Article

Sound Source Localization Using Graph Regularized Neural Network

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Abstract: A single paragraph of about 200 words maximum. For research articles, abstracts should give a pertinent overview of the work. We strongly encourage authors to use the following style of structured abstracts, but without headings: (1) Background: Place the question addressed in a broad context and highlight the purpose of the study; (2) Methods: Describe briefly the main methods or treatments applied; (3) Results: Summarize the article's main findings; and (4) Conclusion: Indicate the main conclusions or interpretations. The abstract should be an objective representation of the article, it must not contain results which are not presented and substantiated in the main text and should not exaggerate the main conclusions.

Keywords: keyword 1; keyword 2; keyword 3 (list three to ten pertinent keywords specific to the article, yet reasonably common within the subject discipline.)

1. Introduction

Sound source localization is an increasingly important component in teleconferencing, autonomous driving, security and human-computer interaction systems.

It might be desired to use compact microphone arrays that have as few microphone elements as possible. By "compact" we here imply that the dimensions of the microphone array are much smaller than the dimensions of source localization space.

There are plenty of source direction of arrival estimation methods utilizing such compact arrays [], but only a few methods are offered for 2D or 3D source localization that can estimate both DoA and the distance or the Cartesian coordinates of the sound source.

Camera aiming can be inaccurate due to the parallax error if the camera and the microphone array are not rotating on the same axis. To accurately steer the camera to a certain point in space in such setup, a complete set of coordinates, either Cartesian or polar, of the target point is needed. Thus, knowing only the direction of arrival (DoA) of the sound source would not be sufficient. At least two DoAs are needed to describe the source position on a plane.

The Steered Response Power - Phase Transform (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 [1].

The performance of SRP-PHAT-based source localization algorithms deteriorate considerable when compact microphone arrays are used [].

Learning-based sound source localization methods might be further advantageous in such circumstances.

There are several learning-based source localization approaches, based on either semi-supervised [2] or supervised [3,4] learning paradigms. In both of these approaches to work, a set of acoustic features from known sound source positions (the labeled dataset) is needed.

Labeled feature acquisition is very costly. It is relatively easy to obtain a large dataset of unlabeled audio features. Considering our setting, it is relatively easy to collect a large amount of acoustic features without labels, and it is very tedious to provide labels (in our case – the coordinates of the sound source) for such data.

In this article we present a method to localize in two dimensions a sound source using a two compact microphone arrays.

2. Results

ar dėti iliustracijas, kai klaidos priklausomybe nuo parametro skaičiuojama iš hyperparameter optimization rezultatų, kai keičiami visi parametrai, ar tik iš eksperimentų rinkinių, kai keičiamas vienas parametras, o kiti laikomi fiksuoti?

After performing a bayesiean hyperparameter optimization for 169 iterations, source position estimation MSE, MAE and RMSE errors were obtained.

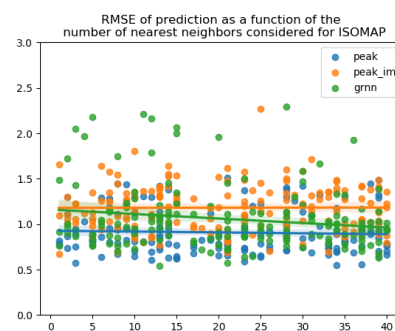The relation between the estimated prediction error and the parameters are presented ....

