

Compressed sensing using a non-uniformly sampled range-azimuth dictionary

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Abstract. FM-bats are known to be able to sense the environment by echolocation. In this paper, assuming the objects in the environment can be characterized by a sparse representation of the echoes in range and azimuth, a compressed sensing algorithm using a range-azimuth dictionary is proposed. The monaural and binaural range-azimuth dictionaries are constructed from measurements collected with a bionic sonar system consisting of one emitter and two receivers fitted with a 3-D printed replica of a real bats external ears. To estimate the range and azimuth of a target, the L1-minimization method is used. Since the high coherence in azimuth templates could cause ambiguity in azimuth estimation, the use of a non-uniform sampled dictionary is investigated. The non-uniform sampling is derived from the coherence between different azimuth templates in the dictionary. The non-uniformly sampled monaural and binaural dictionaries are used to process the echoes collected from a real brick-wall. Results indicate that strong echoes can be correctly localized both in azimuth and range by all three dictionaries, but for weak, highly overlapping echoes, both monaural dictionaries have problems interpreting these echo signals correctly. In addition to missing many of the real brick seams they also generate many false reconstructed objects, but constructing a binaural dictionary the results can be improved significantly.

1 Introduction

Bats can find and identify targets using FM signals even in quite complex environment such as a forest where many echoes from the surroundings are received[1]. The spectrogram correlation and transformation (SCAT) model of the sonar receiver in the big brown bat and its modified versions were proposed to explain how the bats could construct the acoustic image of the environment and targets[2,3]. However, it was shown that these models break down when facing several (more than 3) closely spaced overlapping echoes[4]. However, an alternative method proposed by Fontaine and Peremans could distinguish such closely spaced objects based on a time-domain sparse representation of bat echolocation calls[5].

Considering the azimuth information is also necessary to fully interpret the echoes, a method based on a range-azimuth dictionary (RAD) is proposed in this article. Using a bionic sonar system, the echoes from a real brick-wall are processed by this method.

2 Sparse representation of the echoes

2.1 Range-azimuth dictionary

For an active sonar system, reflections from the surroundings coming from different distances and directions combine into the echo arriving at the receiver. By a similar sparsity assumption as in [5], the received

echo $E(t)$ in the sonar system can be represented as the linear superposition of reflections

$$E(t) = \sum_{i,j} A_{ij} s(r_i, \theta_j) \quad (1)$$

where $s(r_i, \theta_j)$ represents the normalized reflection of an object at the range r_i and the azimuth direction θ_j , A_{ij} indicating its amplitude.

Considering the range as the integer delay of the discretised reflection $s^j(n)$, the sampling of the reflection from azimuth θ_j , the range-azimuth dictionary (RAD) can be constructed, as shown in equation (2)

$$\Psi = \begin{bmatrix} s^1(1) & & & & s^p(1) & & & \\ s^1(2) & s^1(1) & & & s^p(2) & s^p(1) & & \\ s^1(3) & s^1(2) & & & s^p(3) & s^p(2) & & \\ \vdots & s^1(3) & & & \vdots & s^p(3) & & s^p(1) \\ s^1(N-2) & \vdots & s^1(2) & \dots & s^p(N-2) & \vdots & & s^p(2) \\ s^1(N-1) & s^1(N-2) & \dots & s^1(3) & s^p(N-1) & s^p(N-2) & \dots & s^p(3) \\ s^1(N) & s^1(N-1) & & \vdots & s^p(N) & s^p(N-1) & & \vdots \\ & s^1(N) & s^1(N-2) & & & s^p(N) & s^p(N-2) & \\ & & s^1(N-1) & & & & s^p(N-1) & \\ & & s^1(N) & & & & & s^p(N) \end{bmatrix} \quad (2)$$

Every column in the dictionary represents the reflection for a specific time delay and azimuth. The sampled echo $E(n)$ can be expressed as

$$\mathbf{E} = \Psi \mathbf{R} \quad (3)$$

where $\mathbf{R}$ is a sparse representation of the echo in the range-azimuth dictionary Ψ . That is to say, if there are

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targets at multiple positions corresponding to specific columns in $\text{RAD } \Psi$, then $\mathbf{R}$ will have the same number of non-zero values at corresponding positions while all other values are zeros.

