Performance of Neural Networks in Source Localization using Artificial Lateral Line Sensor Configurations

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INTRODUCTION

Artificial lateral lines (ALLs) are used to detect the movement and locations of sources underwater, and are based on the neuromasts (fig. 1) located in the lateral line organ found in fish and amphibians. ALLs consists of a set of biaxial sensors (fig. 2)

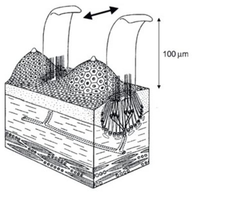

Fig. 1: Superficial neuromasts of a clawed frog. From Görner (1963).

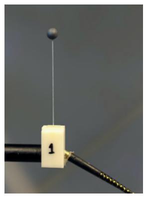

Fig. 2: Biaxial ALL sensor. From Wolf et al. (2018).

RESEARCH QUESTIONS

Can the placement of artificial lateral line sensors be beneficial for improving the accuracy of source localization through the use of convolutional neural networks?

Are convolutional neural networks and extreme learning machines capable of predicting the locations of multiple sources in three-dimensional environments?

SOURCE LOCALIZATION PIPELINE

Source localization pipeline

Data generation:
- *source locations:* } Calculate sensor readings
- *sensor locations:* }
- *teacher object:* 3D matrix containing 1331 density probability points for source locations

Neural networks:
- *convolutional neural network*
- *extreme learning machine*
- *sensor readings* → *3D matrix*

Source prediction process:
- *3D matrix* → *source predictions* (k-means)

METHODS

EXPERIMENT 1

A Cramér-Rao lower bound analysis was performed on a subset of sensor configurations (16 sensors, 1m^3 basin) to estimate their likely performances and indicate the best and worst configurations.

EXPERIMENT 2

The best and worst configurations were used to generate simulated datasets to train and test extreme learning machines (ELMs) and convolutional neural networks (CNNs) on their location accuracy. Simulated datasets consisted of 2 sources in a 3D basin (1m^3) and the sensor readings of 16 ALL sensors.

REFERENCES

Görner, P. (1963). Untersuchungen zur morphologie und elektrophysiologie des seitenlinienorgans vom krallenfrosch (xenopus laevis daudin). Journal of Comparative Physiology A: Neuroethology, Sensory, Neural, and Behavioral Physiology, 47 (3), 316–338.

Wolf, B. J., Morton, J. A., MacPherson, W. B. N., & van Netten, S. M. (2018). Bioinspired all-optical artificial neuromast for 2d flow sensing. Bioinspiration & biomimetics.

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RESULTS

EXPERIMENT 1:

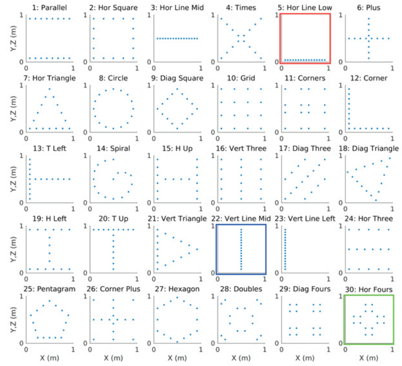

Fig. 3: 2D sensor configurations for 16 sensors. Configurations were applied horizontally (at z:0) and vertically (at y:0). The Cramér-Rao lower bound analysis indicates that *30:HorFours* (green) and *22:VertLineMid* (blue) performed best horizontally and vertically, respectively. *5:HorLineLow* (red) is indicated as the worst performing configuration.

EXPERIMENT 2:

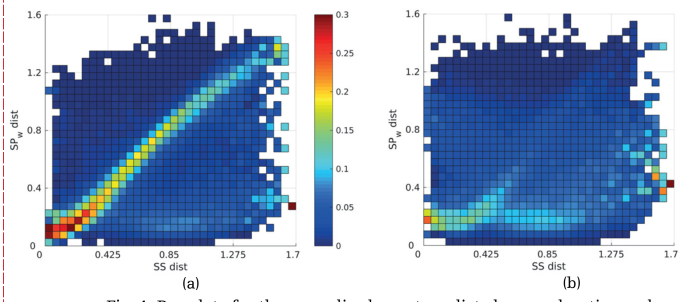

Fig. 4: Bar plots for the normalized worst predicted source location and prediction distributions versus the distance between both source locations (horizontal ALL, using *30:HorFours*). (a): CNN; (b): ELM. Colors indicate distributions. With CNNs, the secondary source performance shows a linear relationship with the distance between sources, which is not the case with ELMs.

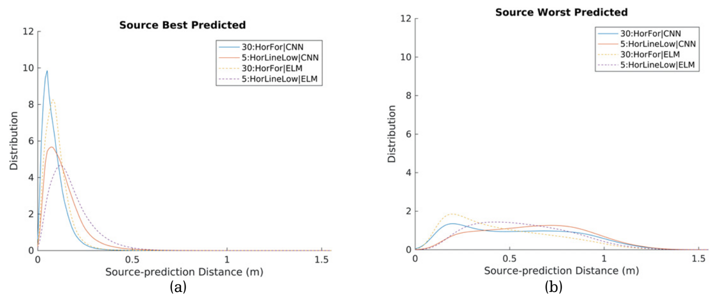

Fig. 5: Estimated probability curves for the distribution of total source-prediction distances for the best (a) and worst (b) predicted sources. ALLs were placed horizontally at z:0. Curves were averaged over 5 repetitions and 4 dataset conditions.

CONCLUSION

The optimal configuration improved performance for both sources, compared to other configurations. Therefore, the main research question can be answered positively in that using an optimal configuration can improve source localization performance using CNNs.

With regard to the secondary research question, both neural networks are capable of detecting two sources in a 3D environment, if sources are an equal distance removed from the ALL. If not, only the closest source to the array is accurately reconstructed.

The optimal configuration also improved ELM results for all source generation conditions; the use of an ELM leads to a higher performance of the worst estimated source, for the majority of conditions, compared to using a CNN.