Figure 1. Dependency of source position prediction (using our algorithm and two baseline algorithms) RMSE and the number of nearest neighbors considered for ISOMAP embedding; linear regression model showed in solid line
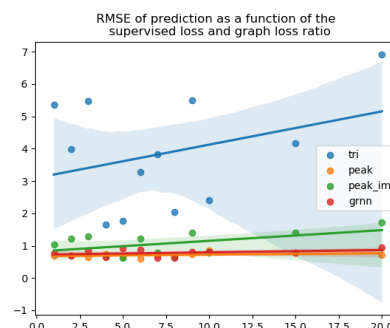

Figure 2. Dependency of source position prediction (using our algorithm and two baseline algorithms) RMSE and the number of nearest neighbors considered during GRNN training; linear regression model showed in solid line
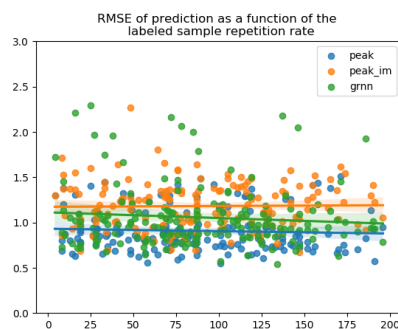
Figure 3. Dependency of source position prediction (using our algorithm and two baseline algorithms) RMSE and the rate of labeled training sample reintroduction; linear regression model showed in solid line
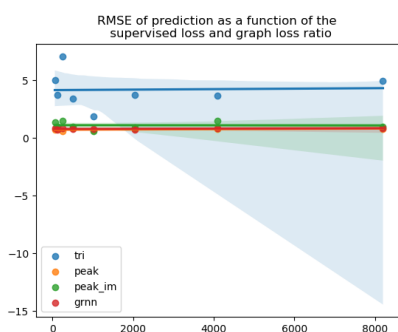

Figure 4. Dependency of source position prediction (using our algorithm and two baseline algorithms) RMSE and the batch size used in GRNN training; linear regression model showed in solid line

2.1. Subsection

2.1.1. Subsubsection

Bulleted lists look like this:

- First bullet
- Second bullet
- Third bullet

Numbered lists can be added as follows:

1. First item
2. Second item
3. Third item

The text continues here.

2.2. Figures, Tables and Schemes

All figures and tables should be cited in the main text as Figure 1, Table 1, etc.

Figure 5. This is a figure, Schemes follow the same formatting. If there are multiple panels, they should be listed as: (**a**) Description of what is contained in the first panel. (**b**) Description of what is contained in the second panel. Figures should be placed in the main text near to the first time they are cited. A caption on a single line should be centered.

60 Text

61 Text

Table 1. This is a table caption. Tables should be placed in the main text near to the first time they are cited.

Title 1	Title 2	Title 3
entry 1	data	data
entry 2	data	data

62 Text

63 Text

64 *2.3. Formatting of Mathematical Components*

65 This is an example of an equation:

$$a + b = c \tag{1}$$

66 Please punctuate equations as regular text. Theorem-type environments (including propositions,
67 lemmas, corollaries etc.) can be formatted as follows:

68 **Theorem 1.** *Example text of a theorem.*

69 The text continues here. Proofs must be formatted as follows:

70 **Proof of Theorem 1.** Text of the proof. Note that the phrase 'of Theorem 1' is optional if it is clear
71 which theorem is being referred to. □

72 The text continues here.

3. Discussion

74 Authors should discuss the results and how they can be interpreted in perspective of previous
75 studies and of the working hypotheses. The findings and their implications should be discussed in the
76 broadest context possible. Future research directions may also be highlighted.

4. Materials and Methods

78 In this section, we provide a theoretical background for our investigation.
79 ANN-based sound source localization can be performed using various acoustic features that
80 depend on the sound source, either relative to the microphone array(s) or the acoustic enclosure.
81 It can be assumed, that acoustic features are spatially smooth, that is, features obtained at spatially
82 close source positions are also close in feature space. The relative distance or affinity of the features
83 can be simply estimated by calculating the Euclidean distance between feature vectors.
84 It can be assumed, that high dimensional acoustic features lie on a low-dimensional manifold,
85 embedded in a high-dimensional feature space. Since the acoustic features are only dependent on the
86 coordinates of the sound source, it is expected that the manifold would represent the spatial relations
87 between the nearby acoustic features. We consider that that the affinity matrix of the low-dimensional
88 embeddings of the acoustic manifold represent the *graph* of the acoustic features.
89 While the obtained embeddings of the acoustic manifold might represent the relative spatial
90 relations between the acoustic features, it is not tied to physical properties and it also might be very
91 non-linear. The translation of embedded space to physical space must be done in a separate step using
92 a nonlinear regression method.

