Estimation of Azimuth and Elevation for Multiple Acoustic Sources Using Tetrahedral Microphone Arrays and Convolutional Neural Networks

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Abstract: A method for multiple acoustic source localization using a tetrahedral microphone array and a convolutional neural network (CNN) is presented. Our method presents a novel approach for the estimation of acoustic source direction of arrival (DoA), both azimuth and elevation, utilizing a non-coplanar microphone array. In our approach, we use the phase component of the short-time Fourier transform (STFT) of the microphone array’s signals as the input feature for the CNN and a DoA probability density map as the training target. Our findings imply that our method outperforms the currently available methods for multiple sound source DoA estimation in both accuracy and speed.

Keywords: acoustic source localization; multiple source localization; machine learning; tetrahedral sensor arrays

1. Introduction

Sound source localization (SSL) is an important topic in robotics, autonomous vehicles, public security, conferencing, sound engineering, and other fields. Applications of sound source localization include speaker location search in teleconference, event detection and tracking, and robot movement in an unknown environment [1,2]. Sound source localization solutions, implemented on edge computing devices may be a complementary localization solution for human rescue challenges in Underground Mine [3], applied as a monitoring or predictive maintenance solution [4–6].

Direction of arrival (DoA) of one or more active sound sources may be used to steer the directivity pattern of a microphone array in ambient intelligence [7] or security-surveillance systems [8].

The DoA is most commonly represented as a set of two angles (azimuth, \( \theta \) and elevation, \( \phi \)). In most physical acoustic–electronic systems, the DoA is derived from the signals of a microphone array using a variety of signal processing methods.

Many numerical SSL methods for the localization of one or more sound sources were proposed throughout the years, such as generalized cross-correlation with phase transform (GCC-PHAT), steered-Response Power Phase Transform (SRP-PHAT) [9], minimum variance distortion-less Response (MVDR) beamformer, multiple signal classification (MUSIC) algorithm. These methods are often either computationally intensive or perform poorly in adverse (noisy, reverberant) acoustic conditions.

The performance of TDoA based SSL methods deteriorate in reverberant environments because of the multipath propagation, which, in the context of the image-source method, creates additional image sources and the real source position is mistaken for an image source position [10].

For another example, the SRP-PHAT algorithm has been shown to be one of the most robust sound source localization approaches operating in noisy and reverberant
environments. However, its practical implementation is usually based on a costly fine grid-search procedure, making the computational cost of the method a real issue [11]. Due to the ability to approximate complex functions, learning-based sound source localization methods might be further advantageous in such circumstances.

In recent years, several authors proposed to apply an artificial neural network (ANN) for SSL [1,12–14]. A wide variety of input features were proposed, ranging from interaural level difference (ILD) [15] and inter-aural time difference (ITD) per frequency [16] to MUSIC eigenvectors [13,17]. The authors also used different output types: a set of the sound source coordinates [15,18]; a likelihood-based coding for localization of multiple active sound sources. An application of recurrent neural networks (RNNs) for SSL was investigated in [19]. Sound source localization using ANN is commonly formulated either as a classification [20–28], or a regression problem [29–33]. In the case of the regression problem, the output of the ANN is a one, two or three-dimensional vector (in the case of a single sound source [34,35]) or a set of vectors (in the case of a multiple source localization [36–38]). In the case of the classification problem, the input features are classified to an array of spatial classes, representing the source coordinates in one, two, or three dimensions.

An end-to-end (audio signal frame to sound source coordinates) solution was proposed by Vera-Diaz et al. [18], but only for a single active sound source. Moreover, for the generation of the data used for the training and evaluation of the ANN, the acoustics of the room were not considered.

