|----------|--------|---|----------|-----|---|----------|
| C07   | 174 | M        | A01    | 1128 | S + 3    | 102 | 4355 | S + 3    |
| C08   | 411 | M        | A02    | 1441 | S + 3    | 102 | 4355 | S + 3    |
| C09   | 307 | M + 1    | A11    | 297  | M + 4    | 104 | 3794 | S + 3    |
| C10   | 245 | M + 1    | A15    | 284  | M + 3    | 105 | 4348 | S + 3    |
| C11   | 707 | M + 2    | A11    | —    | —        | 105 | 3013 | S + 3    |
| C12   | 725 | M + 2    | A11    | —    | —        | 107 | 3153 | S + 3    |
| C13   | 684 | M + 3    | A11    | —    | —        | 107 | 3748 | S + 3    |
| C20   | 422 | M        | —      | —    | —        | —   | —    | —        |
| C21   | 476 | M + 2    | —      | —    | —        | —   | —    | —        |

**CAV3D, AV16.3, UPC SEQUENCES USED TO TRAIN AND TEST OUR METHOD. THE SECOND, FIFTH AND EIGHTH COLUMNS INCLUDE THE NUMBER OF AVAILABLE ACOUSTIC FRAMES IN THE SEQUENCE, AND THE THIRD, SIXTH AND LAST COLUMNS REPRESENT THE CHARACTERISTICS OF EACH SEQUENCE.**

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### B. Dataset Processing

The process of generating the training, validation, and testing subsets is identical in all cases and consists of computing the GCC-PHAT for all the possible signals pairs. We extract each acoustic frame from the whole sequence using a 166 ms signal frame with 50% overlapping and Blackman windowing. Assuming a 96 kHz sampling rate, we use windows with 400 samples, which implies that the network can process time-delays up to approximately ±2 ms. This delay is more than enough, given the maximum separation between microphones in the training data (20 cm, as we only use the CAV3D dataset for training).

For each GCC-PHAT signal, we generate the supervised network output according to equation 4, computing the time-delay between the signals received by the two microphones and the labeled source position. This signal is also generated to be 400 samples in length and has a standard deviation of $\sigma = 5$ samples that we empirically selected in preliminary experiments.

### C. Training Procedure

For the training phase, we followed the same procedure to evaluate all the methods. The loss function consists of the Mean Squared Error (MSE) between the network output and the target signal, generated with equation 4 using the ground truth source position. To minimize the loss, we used the Adam optimizer [17] with a learning rate of $10^{-4}$ and a decay of $10^{-8}$, leaving the rest of the parameters at their default values. Batch size is equal to 100 samples, and we used validation data to stop training if the loss does not improve during 50 consecutive epochs. The CAV3D dataset was the only used for training, and due to the different features of each sequence, we run three different partitions, as shown in Table III leaving the hardest sequences (C09, C10, C11, C12, and especially C13 (that contains speaker positions not available in the training subset)) for validation and testing, and using the other simpler ones for training.
D. Algorithms Comparison

To compare the accuracy of our proposal, we evaluate it against three alternatives. The first one is the well known SRP-PHAT algorithm, considered as the baseline system. The second method is the Deep Learning approach ASLNet \[11\], which estimates the cartesian coordinates of the acoustic source from the spectrogram of the audio signal of a set of microphones. The last evaluated method is based on SELnetXYZ \[12\], a recurrent neural network to estimate the azimuth and elevation of an acoustic source from the spectrogram of the audio signal of a microphone array. In our work, we have modified this architecture to estimate the source 3D cartesian coordinates directly, and we will refer to it as SELnetXYZ.

E. Experimental design

We carried out two different experiments to focus on two performance indicators: ASL precision performance, and environmental robustness:

- For testing the ASL precision performance, we used the C09, C10, C11, and C12 sequences because of the similarity of its labeled positions with the training ones. In this experiment, we expect better performance for the standard Deep Learning approaches ASLNet and SELnetXYZ. We also expect that our proposal will achieve better performance than the SRP-PHAT beamformer. We evaluated the ASL performance as the mean Euclidean distance between the labeled ground truth and the estimated position, provided the training and testing positions are similar.

- For testing the environmental robustness of the different proposals, we measured the localization accuracy when the room geometry, microphone array geometry, and the evaluated positions in the test data significantly differ from those in the training data. IDIAP and UPC sequences were used for this purpose, along with C13, which belongs to the CAV3D dataset, but includes a full range of positions not found in the training subsets. In this case, we expect our DeepGCC proposal to roughly keep the same performance as in the first experiment, while the other Deep Learning methods exhibit a performance decrease due to mismatched evaluation conditions. Note that in the UPC sequences, only the SRP-PHAT and DeepGCC algorithms can be evaluated since the microphone array geometry has changed, and we will not retrain ASLNet or SELnetXYZ.