When ANN is utilized to obtain the sound source position via regression using acoustic features, it might be expected that the predictions of the ANN would also exhibit spatial smoothness. Feature manifold could be used during the training of the ANN to ensure that the ANN learns the relation between the acoustic features and the source positions while also retaining the spatial smoothness. This spatial smoothness as well as the awareness of the relative spatial positions of the acoustic features is especially important when a semi-supervised learning strategy is involved. Using a training dataset that contains both labeled and unlabeled samples, knowledge of the relative distances between unlabeled and labeled samples might help to train the regressor to predict source locations for the unlabeled samples based on their manifold distance to the labeled features.

Our method is comprised of two stages.

1. The low-dimensional embedding of an acoustic feature manifold is obtained from a combined dataset of labeled and unlabeled samples. This manifold represents relative distances between acoustic feature in a low-dimensional embedded space.
2. A neural network is trained on the combined dataset, using a loss function that consist of a supervised loss (calculated only for labeled samples) and a graph loss (calculated for all samples, considering k nearest neighbors). Supervised loss ensures that the regressor is able to learn accurate relations between the acoustic features and the source positions. Graph loss ensures that the source position predictions remain spatially smooth.

Considering that the combined dataset consist of relatively low number of labeled samples and vast amounts of unlabeled samples, the supervised loss acts as a mean to "straighten" the manifold while the graph loss is used to infer the labels for the unlabeled samples based on their distance in feature (or embedded) space to the labeled samples.

4.1. Acoustic Features

We have considered several types of acoustic features, that are discussed further.

4.1.1. Time Difference of Arrival

Time Difference of Arrival (TDoA) is a trivial acoustic feature, that can be estimated using GCC-PHAT. Knowing the TDoA for several non-colinear (or non-parallel?) microphone pairs, it is possible to estimate the position of the sound source using triangulation (trilateration).

While this would be a simple and straightforward method, the accurate TDoA estimation becomes very tricky in reverberant or noisy environments. Moreover, the TDoA contains only very little information about the distance between the sound source and the microphone pair (just one value per pair). For a microphone array with 4 elements, that's only 6 values. TDoA does not explicitly contain any information about the structure of reflections withing the enclosure, nor the geometry or acoustic properties of the enclosure; it only depends on the relative source position with respect to the microphone array(s).

4.1.2. Room Impulse Response and Room Transfer Function

It is assumed that high-dimensional acoustic features, such as room impulse response (RIR) or room transfer function (RTF) contain a unique fingerprint of sound source and microphone positions within an enclosure. This is because the structure of room reflections is unique for every source position and every microphone position (theoretically, there might be some cases when same RIR is obtained for more than one combination of microphone and sound source positions, but this is probably possible in ideal room, which exhibit point symmetry around the center of the room; in real rooms this is impossible; also the microphones must be also placed symmetrically in the enclosure for this effect to occur).

137   While the RIRs and RTFs contain enough information to uniquely determine the position of the
138 source within an enclosure, in practice it is impossible to obtain neither RIR nor RTF without knowing
139 the positions of the sound source and the microphone within the room beforehand.

4.1.3. Steered Response Power

141   Steered Response Power (SRP) and SRP with Phase Transform (SRP-PHAT) vectors can be
142 considered the middle ground between the trivial acoustic features like TDoA and ideal features,
143 like RIR or RTF. SRP-PHAT are obtainable in real world, are relatively high-dimensional and contain
144 information about sound reflections within the room.

