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# A data-driven method for estimating the target position of low-frequency sound sources in shallow seas

**Key words:** Vector hydrophone; Shallow sea; Low frequency; Location estimation; Recurrent neural network

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# Motivation

1. Compared with a deep-sea environment, a shallow sea environment has the complex characteristics of spatio-temporal variability, reflection of the signal from the shallow sea bottom, and human offshore activities that cause aliasing of target signal, thus increasing the difficulty of identification of the sound source signal.
2. With the development of noise reduction technology and stealth technology, the working frequency band of ship sonar is moving towards lower frequencies.
3. Traditional mathematical models need to set more environmental variables.

# Main idea

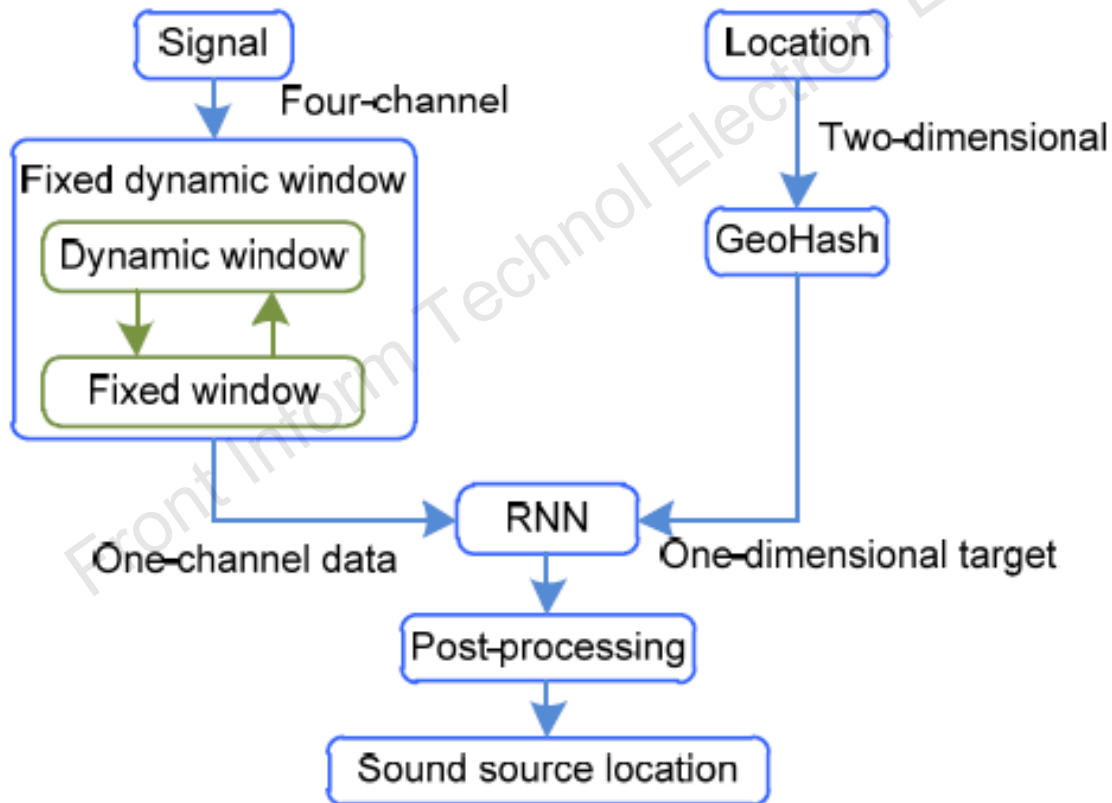
1. Vector hydrophones can obtain information of sound pressure and acoustic particle velocity in the ocean sound field at a particular time and point.
2. As a kind of data-driven model, neural networks have the advantages of self-adaptation, self-organization, and self-learning.
3. GeoHash is a positioning method that converts two-dimensional (2D) labels into one-dimensional (1D) strings.

# Method

1. A compressed recurrent neural network (C-RNN) model is proposed that compresses the signal received by a vector hydrophone into a dynamic sound intensity signal and compresses the target position of the sound source into a GeoHash code.
2. Two types of compressed data are used to carry out prior training on the recurrent neural network, and the trained network is subsequently used to estimate the target position of the sound source.

