Article

Sound Source Localization Using Graph Regularized Neural Network

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Abstract: In this article we present a data-driven approach for a single speech source localization within an acoustic enclosure. Our method consist of high-dimensional acoustic feature extraction, selection based on a fitness criterion, feature manifold learning and low-dimensional embedding, graph dataset construction and an application of a graph-regularized neural network (GRNN) to learn the mapping between the embedded feature coordinates and the Cartesian coordinates of the sound source. Our method relies on the assumption of the feature space spatial smoothness. We present the experimental results of the speech source localization in real acoustic enclosures using two compact circular microphone arrays. We compare the performance of the GRNN for single speech sound source localization to the performance of two baseline algorithms.

Keywords: sound source localization; array signal processing; manifold learning; graph regularization; artificial neural networks

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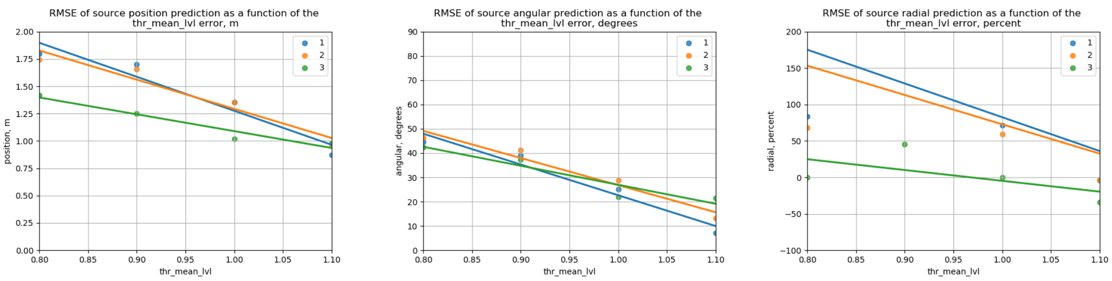
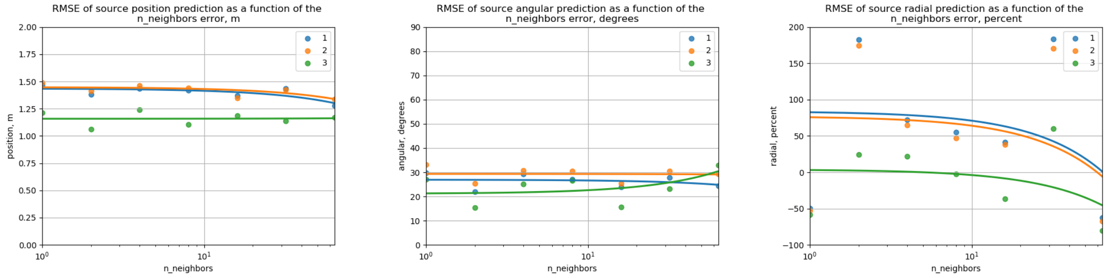


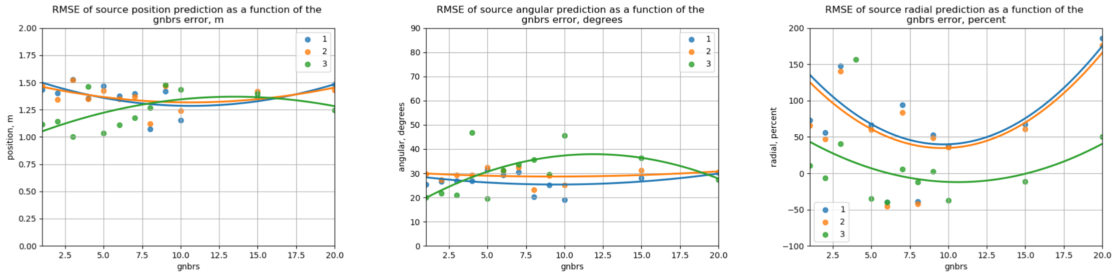
(a) position error (b) angular error (c) radial error

Figure 1. Dependency between the source position prediction, source DoA estimation and radial estimation RMSE and the acoustic feature thresholding level; linear regression model showed in solid line