2.2 Estimation of the range and azimuth of target

From the formula (3), it can be seen that the estimation of target azimuth and distance can be converted into finding the sparse representation of echo signals using a range-azimuth waveform dictionary. Such problems can be solved by the L1 minimization method from convex optimization theory [6], also used in [5],

$$\min \left[\frac{1}{2} \|\mathbf{E} - \Psi \mathbf{R}\|_2^2 + \gamma \|\mathbf{R}\|_1 \right], \mathbf{R} \geq 0 \quad (4)$$

where γ is a weighting coefficient quantifying the compromise between adherence to the data and sparsity. Its value depends on the input SNR and should increase with the level of noise.

2 Measurements and processing

2.1 Dictionary construction

A bionic sonar system was used to construct the RAD and measure the echo from a real wall. The experimental bionic sonar system is mainly composed of a sound transducer, a pair of 3D printed bat outer ears and receiving microphones, as shown in Fig.1.

A cardboard cylindrical tube was used as a target to measure the reflected waveforms for azimuths ranging from -30° to 30° as shown in Fig.2. A broadband harmonic signal with a fundamental component whose frequency sweeps down from 30 to 20kHz, 2ms in duration similar to an FM-bat was transmitted from the sonar; the target echoes for different azimuth values were collected by the right and left ear receivers. Every azimuth measurement was repeated 100 times and the average waveform was stored, as shown in Fig.3.

According to the equation(2), these average waveforms are used to construct the two monaural dictionaries for the left ear and right ear respectively. Put the left ear and the right ear signals of the same azimuth in a vector noted as a binaural signal, and then a binaural dictionary also could be constructed.

2.2 non-uniform sampling of the RAD

Using the L1 minimization method to estimate the target distance and azimuth actually tries to match the received signal with a weighted sum of waveforms from the dictionary. This method requires no redundancy in the dictionary; otherwise it will produce ambiguity in the estimation. In order to investigate the redundancy of the waveform dictionary constructed here, we use the coherence between dictionary column vectors

$$\rho = \langle \Psi(:, i), \Psi(:, j) \rangle \quad (5)$$

where $\langle \cdot, \cdot \rangle$ denote the inner product.

In the most ideal case, there is no redundancy in the dictionary, so the coherence between different column vectors is zero, that is, the coherence matrix is the unit diagonal matrix. In order to collect information from a larger field, the beamwidth of bat sonar is more than 20 degrees[1]. Therefore, the dictionary constructed from uniformly sampled azimuth waveforms as received by the bionic sonar system would show obvious redundancy. Indeed, as shown in Fig.4, coherence in the mainlobe direction for the left and right ear was relatively high. To deal with this, we non-uniformly selected azimuths and constructed a non-uniformly sampled dictionary. For the monaural right-ear dictionary we selected azimuths: $-30^\circ, -28^\circ, -26^\circ, -23^\circ, -20^\circ, -17^\circ, -13^\circ, -12^\circ, -10^\circ, -5^\circ, -1^\circ, 0^\circ, 6^\circ, 8^\circ, 10^\circ, 12^\circ, 16^\circ, 22^\circ, 28^\circ$. For the monaural left-ear dictionary we selected azimuths: $-30^\circ, -24^\circ, -16^\circ, -11^\circ, -6^\circ, -2^\circ, 0^\circ, 4^\circ, 6^\circ, 8^\circ, 10^\circ, 14^\circ, 16^\circ, 18^\circ, 21^\circ, 24^\circ, 26^\circ, 28^\circ, 30^\circ$. For the binaural dictionary we selected azimuths: $-30^\circ, -24^\circ, -15^\circ, -12^\circ, -10^\circ, -7^\circ, -4^\circ, -2^\circ, 0^\circ, 3^\circ, 6^\circ, 7^\circ, 8^\circ, 10^\circ, 12^\circ, 16^\circ, 18^\circ, 22^\circ, 28^\circ$.

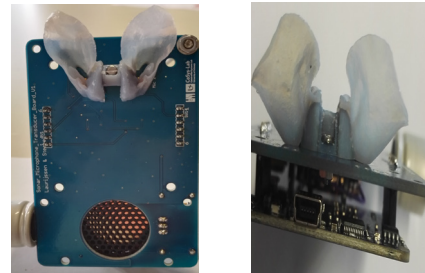


Fig. 1. The bionic sonar system.



Fig. 2. Measurement of the dictionary.

