Sonar imaging of structured sparse scene using template compressed sensing

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***Abstract*—To solve the low efficiency of traditional synthetic aperture sonar (SAS) imaging problem, a sonar imaging system combining compressed sensing (CS) and template compressed sensing (TCS) was proposed. The system used sonar network to image scenes. With 10% amount of traditional SAS data, CS and TCS algorithms could recover the image exploiting the structured sparsity of the interested scene with the same resolution. TCS method even recovered the image perfectly. Simulations shows the good performance.**

Keywords-sonar imaging; compressed sensing; template compressed sensing

I. INTRODUCTION

Synthetic aperture sonar (SAS) techniques have been applied widely in sonar imaging applications. According to the techniques, high range resolution is obtained by transmitting wideband signals, and high azimuth or along-track resolution is gained by coherent integrated echoes from different lines of sight (LOS). Nevertheless, as the pulse repetition interval (PRI) between pings is long due to the low velocity of sound, to obtain a high azimuth resolution image is time-consuming. Meanwhile, the range cell motion compensation (RCMC) process is mathematically complex due to the short wavelength and the uncertain relative motion during the long PRI. Conventionally, an along-track deployed array of hydrophones are used to lower the PRI equivalently [1], and a number of algorithms are proposed based on the approach [2]. Further, multistatic sonar network is proposed for a more varied arrangement of hydrophones.

Compressed sensing (CS) [3] has been applied as a tool to recover signals from fewer samples. It exploits the sparsity of a signal, stating if the sampling scheme of the signal meets certain requirements, the signal can be recovered exactly [3].

The first attempt combining radar imaging and CS dates back to 2007. The authors managed to omit the matched filter part in traditional radar [4]. Paper [5] introduced a method to random sample the echoes and reconstruct the imaging scene. Paper [6] concluded the use of CS in radar imaging. On the other hand, the treatise on CS sonar imaging is very limited. In SAS applications, the number of echoes is small compared to that of radar in the same period. Meanwhile, SAS often observes targets floating in the water rather than the seabed, so the image scene shows better sparsity. Furthermore, the nonzero entries are cluttered in the centre and present a structured sparsity. These characteristics imply that a more targeted approach may be utilized in sonar imaging.

In this paper, a novel sonar imaging method is proposed. The method exploits the structured sparsity feature of the interested scene, uses template compressed sensing (TCS) method, images the scene with far few echoes from random angles, and still gets high resolution.

II. MODELLING OF CS SONAR IMAGING

Consider a wideband sonar network with one transducer and m multistatic hydrophones. This is often the case of detecting targets in a sea area with a sonar network system. The sonar transducer transmits wideband signals. The echoes encode backscatter signals from a target and are received by those hydrophones as Fig. 1a shows. With only one ping, m echoes will be received. The high resolution range profile (HRRP) of the target can be achieved using matched filter. In a far field plane wave assumption, the HRRP could be interpreted as the projection of the backscatter power of the target along direction perpendicular to the line between the transducer and the hydrophone. Or the process is equivalent to m monostatic sonars working simultaneously (see Fig. 1b).

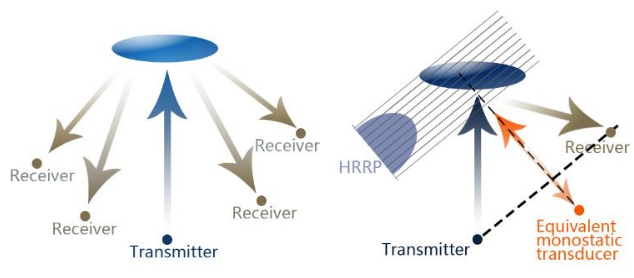

Figure 1. System structure and working principle
a System structure
b The equivalent monostatic sonar and its HRRP

It should be noted that the length of the HRRP hints the distribution of the scatters along the signal transmitting direction. In Fig. 1b, the resolution of the HRRP is determined by the matched filter.

The target along with the background is first divided into squares with each square representing a scatter point of the scene. The size of the squares is set as the resolution of the HRRP. Thus a target matrix $\boldsymbol{X}_{n\times n}$ is obtained. The size of the matrix n depends on the largest length of the HRRPs. If we vectorize $\boldsymbol{X}$ along the column direction to form vector $\boldsymbol{x}_{n\cdot n\times 1}$, then each echo could be considered as a linear projection of $\boldsymbol{x}$, denoted as $\boldsymbol{y}$ whose size is also $n\times 1$. $\boldsymbol{A}$ is denoted as the projection matrix of size $m\times n^2$ which is composed of zeros and ones. For traditional SAS, $\boldsymbol{y}$ is coherent integrated according to the Doppler information. As most of the time, the matrix $\boldsymbol{X}$ to be recovered is sparse, i.e. most of its entries are zero, except those corresponding to the scatters on the target. We present a CS method to solve the problem. With $m(m<<n)$ echoes received, a list of formulas are obtained,

$$\begin{cases} \boldsymbol{y}_1 = \boldsymbol{A}_1\boldsymbol{x} \\ \boldsymbol{y}_2 = \boldsymbol{A}_2\boldsymbol{x} \\ \quad\vdots \\ \boldsymbol{y}_m = \boldsymbol{A}_m\boldsymbol{x} \end{cases}. \tag{1}$$