In all the experiments, we have used all the possible microphone pair combinations to build a volumetric acoustic power map with a 10cm x 10cm x 10cm grid resolution, generated from the DeepGCC model output. We then extract the acoustic source cartesian coordinates from the location of the maximum acoustic power.

V. Results

Figure 3 (left) shows a particular example of the output obtained with DeepGCC and GCC-PHAT (SRP-PHAT). Figure 3 (right) shows the APMs using equation (3), which involves all microphone pairs. The map built with DeepGCC is considerably smoother than that built with SRP-PHAT.

![GCC-PHAT input and DeepGCC result](image)

Fig. 3. Example of a GCC-PHAT input and the DeepGCC result and their respective Acoustic Power Maps.

Table \[IV\] shows the results of the first experiment (focused on ASL performance). The average MSE is shown in cm, and we also include the relative improvement achieved by each method as compared with the SRP-PHAT algorithm ($\Delta_r \text{MSE} = \frac{\text{MSE}_{\text{method}} - \text{MSE}_{\text{SRP-PHAT}}}{\text{MSE}_{\text{SRP-PHAT}}}$). SELnetXYZ obtains, as expected, the best results because testing and training positions are similar. Our DeepGCC proposal is the second-best strategy, getting better results than SRP-PHAT in all cases, and better than ASLNet in 3 out of 4 sequences.

| Sequence | SRP-PHAT $\Delta_r \text{MSE}$ | DeepGCC $\Delta_r \text{MSE}$ | ASLNet $\Delta_r \text{MSE}$ | SELnetXYZ $\Delta_r \text{MSE}$ |
|----------|-------------------------------|-------------------------------|-----------------------------|-------------------------------|
| C10      | 101.3                         | 94.5                          | 92.5                        | 55.2                          |
|          | 6.71%                         | 8.69%                         |                             | 45.51%                        |
| C12      | 114.5                         | 101.5                         | 103.5                       | 73.4                          |
|          | 11.35%                        | 9.61%                         |                             | 35.89%                        |
| C09      | 94.9                          | 82.1                          | 87.6                        | 62.0                          |
|          | 13.49%                        | 7.69%                         |                             | 34.67%                        |
| C11      | 117.5                         | 106.4                         | 133.3                       | 94.6                          |
|          | 9.45%                         | 3.57%                         |                             | 19.49%                        |

Table \[IV\] shows the results of the second experiment (focused on environmental robustness), in which our DeepGCC proposal clearly outperforms all the other methods. The fact that we aim to estimate the GCC function (that mainly depends on the relative time delay) makes it more robust to changes in the room and array geometry or the source positions with respect to the microphone arrays. The other deep learning methods are not able to properly face the mismatched conditions, performing far worse than the standard SRP-PHAT. We remark the fact that the DeepGCC proposal has a 13.82% relative improvement over the SRP-PHAT algorithm even though the microphone geometry (UPC sequences) changes. This is a difficult task for a Deep Learning method since it has to deal with unseen conditions in the GCC-PHAT signal.
Table V

| Sequence | SRP-PHAT | DeepGCC | ASINet | SELnetXYZ |
|----------|----------|---------|--------|------------|
| C13 \[\Delta_{MSE}\] | 86.9 | 79.2 | 136.7 | 135.5 |
| A01 \[\Delta_{MSE}\] | 103.0 | 84.4 | 348.3 | 347.8 |
| A02 \[\Delta_{MSE}\] | 68.8 | 64.6 | 350.4 | 363.2 |
| A03 \[\Delta_{MSE}\] | 73.7 | 57.7 | 352.3 | 360.4 |
| A11 \[\Delta_{MSE}\] | 84.1 | 69.1 | 274.3 | 284.1 |
| A15 \[\Delta_{MSE}\] | 140.3 | 110.3 | 387.1 | 386.4 |

Results for the environmental robustness experiments (error in cm, \[\Delta_{MSE}\] is relative MSE improvement over the SRP-PHAT algorithm).

VI. Conclusions

In this paper, we have described DeepGCC, a method based on deep learning that transforms the GCC-PHAT of two signals, emitted from the same source and received in two microphones, into a Gaussian function whose maximum appears at the time difference between the two signals. We use DeepGCC to estimate a smoother and more accurate acoustic power map, as compared to that generated by the standard SRP-PHAT method. We obtain the acoustic source position finding the position where this map is maximum. In our experiments, DeepGCC yields more accurate localization than GCC-PHAT in all cases. We also compare DeepGCC with existing deep learning methods that estimate the source position from the microphone signals directly. Our approach is consistently more accurate than these methods when testing and training conditions vary significantly, which makes it better suited for deployment in real scenarios.

As future work, our method will be combined with sparse denoising [13] to improve localization accuracy based on acoustic maps. We also plan to extend DeepGCC to multiple speaker localization tasks.

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