A method for the estimation of the DoAs of an unknown number of sound sources using an ANN was proposed by He et al. [39]. The authors used a multi-layer perceptron (MLP) with GCC-PHAT coefficients as input features and a CNN with GCC-PHAT on a mel-scale filter bank as input features for the estimation of an unknown number of sound sources. The microphone array consisted of four coplanar microphones, mounted on a robot head. Features were calculated for 170 ms duration audio frames. The system was able to estimate the azimuth angles for two simultaneously active sound sources with features obtained from real audio recordings. He et al. proposed a format of ANN output coding that resembles a spatial spectrum, which is a function that peaks at the true DoAs and that is constructed using Gaussian kernels. The output coding is a vector that represents the probability density of a sound source being active at a particular azimuth.

A method for multiple acoustic source DoA estimation (azimuth only) using a CNN, trained on synthetic noise signals, was proposed by Chakrabarty and Habets [21]. Phase components of the STFT frame of the source signal were used as CNN input features and a vector representing the posterior probability of a sound source being active at a particular azimuth was used as a desired output during CNN training.

Laufer-Goldshtein et al. in their work showed that the multidimensional acoustic features lie on a manifold embedded in a low-dimensional space and that these multidimensional acoustic features exhibit spatial smoothness [40]. From their investigation, it was clear that for sound sources that are spatially close, the acoustic features are also close in the embedded low-dimensional space.

It might be speculated that the multipath propagation artefacts that manifest themselves in the acoustic features and that cause the deterioration of the performance of the conventional SSL algorithms, are used in an advantageous manner by the ANN to actually increase the accuracy of the predicted sound source location and also taking into account the spatial smoothness of the input feature space.

2. Materials and Methods

We propose a method for multiple acoustic source azimuth and elevation estimation using CNN. The neural network trained using the phase component of the STFT, estimated from the microphone array signals, as the input feature and a 2-dimensional map of DoA posterior probability, referred to as a DoA heatmap from now on, as the output feature.
Our method based on the idea of azimuth angle estimation for multiple acoustic sources proposed by Chakrabarty and Habets [21]. However, we extend the method to estimate the elevation of the acoustic source besides the azimuth angle.

We extend on our previous work [41], where we have used the same approach regarding the tetrahedral microphone array geometry and the structure of the target 2D DoA heatmap feature. However, instead of features based on a Cross-Correlation of frequency bands we now use the phase component of the STFT applied to the microphone array signals. Thus, we omit the explicit feature extraction step and rely on the CNN to learn the feature extraction during the training.

An additional contribution in this paper is the ability of our proposed method to estimate the azimuth and elevation for multiple active acoustic sources simultaneously.

2.1. Justification of Tetrahedral Array Geometry

It can be shown that by utilizing a co-planar array it is impossible to uniquely estimate the azimuth and elevation of the source, since there are two valid candidate positions for every source elevation that is not co-planar with the array [42]. To overcome this, we propose utilizing a non-co-planar microphone array. The simplest non-co-planar geometry is a tetrahedron. Therefore, as in our previous investigation, we used the same tetrahedral microphone array geometry [41].

Vertex coordinates \( M = \{A, B, C, D\} \) of a tetrahedron that is centered at \( m_c \) and has a side length of \( m_{\text{side}} \) are calculated as follows:

\[
A = \left[ \begin{array}{c} m_c(x) - \frac{m_{\text{side}}}{2}, m_c(y) - \frac{\sin(\pi/3) \cdot m_{\text{side}}}{2}, m_c(z) - \frac{\sin(\pi/3) \cdot m_{\text{side}}}{2} \end{array} \right],
\]

\[
B = \left[ \begin{array}{c} m_c(x), m_c(y) + \frac{\sin(\pi/3) \cdot m_{\text{side}}}{2}, m_c(z) - \frac{\sin(\pi/3) \cdot m_{\text{side}}}{2} \end{array} \right],
\]

\[
C = \left[ \begin{array}{c} m_c(x) + \frac{m_{\text{side}}}{2}, m_c(y) - \frac{\sin(\pi/3) \cdot m_{\text{side}}}{2}, m_c(z) - \frac{\sin(\pi/3) \cdot m_{\text{side}}}{2} \end{array} \right],
\]

\[
D = \left[ \begin{array}{c} m_c(x), m_c(y), m_c(z) + \frac{\sin(\pi/3) \cdot m_{\text{side}}}{2} \end{array} \right].
\]