4.1.4. Properties of acoustic features

146   The most important property of all acoustic features in this investigation is the spatial smoothness
147 of feature space. In other words, acoustic features are similar to each other for sound source positions
148 that are close together.
149   In our investigation, we use the SRP-PHAT spatial vectors as acoustic features.

4.2. Acoustic feature acquisition

151   Acoustic features were obtained within an acoustic enclosure using a single sound source, z
152 coordinate was fixed at height m_s. N_M circular microphone arrays were used for acoustic signal
153 acquisition, each with N_m microphone elements and radius m_M. Planes of the microphone arrays were
154 parallel to the ground (normals of the circles coincided with the z axis of the enclosure). The both
155 arrays were held at a fixed height m_M. Signals of the microphones are recorded at sampling frequency
156 f_s and resolution Q.

4.2.1. Unlabeled dataset

    The unlabeled dataset may be obtained from an array audio recording where the sound source is
slowly moving inside the acoustic enclosure. The maximal speed of the sound source movement $v_{s\,max}$
should be lower than the maximum expected localization error distance e_{max} per frame duration T_{fr}:

$$v_{s\,max} = \frac{e_{max}}{T_{fr}} \tag{2}$$

4.2.2. Labeled dataset

159   The labeled dataset may be obtained from an array audio recordings where the sound source
160 is stationed at a known position $\mathbf{s}_n$ within the acoustic enclosure and is producing signal (speech or
161 noise) for a period of T_s seconds. A collection of $n \in N_s$ recordings at fixed source positions may be
162 obtained.

4.3. Audio signal framing

164   Audio signals obtained from the microphone arrays are split into frames of duration T_{fr} seconds
165 to obtain N_{fr} frames. For each audio frame $j \in N_{fr}$ and for each microphone array $i \in N_M$, a
166 time-frequency representation is calculated with N_{FFT} FFT points and N_{hop} an SRP-PHAT spatial
167 spectrum $\mathbf{S}_{SRP\text{-}PHAT(j,i,(x,y,z))}$ is obtained. SRP-PHAT spectra of all arrays are then concatenated per
168 frame to obtain the acoustic feature.
169   If the audio recording has an associated location label (known coordinates), a frame is assigned
170 the position label $\bar{s}_{i,(x,y,z)}^{(x,y,z)}$.

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Describe the SRP-PHAT acquisition

4.4. Acoustic features selection (thresholding)

It is considered that the sound source might not be active a all times, and that the signal is non-stationary (in case of speech signal, it might be considered quasi-stationary for frames that contain only one phoneme or a part of a phoneme). Thus, in case of an audio frame where the source is not active, the DoA of a sound source can not be determined, and the acoustic feature is considered to contain only noise. Such frames are to be discarded. For the selection of the audio frames in which the acoustic feature is usable, a thresholding algorithm was used. For each of the frame, a metric $p_{i,j}$ was calculated for and compared to the scaled mean of the metric of all obtained frames $k_p \sum_{j \in N_{\text{fr}}} p_j$, where k_p is the scaling coefficient used to control the threshold value. The metric used to evaluate the fitness of the acoustic feature of the particular audio frame are:

1. Root-mean-square value of the SRP-PHAT spectrum, $p_{\text{RMS},i,j}$.
2. Crest factor of the SRP-PHAT spectrum, $p_{\text{CF},i,j}$.

4.4.1. Training/testing dataset split

The labeled dataset is split into training and testing subsets by randomly selecting samples from $N_{\text{ts.}}$ source positions for training and the rest of the source positions $N_{\text{tr.}} = N_{\text{s}} - N_{\text{ts.}}$ for testing from the entire set of labeled source positions. Following operations are performed separately for training ant testing labeled datasets.

4.5. Acoustic manifold embedding learning

Manifold embedding can be learned using a Nonlinear Dimensionality Reduction (NLDR) algorithm, such as isometric mapping (ISOMAP), t-distributed stochastic neighbor embedding (t-SNE) or localli linear embedding (LLE).