Denote $\mathcal{Y}_{m\cdot n\times 1} = \begin{bmatrix} \boldsymbol{y}_1^T & \boldsymbol{y}_2^T & \cdots & \boldsymbol{y}_m^T \end{bmatrix}$ and $\mathcal{A}_{mn\times nn} = \begin{bmatrix} \boldsymbol{A}_1^T & \boldsymbol{A}_2^T & \cdots & \boldsymbol{A}_m^T \end{bmatrix}$,

(1) can be rewritten as

$$\mathcal{Y} = \mathcal{A}\boldsymbol{x}. \tag{2}$$

CS theory states that if $\boldsymbol{x}$ is sparse, and $\mu(\mathcal{A})$ is small, $\boldsymbol{x}$ could be recovered via a ℓ_1 norm minimization problem. And $\mu(\mathcal{A})$ is defined as the largest off-diagonal entry of the normalized Gram matrix of $\mathcal{A}$. Numbers of tests indicate that if the hydrophones are distributed so that the echoes are not strongly correlated, the formed $\mathcal{A}$ meet the requirement.

$$\begin{aligned} &\min \quad \|\boldsymbol{x}\|_1 \\ &s.t. \quad \mathcal{Y} = \mathcal{A}\boldsymbol{x}. \end{aligned} \tag{3}$$

III. TCS MODEL OF CS SONAR IMAGING

CS exploit the sparsity of the image. However we can see that the scatters are distributed mostly in the centre of the image, the distribution of the scatters can be also estimated from the length of the echoes. These structures could be used as a priori for image recovery.

Generally, a priori will be added as a regularization to restrict the result. We propose a template CS method to exploit this a priori instead of regularization. Equation (3) is rewritten as

$$\begin{aligned} &\min \quad \|\mathrm{vec}(\boldsymbol{W}\odot\boldsymbol{X})\|_1 \\ &s.t. \quad \mathcal{Y} = \mathcal{A}\boldsymbol{x}. \end{aligned} \tag{4}$$

in which $\boldsymbol{W}$ is the template matrix, $\odot$ represent Hadamard product, and $\mathrm{vec}(\cdot)$ is the reshaping operator to vectorize a matrix along its column direction . $\mathrm{vec}(\cdot)$ is set according to the distance between the entry and matrix centre, and the length of each echo. $\boldsymbol{W}$ is termed as a template due to its representation of the a priori. By exploiting more prior information, the observed echo number can be reduced further than traditional CS method.

IV. NUMERICAL RESULTS

In this part, a comparison of traditional SAS imaging method, CS and TCS methods will be made.

Suppose an interested target is 700m away from the sonar and the size of the target is unknown, but less than $100\text{m}\times 100\text{m}$ according to HRRP. 8 hydrophones form an arc with the centre of the arc colocating with the target and the radius of the arc being 700m. The hydrophones are about 250m away from each other. A comparison of traditional SAS, CS and TCS methods are made with linear frequency modulated (LFM) signal.

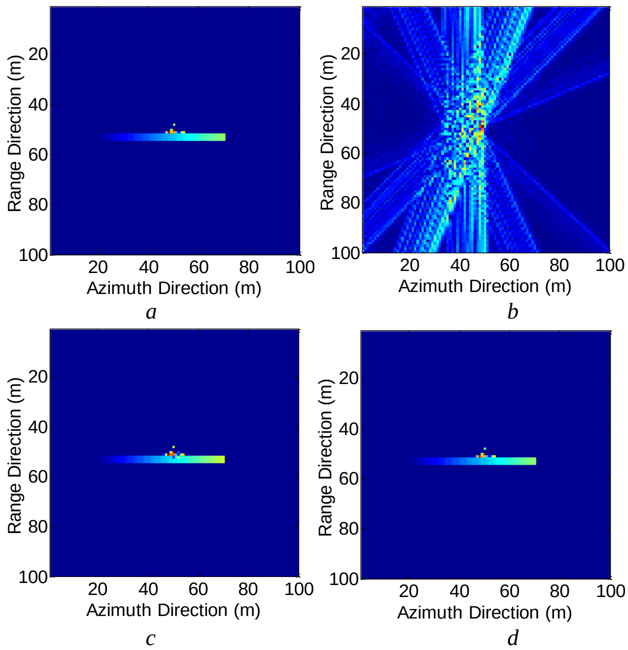

Figure 2. Simulation result
a The target and the background to be imaged
b Imaging result via back projection algorithm
c Imaging result via CS method
d Imaging result via TCS method

Fig. 2 shows the result. The target is shown in Fig. 2a, adopting traditional SAS method (here back projection algorithm is used) result is show in Fig. 2b, result of CS method is shown in Fig. 2c, and in Fig. 2d TCS method recovers the scene perfectly. Traditional SAS method fails in recovering the scene, because the number of coherent integrated echoes is too small. Theoretically 82 echoes are needed for the reconstruction of the image in a small angle extent. And compared to the theoretical number, the data is no more than 10% of traditional SAS method when resolution is the same.

V. Conclusion

This paper proposes a sonar imaging system exploiting sonar network. With only one ping information, the image scene can be recovered using CS and TCS methods. These methods exploit a priori of the imaging scene sufficiently. By using no more than 10% data amount of the traditional SAS, the recovery can be perfect.

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