2.2. The Role of the CNN in DoA Estimation

Acoustic source positions can be estimated from the acoustic signals received by a microphone array. We propose a CNN-based method to obtain the estimates of the azimuth and elevation of the acoustic sources with respect to the position and orientation of the microphone array. The CNN must be trained by providing training samples consisting of the input features and the corresponding outputs. After training, the CNN provides an estimate of the azimuth and elevation angle for a current set of features presented to the input.

2.3. Estimation of Input Features

Extending the work of Chakrabarty and Habets [21], we used the phase component of the STFT calculated for microphone array signals. However, we did not explicitly take into account the W-disjoint orthogonality of the signals. According to Chakrabarty and Habets [21], in the case of a \( N_S \)-source scenario, each of the sources is simulated using the image-source method separately. Then the STFTs of the receiver signals are concatenated and randomly permuted in both time and frequency domains (leaving only the channel order unchanged). In our case, we permute the signals in the time and frequency domains, only preserving the original order of the channels, and we simulate all the \( N_S \) acoustic sources at once, so their respective spectral components are present in each time frame.

The preparation of input features is carried out in several steps. First, the STFTs of the simulated microphone signals are calculated. For each of the \( N_M = 4 \) microphone channels were set the number of Fast Fourier Transform (FFT) points equal to \( N_{\text{STFT}} = 512 \), with 256 point overlap and a Hann windowing function. The number of frequency bins
in the STFT was $N_f = N_{\text{STFT}}/2 + 1 = 257$. For each simulation $N_T = 4$ temporal STFT frames were obtained. As a result, we created an array of size $(N_S \times N_M) \times N_f \times N_T$.

Next, the concatenated STFT is randomly permuted along the time and frequency dimensions, keeping the original order of elements only in the channel dimension.

Examples of the prepared input features are presented in Figure 1. STFT frames for four microphones are presented; training STFT sample (noise signal) in Figure 1a and the testing STFT sample (speech sample) in Figure 1b.

![Figure 1](image-url)

Figure 1. Examples of STFT input features: STFT magnitude and phase of a training sample (a) noise signal; (b) speech signal).

As the input features, we use a single temporal frame of the resulting data structure—a matrix with $N_M \times N_f = 4 \times 257$ elements. Each matrix of input features in the training dataset has an associated desired output—a two-dimensional DoA heatmap.

2.4. Desired Outputs

In the proposed method, a 2D DoA heatmap is used as a desired output for each matrix of input features. The heatmap is a matrix of $N \times M$ elements, where each element represents a certain azimuth and elevation angle range. The value of each element represents the probability of an acoustic source being active at a particular azimuth and elevation. Total range of the DoA heatmap represents a 360° azimuth range along $\theta$ axis and a 180° elevation range along $\phi$ axis. The number of elements of the heatmap per azimuth and elevation axes, respectively, $Q_\theta$ and $Q_\phi$ represent the angular resolution of the DoA heat map.

During the generation of the training dataset, to reduce the sparsity of the target feature, we additionally applied Gaussian blurring to the DoA heatmap using a 2D Gaussian kernel with separately controllable spread parameters $\sigma_\theta$ and $\sigma_\phi$ on the $\theta$ and $\phi$ axes, respectively. Acoustic features exhibit spatial smoothness that is reflected in the feature space [40]. Conversely, an ANN is expected to classify such neighboring input features to neighboring classes in the output. Therefore, we speculate that the DoA heatmap blurring operation would allow the CNN to learn to map features that are nearby in the feature space to neighboring DoA classes. The values at the output layer of the ANN represent the posterior probability of a feature being obtained for a sound source at a particular DoA. A feature for a source with a particular DoA can be viewed as having lower but non-zero posterior probability of being obtained for a source with a slightly different (neighboring) DoA. Thus we believe that this angular smoothing of the DoA heatmap would be beneficial for the learning of the ANN as well as its robustness.