4.5.1. ISOMAP embedding

SRP-PHAT features from both labeled and unlabeled training datasets are embedded into D_{ISO}-dimensional embedded space using ISOMAP, with k_{ISO} nearest neighbors considered. In the resulting embedding, SRP-PHAT features are grouped by similarity, while at the same time preserving the spatial structure of the high-dimensional (?) space

4.6. Graph dataset

4.6.1. Dataset preprocessing

The combined dataset for training the neural network is comprised of two datasets: N_{u} acoustic feature samples without source position labels (the unlabeled dataset) and N_{l} acoustic feature samples with source position labels (the labeled training dataset). Each sample in the combined dataset also has a corresponding ISOMAP embedding. In order to train the GRNN with graph regularization, the dataset must be preprocessed: for each sample, regardless of whether it is a labeled or an unlabeled sample, alongside the main feature, neighbor features and their weights must be introduced. This is done by first determining the k_{ISO} nearest neighbors of a particular sample in the embedded feature space and then appending those features as well as their weight coefficients to the training sample.

4.6.2. Affinity matrix calculation

In the embedded space, Euclidean distances are calculated between every feature. The distances between each data sample constitute the distance matrix $\mathbf{D}$, which is in turn used to calculate the affinity matrix. Affinity matrix $\mathbf{A}$ is calculated by subtracting $\mathbf{D}$ from 1: $\mathbf{A} = 1 - \mathbf{D}$. The distance matrix contains the Euclidean distances between each sample in the low dimensional embedded space:

$$\mathbf{D} = (d_{ij}); \tag{3}$$

$$d_{ij} = \|\mathbf{p}_i - \mathbf{p}_j\|_2^2 \tag{4}$$

here $\mathbf{p}_i = (\alpha_i, \beta_i)$ is the point coordinate vector in the embedded space (in case of $N_{\mathrm{ISO}} = 2$), α and β are the Cartesian coordinates in the embedded space.

Neighbor weights are inversely proportional to the Euclidean distances between the main feature and the neighbor features in the low-dimensional embedded space.

4.6.3. Neighbor samples and neighbor sample weights

For the training of the GRNN, each training sample must contain the main SRP-PHAT feature and k_{ISO} neighbor SRP-PHAT features (used for calculating the graph loss). Additionally, each neighbor feature is associated with its weight w, which is the corresponding element in the affinity matrix. To obtain the k_{ISO} neighbors of each sample, each row of the affinity matrix is thresholded so that only the k_{ISO} highest-valued elements remain their value, while other row elements are set to zero. The dataset is then expanded so that each sample now has associated neighbor SRP-PHAT features (indices of which are the non-zero elements in the rows of the affinity matrix).

4.6.4. Labeled/unlabeled sample marking

For the training dataset, a flag m denoting wether the sample is labeled or unlabeled is introduced. This flag holds value of either "True" of "False" (1 or 0). Content of this field is interpreted by the GRNN during the calculation of the loss function. Effectively, the supervised loss component is multiplied by the flag. In case of an unlabeled sample, the supervised loss is ignored, and only the graph loss is considered. In real-world scenario, GRNN expects all fields, including the target feature (the label, the coordinates of the source) to be passed during training. In case of the unlabeled sample (whether during the training phase or during the prediction phase), the supervised loss is not calculated, the label is ignored, and thus it can be set to random values or to zero.

4.6.5. Labeled samples repetition

We wish to train the GRNN using as few as possible labeled samples. It was found that the network is trained more effectively when the labeled samples are introduced more times (more often) than the unlabeled samples. It might be called "dataset balancing" []. Labeled samples (those with $m = 1$) are repeated N_R times ($N_R \in \{1, \ldots, 199\}$) and appended to the training data subset.

4.7. Graph-Regularized Neural Network

In our proposition, a neural network that is trained considering not only the labeled samples, but also neighboring labeled and unlabeled samples.