# Major results

## Compressed recurrent neural network



**Fig. 6 Compressed recurrent neural network model**

# Major results (Cont'd)

Test results of our model and related methods

Table 4 Experimental results of different sound source localization models

Experiment		Lat (m)				Lng (m)				Iteration time (s)
Type	Structure	Before		After		Before		After		
		Mean	RMSE	Mean	RMSE	Mean	RMSE	Mean	RMSE	
Interception method	NW	116.0	135.7	116.0	135.7	487.4	584.9	487.4	584.9	<b>0.04</b>
	FW	36.3	47.2	19.7	23.8	250.7	330.3	209.1	228.8	0.53
	O-FW	25.9	35.6	14.7	18.4	154.2	240.2	124.8	146.8	0.26
	DW	130.6	155.2	130.6	155.2	304.2	365.7	304.2	365.7	0.17
	FDW	18.4	<b>21.7</b>	18.4	21.7	151.3	180.8	151.3	180.8	0.34
	O-FDW	<b>17.1</b>	23.3	<b>8.9</b>	<b>10.7</b>	<b>104.8</b>	<b>177.5</b>	<b>57.7</b>	<b>70.8</b>	0.15
Information fusion	SP	19.7	28.0	10.4	15.0	124.7	208.3	92.7	112.5	0.16
	VV	25.5	36.1	14.5	17.5	140.4	221.6	103.8	116.1	<b>0.13</b>
	SPVV	26.8	37.6	15.8	19.7	175.6	270.6	148.0	175.9	0.15
	SI	<b>8.9</b>	<b>10.7</b>	<b>8.9</b>	<b>10.7</b>	<b>57.7</b>	<b>70.8</b>	<b>57.7</b>	<b>70.8</b>	0.16
Network	RNN	<b>20.4</b>	<b>26.6</b>	<b>10.7</b>	<b>13.0</b>	<b>111.3</b>	<b>185.7</b>	<b>69.0</b>	<b>83.3</b>	<b>0.24</b>
	LSTM	60.1	65.5	59.3	64.5	244.1	276.8	239.3	271.0	0.28
	One-BiLSTM	59.7	66.2	59.2	65.0	242.2	273.2	238.7	266.6	0.50
	Two-BiLSTM	57.9	63.3	57.9	63.3	226.4	260.7	226.4	260.7	0.73
Structure	SPVV+LSTM	<b>10.3</b>	<b>12.0</b>	10.3	12.0	<b>89.8</b>	<b>99.4</b>	89.8	99.4	<b>0.08</b>
	SPVV+RNN	24.1	29.0	24.1	29.0	133.7	171.4	133.7	171.4	0.21
	SPVV+O+RNN	15.5	19.2	15.2	18.6	115.4	135.8	111.5	129.0	0.60
	SI+O+RNN	14.2	16.7	14.2	16.7	106.5	123.5	106.5	123.5	0.63
	GEO+SI+O+RNN	17.1	23.3	<b>8.9</b>	<b>10.7</b>	104.8	177.5	<b>57.7</b>	<b>70.8</b>	0.16
Sample	10-min+50-sample	<b>14.6</b>	<b>19.5</b>	<b>8.7</b>	<b>9.9</b>	<b>76.1</b>	<b>143.5</b>	<b>56.4</b>	<b>68.1</b>	0.20
	30-min+50-sample	63.2	90.4	48.2	57.8	223.1	330.4	145.3	162.9	<b>0.15</b>
	30-min+200-sample	53.6	79.4	37.5	48.8	193.5	302.8	131.5	184.6	0.18
	60-min+500-sample	35.9	44.5	35.9	44.5	188.4	300.0	188.4	300.0	<b>0.15</b>
	60-min+1000-sample	46.6	66.0	29.1	38.6	229.2	365.0	167.6	231.5	0.17

Before: before the averaging; After: after the averaging. Best results are in bold

# Conclusions

1. A C-RNN model has been proposed which is used to achieve the localization of unknown signals.
2. The model considers that the chirp signal received by the vector hydrophone must be related to the signal in a certain time domain.
3. The C-RNN model improves the operating speed for low-frequency sound source signals, and can provide accurate positioning. The average error radius is approximately 56 m.



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