The values at each grid element are determined by first calculating the azimuth and elevation of the simulated acoustic source with respect to the center of the microphone array. An empty DoA heatmap grid is created, upon which a Gaussian kernel centered at
exact azimuth and elevation is superimposed for each source DoA. The position of each of the Gaussian peaks corresponds to the 2D DoA of the source.

During the training, the CNN learns to extract features from the STFT phase component and to map those extracted features to the DoA heatmap.

Examples of the prepared desired outputs at respectively $Q = 10^\circ$ and $\sigma = 5$ and $Q = 10^\circ$ and $\sigma = 5$ are presented in Figure 2.

Figure 2. Examples of 2D DoA heatmap ((a) with parameters $Q = 10^\circ$, $\sigma = 5$; (b) with parameters $Q = 10^\circ$, $\sigma = 5$; ground truth DoAs are marked with magenta crosses).

2.5. Post-Processing of the Outputs

To obtain the DoAs of the acoustic sources from the DoA heatmap, a peak detection is performed on the heatmap and the indices of the $N_S$ most prominent peak elements of the heatmap are converted to azimuth and elevation angles for each of the $N_S$ peaks. These angles correspond to the 2D DoA of the acoustic source with respect to the center of the microphone array.

A simple algorithm is used to find a local maxima. This operation dilates the original DoA heat map. After a comparison of the dilated and original image, this function returns the coordinates or a mask of the peaks where the dilated heat map equals the original image.

2.6. CNN Architecture

We used a similar architecture of the CNN as provided by Chakrabarty and Habets in their work [21], but we have altered the number of elements in each convolutional layer, as well as adjusted the number of output nodes to match the number of elements in the target DoA heatmap.

Chakrabarty and Habets provide an explanation that the architecture of the CNN used with $N_M$-channel STFT phase features can have, at most, $N_M - 1$ convolution layers, where $N_M$ is the number of microphones (four in our case), since after $N_M - 1$ layers, performing 2D convolutions is no longer possible as the feature maps become vectors. They have also experimentally demonstrated that, indeed, $N_M - 1$ convolution layers are required to obtain the best DOA estimation performance for a given microphone array. In the convolution layers, small filters of size $2 \times 1$ were applied to learn the phase correlations between the neighboring microphones at each frequency sub-band separately. These learned features for each sub-band were then aggregated by the fully connected layers for the classification task.

We used a CNN with three convolutional layers, after which a dropout layer was used, as well as two deep fully-connected layers, followed by a dropout layer (see Figure 3). The output layer had the size of $N_{\text{DoA}} = Q_\theta \times Q_\phi$. The dropout rates were fixed to 0.125 and the Binary cross-entropy was used as the loss function.
2.7. Preparation of Training and Testing Dataset

To evaluate the performance of our method, we synthesized a set of datasets for training and testing. Training datasets were synthesized with white noise as the sources’ signals and the target DoA maps were synthesized with $Q \in \{5, 10, 20\}$° and $\sigma \in \{5, 10, 15, 20\}$. Training datasets contained 100,000 samples each. Training datasets were created with the STFT frequency random permutation, also without permutation, with one, two, or three active sound sources. Each sample in the datasets contained a matrix of input features and a desired output.

The testing dataset with speech signals from AMI Corpus [43] without STFT scrambling, assuming the W-disjoint orthogonality of speech signals.

We trained the proposed structure of CNN on each of the training datasets and evaluated its performance using a testing dataset with corresponding DoA heatmap grid resolution and Gaussian spread. A Keras implementation of CNN training was used during experimental investigation.

We synthesized the microphone array’s signals using an image source model implemented in the Pyroomacoustics package [44]. The acoustic signals were simulated in a cuboid shaped acoustic enclosure with dimensions matching a real room described in our previous experimental investigations [41]. The tetrahedral microphone array was set to have an arbitrarily selected side length of 0.4 m and its center was placed at an arbitrary location within an acoustic enclosure.