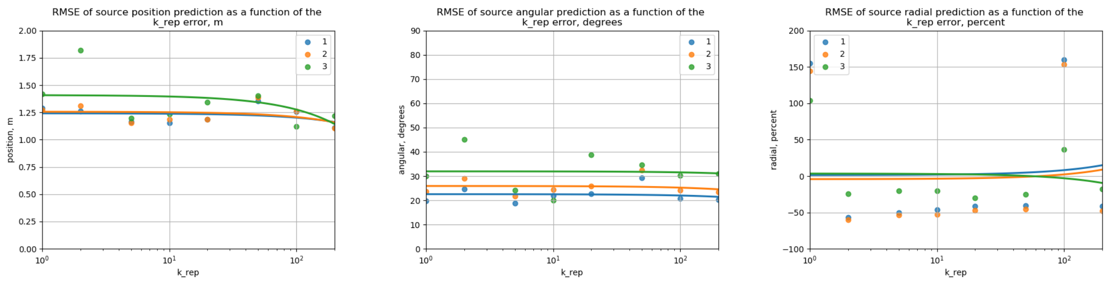
(a) position error (b) angular error (c) radial error

Figure 2. Dependency between the source position prediction, source DoA estimation and radial estimation RMSE and the number of nearest neighbors considered for ISOMAP embedding; linear regression model showed in solid line



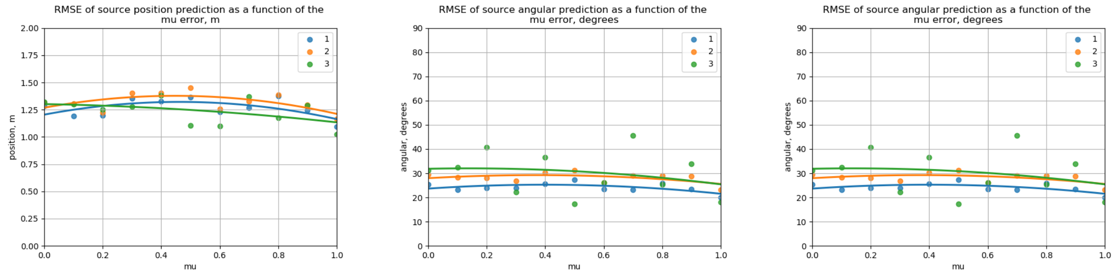
(a) position error (b) angular error (c) radial error

Figure 3. Dependency between the source position prediction, source DoA estimation and radial estimation RMSE and the number of nearest graph neighbors considered during the training dataset construction; linear regression model showed in solid line



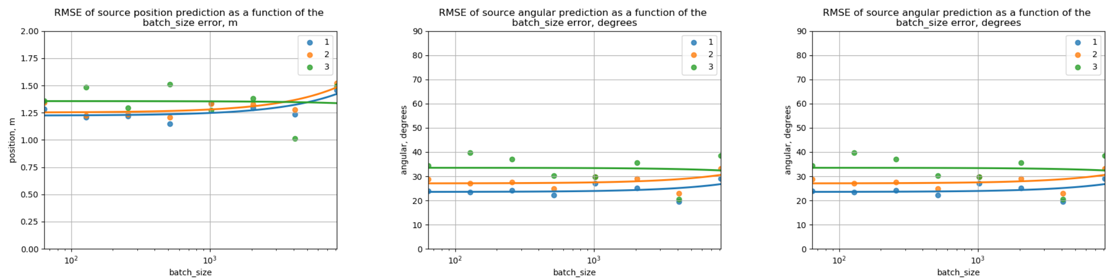
(a) position error (b) angular error (c) radial error

Figure 4. Dependency between the source position prediction, source DoA estimation and radial estimation RMSE and the labeled samples repetition rate during GRNN training; linear regression model showed in solid line



(a) position error (b) angular error (c) radial error

Figure 5. Dependency between the source position prediction, source DoA estimation and radial estimation RMSE and the ratio between the supervised and unsupervised loses considered during the GRNN training; linear regression model showed in solid line



(a) position error (b) angular error (c) radial error

Figure 6. Dependency between the source position prediction, source DoA estimation and radial estimation RMSE and the GRNN training sample batch size; linear regression model showed in solid line