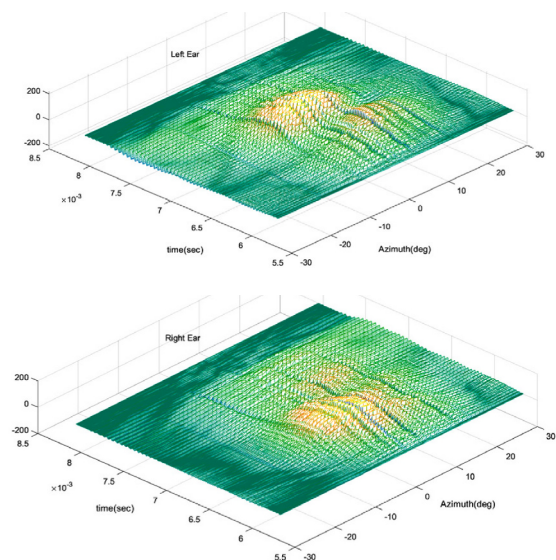


Fig. 3. Echoes received by left ear (top) and right ears (bottom).

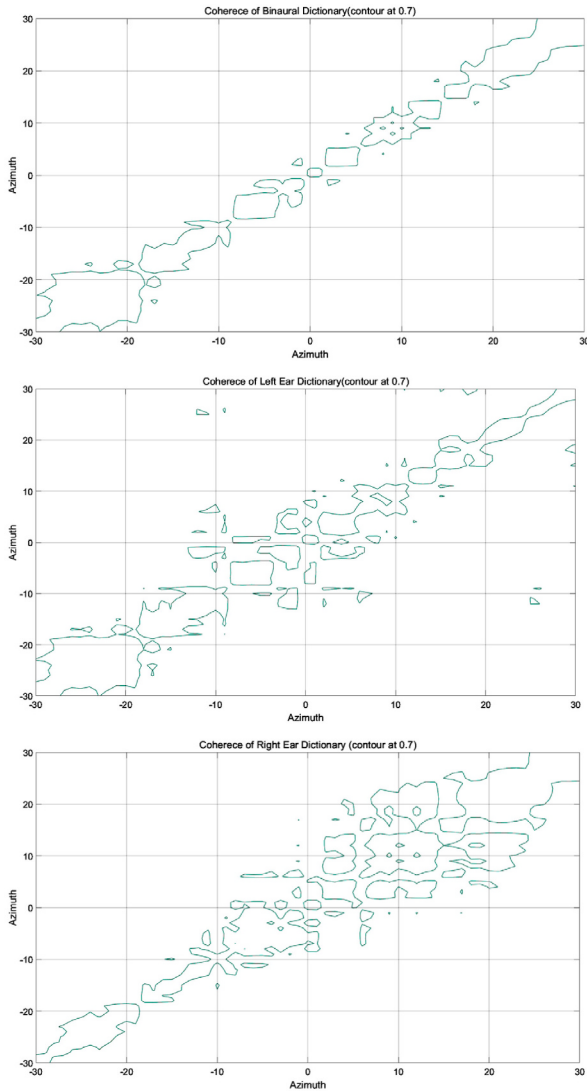


Fig. 4. Coherence of uniform Azimuth Dictionary.

2.3 Wall surface echo processing and analysis

As shown in Fig.5, the bionic sonar system was placed parallel to the side of a brick wall; the received signal of the left and right ears is shown in Fig.6. The transmitted signal was 2ms in duration, and the echo was measured after transmitting. It can be seen that as the right ear was closer to the wall, the echoes received in it were stronger than in the left ear. Although the doorframe was the reflector farthest away, its echo signal was the strongest due to its retroreflector properties, and its echoes received in left and right ear were quite close in signal intensity.

The monaural dictionaries of left ear and right ear and the binaural dictionary are used to process the echo. Results are shown in Fig.7.

The origin point of Fig.7 is the location of the sonar system, 15cm in the horizontal plane from the wall. Due to the small incident angle, the wall bricks mainly generated forward reflections, i.e. echoes reflected away from the sensor, whereas the backward scattering mainly came from the joints between the bricks and the farthest doorframe. The true locations of these points are marked with a red cross in Fig.7. To judge the accuracy of the

information about the walls we compare the results from monaural and binaural dictionaries respectively with the red crosses.



Fig. 5. Measurement of the wall.