4.7.1. Neural network

Any neural network can be converted to graph-regularized neural network (GRNN) by introducing additional inputs for neighboring features as well as modifying the loss function to accommodate the graph loss.

A general architecture (one of possibilities) of a GRNNmodel is provided in Figure 6. In this figure, dotted lines encompasses the input vectors. Dahsed lines inside the GRNN block denote prediction (a forward pass). The loss function is given by $L = m(\hat{y}_0 - y) + \sum_{i \in k_g} a_i(\hat{y}_0 - \hat{y}_1)$. The loss function is discussed further in more detail.
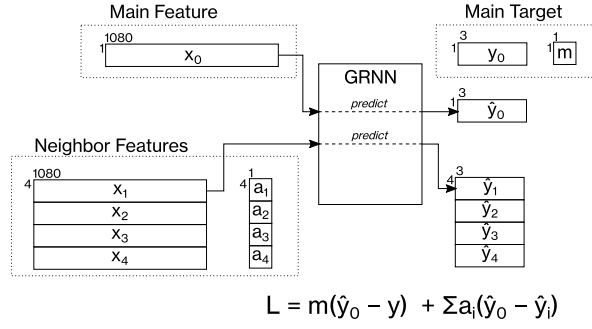
Figure 6. General architecture of a graph regularized neural network (considering 4 neighbor features). x_0 is the main input feature, $x_{1..4}$ are neighbor input features, $a_{1..4}$ are corresponding neighbor input feature weights, y_0 is the target feature, m is the labeled/unlabeled flag, $\hat{y}_0$ is the label prediction for main input feature, $\hat{y}_{1..4}$ are the label predictions for the neighbor input features

4.7.2. Architecture

Apart from the introduction of additional inputs (neighbor features, weights and flags), the actual neural network is just a multilayer perceptron. During prediction phase, only the main input contributes to the prediction.

In this experiment, a simple multilayer perceptron architecture was used. It contained these layers:

1. A 1080-dimensional input layer (to accept a concatenated SRP-PHAT feature using $N_M = 3$ microphone arrays, each covering 360° azimuth with 1° resolution).
2. A fully-connected layer with 10 units and linear activations.
3. A fully-connected layer with 31 units and ReLU activations.
4. A 3-dimensional output layer with linear activations.

This architecture was the found during previously performed hyperparameter optimization.

4.7.3. Loss function

Nearby source positions produce similar acoustic features. Therefore, the predicted source positions for the nearby acoustic features should also be similar If they are similar, the graph loss is small. If they are not similar, we need to penalize the predictor with a large graph loss

The loss function used for the GRNN training is comprised of two parts: the supervised loss (the difference between the ground truth label and the predicted label) and the graph loss (the difference bewteen the main input feature label prediction and the weighted sum of neighbor input features label predictions). It can be expressed as

$$L = \mu m \sum_{i \in N_b} (\hat{y}_i - y_i)^2 + (1 - \mu m) \sum_{i \in N_b} \sum_{j \in k_g} a_{ij}(\hat{y}_i - \hat{y}_j)^2 \tag{5}$$

here N_b – number of samples in one training batch, k_g – size of the neighborhood, a_{ij} is the neighbor weight, equal to the corresponding element in the affinity matrix.

4.8. Experimental setup

We have evaluated the performance of our proposed method using a real-world microphone array audio dataset with speech signal as the sound source, which was recorded in a particular acoustic enclosure.