For all experiments, the geometry of the microphone array, its position and orientation remained constant. Simulated acoustic source coordinates were selected from a uniform random distribution within the volume of the simulated acoustic enclosure. CNN was trained on a training dataset with 100,000 samples during five epochs with a learning rate of 0.001.

2.8. Evaluation of the Proposed Method Performance

To compare the performance of our proposed method with alternatives, we used the Steered Response Power Phase Transform (SRP-PHAT) algorithm as a baseline. We used the pyroomacoustics implementation, which allowed us to estimate the response power of the beamformer and presented it as a 2D (azimuth and elevation) heatmap, which is compatible with the output of our proposed method. We estimated a DoA heatmap at the same resolution as with our proposed method.

We measured the Mean Average Error (MAE) of source 2D DoA prediction using our proposed method and the baseline method. The DoA estimation error is the Euclidean distance in the polar coordinate system between the estimated source DoA and the ground truth DoA.

The ground truth DoA was calculated geometrically from a known source and microphone array positions. The estimated DoA was obtained from the DoA heatmap using a simple 2D peak detection algorithm. The DoA estimation errors were obtained in two steps:

1. Euclidean distances between all pairs or ground truth and estimated DoAs were calculated;
2. $N_S$ smallest errors were selected as the DoA prediction errors for $N_S$ sources.
This two-step approach allows the determination of the angular distance between the ground truth and the estimated closest candidate positions.

During the experimental investigation, for each STFT input frame the DoA heatmaps and DoA prediction errors were estimated to evaluate the performance of our proposed method and the baseline method. If the peak detection algorithm locates the number of peaks under inequality $N_{\text{Est.}} < N_S$, only $N_{\text{Est.}}$ errors are calculated.

The MAE is calculated using the following equation:

$$\text{MAE} = \frac{1}{N_T} \sum_{i \in N_T} \sum_{j \in N_{\text{Est.}}} e_{ij}. \quad (5)$$

3. Results

We evaluated the performance of our proposed method at various DoA heatmap resolutions and Gaussian kernel spreads. Azimuth and elevation resolution were equal: $Q_\theta = Q_\phi = Q$, as well as azimuth and elevation Gaussian kernel spreads: $\sigma_\theta = \sigma_\phi = \sigma$. We performed experiments at resolution values $Q \in [5, 10, 20]$ and Gaussian kernel spread values $\sigma \in [5, 10, 15, 20]$. The results are presented in Figure 4. In this figure, errors of three sources DoA prediction for each testing sample are presented.

![Figure 4](image.png)

Figure 4. Angular errors of three sources DoA estimation using our method ((a) STFT not permuted; (b) STFT with permuted time and frequency dimensions; (c) GCCPHAT); data were unavailable for the CNN trained on STFT features with permuted time and frequency dimensions with $\sigma \in [5, 10]$ and CNN trained on regular STFT features with $\sigma = 5$.