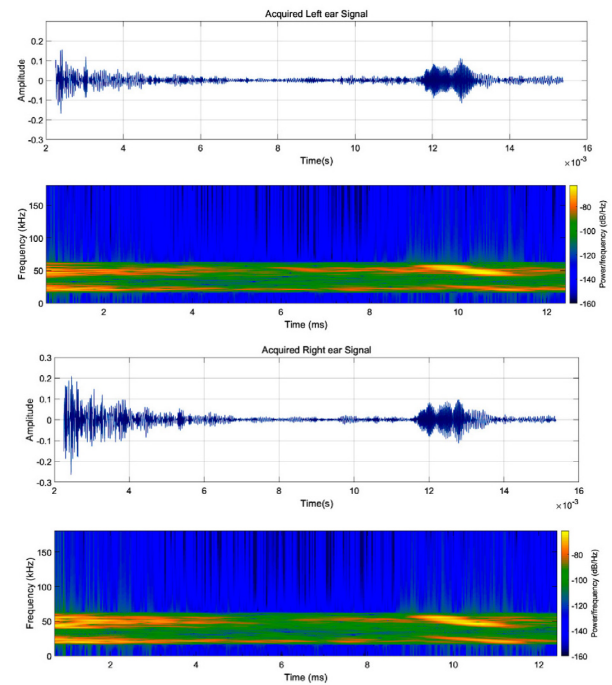


Fig. 6. Echoes from the wall received by left ear (top) and right ear (bottom).

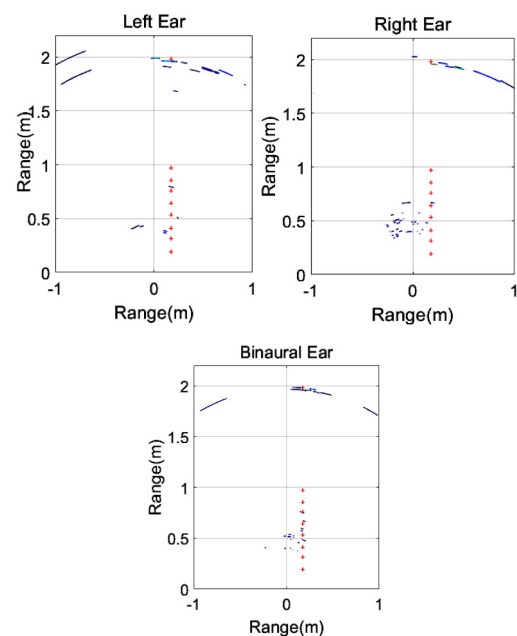


Fig. 7. Acoustic imaging of the wall using the monaural and binaural dictionaries.

Results (Fig.7) show that all of the three dictionaries were able to locate the doorframe. Due to the strong echo there is no serious aliasing with the echoes from other locations. But for reconstructing the brick seams, the performance of the binaural dictionary is the best. More than three brick seams are successfully located (the positions of the pink colour stickers marked in Fig.5), while the number of false reconstructed objects is minimal. On the other hand, both monaural dictionaries have problems interpreting these echo signals correctly. In addition to missing many of the real brick seams they also generate many false reconstructed objects.

3 Conclusions

In this paper, a target location method based on the sparse representation of range-azimuth dictionary was proposed. A bionic sonar system is used to construct the waveform dictionary, and non-uniform sampling in azimuth was investigated. The real-world experimental results showed that a non-uniformly sampled binaural dictionary can distinguish multiple overlapping echoes with a bionic sonar system.

References

1. W. W. L. Au, J. Simmons, *Physics Today*, Sept., 40-45(2007)
2. P. Saillant, J. Simmons, S. Dear, and T. McMullen, *J. Acoust. Soc. Am.* **94**, 2691-2712(1993)
3. A. Boonman,, and J. Ostwald, *Biol. Cybern.*, **97**, 159-172(2007)
4. H. Peremans and J. Hallam, *J. Acoust. Soc. Am.*, **104**, 1101-1110(1998)
5. B. Fontaine, H. Peremans, *J. Acoust. Soc. Am.* , **125**, 3052-3059(2009)
6. S. J. Kim, K. Koh, M. Lustig, S. Boyd, and D. Gorinevsky, *IEEE J. Sel. Top. Sign. Process.*, **1**, 606-617(2007)