4.8.1. Enclosure

All audio data used for the experimentation was collected in an irregular shaped room with the side dimensions of 4.902 m in x axis, 5.361 m in y axis and 3.75 m in z axis. The geometry of the enclosure is presented in Figure 7.
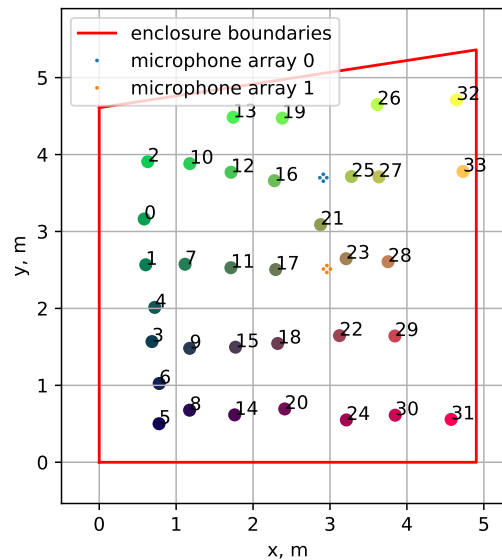

Figure 7. The geometry of the acoustic enclosure used for real-world dataset collection and labeled sound source positions; height of the enclosure was 3.75 m

4.8.2. Sound source

Source signal

The signal of the sound source was a 1 min excerpt from the AMI Corpus [5], the mix of close-talking microphone signals, containing male and female speech samples.

Sound source signal was reproduced using a compact battery powered loudspeaker that was mounted on an adjustable height stand.

Source positions

A set of 34 array audio recordings was obtained with the sound source held stationary for 1 min in one of 34 positions within the enclosure. The coordinates of the sound source were measured using a handheld laser distance measurement tool with accuracy of 1 mm. The locations of the known source positions are presented in Figure 7 as colored circles. The values of the red, green and blue components of each circle color are proportional to the x_s, y_s and z_s coordinates of the sound source position. The vertical coordinate, $z_s = 1.9$ m, was constant for all source positions.

4.8.3. Unlabeled audio dataset

The unlabeled audio dataset was collected using the same microphone array setup and the same audio source and signal. The loudspeaker was moved manually at a reasonably constant speed of approximately $0.1 \, \text{m s}^{-1}$, scanning the entire floor area of the enclosure

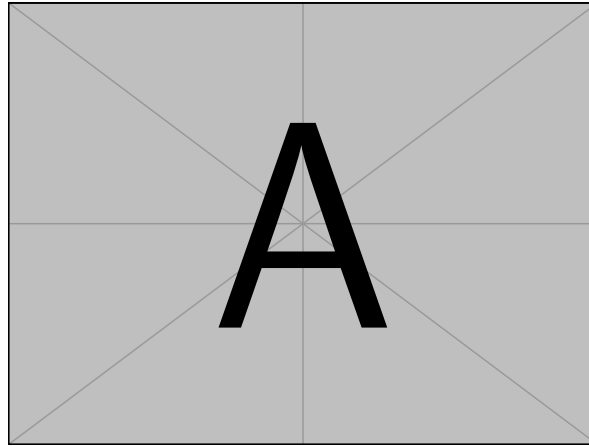by moving along y axis and then along y axis – kaip aprašyti?

Figure 8. ISOMAP embeddings of acoustic features for unlabeled audio signal, obtained using $T_{\text{fr}} = 0.05\,\text{s}$

. The vertical coordinate of the sound source, $z = 1.9\,\text{m}$, was held constant during the entire collection of the unlabeled dataset. The total duration of the recording was 511 s .

SMF3; SMF4 was 40 minut long; unused

4.8.4. Microphone arrays

In our experimentation we have used $N_{\text{M}} = 2$ radial microphone arrays with radius $m_{\text{M}} = 0.045\,\text{m}$, each consisting of $N_{\text{m}} = 4$ microphone elements spaced at equal angles $\phi_{\text{m}} = 90°$. The centers of the microphone arrays were placed at coordinates $\mathbf{M}_{\text{C},1}^{(x,y,z)} = [2.913, 3.699, 1.313]\,\text{m}$ and $\mathbf{M}_{\text{C},2}^{(x,y,z)} = [2.960, 2.512, 1.309]\,\text{m}$.

First element of each array was oriented towards the positive x axis with respect to the microphone array center (the rotation of the elements of the microphone array relative to the x axis was $0°$).