To evaluate the performance of the proposed method when subjected to background and acquisition system noise, experimentation with the best-performing $Q$ and $\sigma$ configuration was carried out with varying Signal-to-Noise Ratio (SNR) of the simulated microphone array signals. For the evaluation, the training dataset was augmented by adding an uncorrelated noise signal sampled from the uniform distribution to the original signal to obtain a signal with a specific SNR. The MAE of DoA estimation of three simultaneously active speech sources was obtained with testing signals with SNR $= [30, 20, 10]$ dB, and the results are presented in Figure 5. It can be seen that the angular MAE of three sound source DoA estimation increases with increased noise level (decreased SNR) for both our proposed method and the baseline method. Nevertheless, our method has reached DoA estimation MAE as low as 23.13° with 30 dB SNR and 27.21° with 10 dB SNR. To compare, the SRP-PHAT method gives MAE 51.6° and 52.36° at respective SNR values. To summarize, our proposed method allows us to achieve at least 48% lower DoA estimation angular MAE than SRP-PHAT at all evaluated SNR values.
To determine the influence of the CNN architecture on the performance of the proposed method, three architecture variations were additionally evaluated, having only a single convolutional layer, two convolutional layers and also the originally proposed architecture with three convolutional layers, with $10^\circ$ angular resolution output layer ($36 \times 18$ elements), trained on a dataset with target feature $\sigma = 10$. After the evaluation of these CNN architecture variations on a dataset with three active speech sources, it was discovered that a higher number of convolutional layers contributes positively to reducing the MAE of source DoA estimation, as shown in Figure 6. With only a single convolutional layer in the CNN, the source DoA estimation MAE was 19.8°, while increasing the number of convolutional layers to three allowed us to achieve source DoA estimation MAE of 18.14°, which is an 8.4% improvement.

Examples of DoA heatmaps are presented in Figure 7. These examples were obtained for an array audio frames with two speech sources active at DoAs situated respectively at $(-153.1^\circ, -23.8^\circ)$ and at $(46.3^\circ, -22.6^\circ)$. An example of a spatial power spectrum extracted using SRP-PHAT algorithm is presented in Figure 7a. Here the SRP objective function is evaluated on a grid with an angular resolution $Q_\theta = Q_\phi = 5^\circ$). An example ground truth DoA heatmap that is used to train the CNN is presented in Figure 7b. The angular resolution of the DoA heatmap is the same as SRP-PHAT spatial spectrum. The Gaussian
spread selected to prepare the the desired outputs for this CNN training was $\sigma_\theta = \sigma_\phi = 10$. An example of CNN DoA heatmap estimation using the proposed method is presented in Figure 7c).

![CNN DoA heatmap estimation](image.png)

**Figure 7.** Examples of DoA heatmap output: (a) SRP-PHAT spatial power spectrum; (b) ground truth (used as a target for training of the CNN; $Q_\theta = Q_\phi = 5^\circ$); (c) CNN estimated DoA heatmap ($Q_\theta = Q_\phi = 5^\circ$); same STFT input feature was used for both SRP-PHAT and our CNN method.

4. Discussion

As can be seen from the Figure 4, our method outperforms the baseline SRP-PHAT algorithm in estimating the azimuth and elevation of multiple acoustic sources. While the lowest source DoA estimation MAE was $25^\circ$ for the baseline method, at $Q = 5^\circ$ and $\sigma = 20$, our method achieved MAE of $16^\circ$ with the same $Q$ and $\sigma$ values. This can be interpreted as a performance increase by 36%.

Generally, our method outperformed the baseline in all experiments by at least 29%, with the largest performance increase by 70% at $Q = 5^\circ$ and $\sigma = 10$. Thus, we can conclude that our proposed CNN-based multiple acoustic source 2D DoA estimation algorithm allows for a more precise source DoA estimation than the GCCPHAT-based method. Proposed method also outperformed the baseline in decreased SNR scenario, where at SNR = 30 dB, sound source DoA estimation MAE was $23.13^\circ$, which is a 55% improvement compared to the baseline method. The number of convolutional layers in the CNN architecture was found to improve the accuracy of the source DoA estimation; increasing the number of convolutional layers from one to three decreases the source DoA estimation error by 8.4%.

Further investigation of input and output feature processing and CNN hyperparameter optimization would be needed to potentially increase the performance of our proposed method. In addition, our method might be extended to 3D acoustic source position estimation, either in the Cartesian or polar coordinate systems, by constructing a 3D heatmap output feature instead of the 2D DoA heatmap feature. The authors are keen to investigate these possibilities.

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Abbreviations
The following abbreviations are used in this manuscript:

- DoA Direction of Arrival
- ANN Artificial Neural Network
- CNN Convolutional Neural Network
- SRP Steered Response Power
- PHAT Phase Transform
- MAE Mean Average Error

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