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4.8.5. Acoustic feature acquisition

Audio signals obtained from the microphone arrays were split into frames with the duration of 0.05 s. This frame duration was chosen so that every audio frame would contain only one speech phoneme.

For each audio frame and for each array, a SRP-PHAT spatial spectrum with 360 elements, covering DoA of $360°$ (1 degree resolution) was calculated using `pyroomaoustics` *Python* implementation [6] of a method presented in [**?**]. During SRP-PHAT spectra calculation, $N_{\text{FFT}} = 512$ FFT points were used, with 50 % overlap, for the STFT snapshot calculation. For each frame, SRP-PHAT spectra were concatenated to produce a single 720-dimensional acoustic feature.

4.8.6. Acoustic feature selection

To select

4.8.7. Acoustic feature manifold learning

Acoustic feature manifold embeddings were found using ISOMAP NLDR algorithm, implemented in [7]. We have chosen to embed the manifold into 2-dimensional embedded space, since in our experimentation, the only the x and y coordinate of the sound source was changing, thus, the acoustic feature are expected to rely only on two variables. The number of nearest neighbors considered for each sample was selected in the range $k_{\text{ISO}} = 2^n; n \in [0, 1, \ldots, 6]$. The same settings were used for both unlabeled and labeled audio dataset. The acoustic manifold was first learned on unlabeled dataset and then the labeled dataset was transformed into low-dimensional embedded space using the already learned manifold.

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4.8.8. Dataset construction

5. Conclusions

This section is not mandatory, but can be added to the manuscript if the discussion is unusually long or complex.

6. Patents

This section is not mandatory, but may be added if there are patents resulting from the work reported in this manuscript.

Author Contributions: For research articles with several authors, a short paragraph specifying their individual contributions must be provided. The following statements should be used "Conceptualization, X.X. and Y.Y.; methodology, X.X.; software, X.X.; validation, X.X., Y.Y. and Z.Z.; formal analysis, X.X.; investigation, X.X.; resources, X.X.; data curation, X.X.; writing–original draft preparation, X.X.; writing–review and editing, X.X.; visualization, X.X.; supervision, X.X.; project administration, X.X.; funding acquisition, Y.Y. All authors have read and agreed to the published version of the manuscript.", please turn to the CRediT taxonomy for the term explanation. Authorship must be limited to those who have contributed substantially to the work reported.

Conflicts of Interest: Declare conflicts of interest or state "The authors declare no conflict of interest." Authors must identify and declare any personal circumstances or interest that may be perceived as inappropriately influencing the representation or interpretation of reported research results. Any role of the funders in the design of the study; in the collection, analyses or interpretation of data; in the writing of the manuscript, or in the decision to publish the results must be declared in this section. If there is no role, please state "The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results".

Abbreviations

The following abbreviations are used in this manuscript:

GRNN	graph regulzarized neural network
SRP	steered response power
PHAT	phase transform
DoA	direction of arrival
RMS	root mean square
MSE	mean squared error
MAE	mean average error
RMSE	root mean squared error
ISOMAP	isometric mapping
NLDR	non-linear dimensionality reduction

Appendix A

Appendix A.1

The appendix is an optional section that can contain details and data supplemental to the main text. For example, explanations of experimental details that would disrupt the flow of the main text, but nonetheless remain crucial to understanding and reproducing the research shown; figures of replicates for experiments of which representative data is shown in the main text can be added here if brief, or as Supplementary data. Mathematical proofs of results not central to the paper can be added as an appendix.

Appendix B

All appendix sections must be cited in the main text. In the appendixes, Figures, Tables, etc. should be labeled starting with 'A', e.g., Figure A1, Figure A2, etc.

References

1. Marti, A.; Cobos, M.; Aguilera, E.; Lopez, J.J. Speaker Localization and Detection in Videoconferencing Environments Using a Modified SRP-PHAT Algorithm. p. 8.
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Sample Availability: Samples of the compounds ...... are available from the authors.