CS BASED PROCESSING FOR HIGH RESOLUTION GSM PASSIVE BISTATIC RADAR

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ABSTRACT

Passive bistatic radar (PBR) systems use existing RF broadcast and communication signals in the environment for surveillance and tracking applications. GSM mobile communication signal based PBR systems are suitable for short-range surveillance systems, but the low-bandwidth of the signal results in low range resolutions when classical cross-correlation based processing is used for target detection. An alternative and more robust approach based on compressive sensing (CS) is proposed here to achieve high range resolution by performing fine gridding for the target scene. To avoid the increased coherence and computational load associated with the fine gridding, preprocessing steps are introduced in this paper, which involve choosing a suitable CS basis by application of spectral and subspace transformations. By so doing, resolution improvement is achieved when a single channel GSM signal and CS are employed for target detection.

***Index Terms*—** Radar, compressive sensing, passive bistatic radar, principle component analysis

1. INTRODUCTION

Passive bistatic radar systems utilize signals radiated by various existing communication systems (e.g., FM, GSM, DVB-T etc) [1, 2, 3, 4]. These systems have some advantages over classical active radar systems as they are covert and require low building and operational costs. In addition, they require no frequency allocation due to their use of third party signals. Thus, PBR systems are attractive for various military and commercial target detection and tracking applications [3].

In spite of the advances in PBR technology, for some of the signals of opportunity, the detection performance is lower than what is achievable in active radars. For standard single channel GSM signal (of 200 kHz) the achievable range resolution is limited to being $>$ 1854m [2, 3, 4]. By contrast the Doppler resolution can be reasonable as it can reach $\approx$1 m/s for a 0.2 second integration time. Thus it is of interest to formulate a PBR processing method which can ultimately improve the GSM-PBR range resolution. Utilization of multiple channels have been reported for this said purpose, for various PBR modalities [5, 6, 7]. However, the multiband processing requires higher bandwidth (thus larger data set), and the results get affected due to waveform variations [7], differences in Doppler resolutions for different channels and increased ambiguity function sidelobes due to unequal channel spacing [8, 9]. Therefore, GSM based classical multi-channels PBR case, may suffer of all or some of these issues.

Here, compressive sensing (CS) [10, 11] based processing is considered to achieve high range resolution in GSM-PBR. CS is a sparse signal processing technique which can recover either sparse or compressible but noisy signals by solving a computationally tractable ℓ_1-norm regularized inverse problem. This technique, which involves measurement matrix ($\mathbf{\Phi}$), dictionary ($\mathbf{\Psi}$), and scene coefficient vector ($\boldsymbol{\alpha}$), is able to provide better (range and Doppler) resolution without being directly constrained by the sampling rate or pulse length [12]. The application of CS to PBR has recently been addressed in several papers to achieve various goals, though not specifically for GSM-PBR systems. In particular, target detection and tracking was described in [13] using reduced number of training symbols for DVB-T/DAB signals. In [14] CS techniques have been applied to detect targets in WiFi-based PBRs using known training sequence to create the basis while the measurement matrix consisted of a subset of this discrete Fourier basis. Few other papers focused on utilizing suitable reconstruction methods [15, 16], data fusion in multistatic passive radar (MPR) systems [17, 18] etc.

In this paper we propose a CS based processing to achieve high-resolution GSM-PBR by over-gridding the targets' scene. This, of course, intensifies the coherence among dictionary's columns which degrades the performance of CS reconstruction algorithms; in addition, it leads to large dictionary size. To remedy these problems, we perform the following:

1. We transform the time-domain data constituting the dictionary to frequency domain to obtain a limited number of useful data samples; hence the dictionary size is greatly reduced.

2. We apply the principle component analysis (PCA) and whitening to frequency domain samples to reduce coherence among columns of dictionary.

The authors would like to acknowledge the support of KACST - RFTONICS, Riyadh, Saudi Arabia.

The rest of the paper is organized as follows. A CS based PBR model and the generation of time-domain dictionary is presented in Section 2. Section 3 presents the concept behind the use of spectral and subspace transformation analysis to reduce the data coherence and computational load. The simulation results for the detection and localization of multiple close targets using the proposed CS method are discussed in Section 4. Finally, concluding remarks are given in Section 5.

2. CS GSM-PBR MODEL

The PBR target detection problem can be formulated as a sparse recovery problem, as the possible range/Doppler combinations are much larger compared to the actual number of targets. It is assumed that the direct path and the clean echo (from direct path interference) signals are available.

2.1. CS PBR model

A PBR arrangement is shown in figure 1. A receiver is placed at a distance (approximately 10-15 km) from a highway GSM transmitting tower. The set-up is therefore suitable for detecting ground moving or low flying targets. The surveillance space can be discretized in a spatial grid with equally spaced (square) cells. Possible targets from these cells will give rise to the delay and Doppler values according to their bistatic positioning [19]. In order to limit the number of unknowns to only range and Doppler, avoiding the need for the direction of arrival (DOA) information, it is assumed that the PBR arrangement is such that the spatial grid is closer to the transmitter.

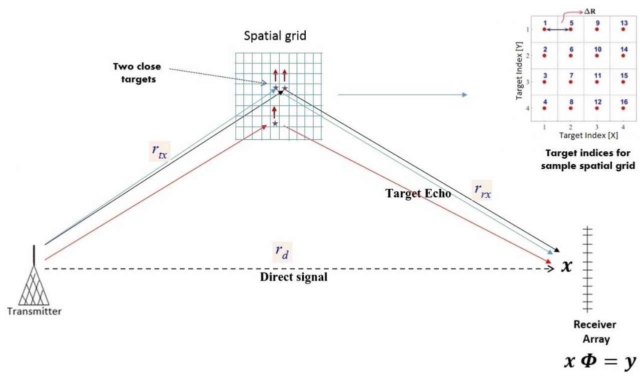

Fig. 1. CS PBR scene model.

2.2. Time domain dictionary formation

Using the time delayed and Doppler shifted versions of the single channel GSM direct signal, a (time domain) dictionary $\mathbf{\Psi}$ can be formed. The target's position refers to a specific differential delay ($\tau = {}^{(r_{tx}+r_{rx}-r_d)}/_{c}$), but its velocity can be of any possible value. One needs to consider a finite number of possible velocities as $(v_1, v_2, ..., v_D)$ with lowest possible resolution, to keep the dictionary size low. The bistatic Doppler (f_d) depends on the target velocity as well as the bistatic spatial positioning (as in figure 1) [19]. The target-scene coefficient vector, $\boldsymbol{\alpha}$ is thus formed by vectorizing the coefficients corresponding to these bistatic $\tau - f_d$ values.

2.3. CS based target recovery process

According to the CS theory, if a signal $\mathbf{x}\in\mathbb{R}^{P\times 1}$ is k-sparse in some basis $\mathbf{\Psi} \in \mathbb{R}^{P\times N}$, i.e. only $k\,(\ll N)$ columns of $\mathbf{\Psi}$ are sufficient to model $\mathbf{x}$, then it is possible to recover it with high probability from $\mathcal{O}(k \log N)$ measurements via ℓ_1-norm minimization [11]. A measurement matrix $\mathbf{\Phi} \in \mathbb{R}^{M\times P}$ is formulated with $M \ll N$, to recover the signal from M linear measurements as

$$\mathbf{y} = \mathbf{\Phi x} + \mathbf{e} = \mathbf{\Phi\Psi}\boldsymbol{\alpha} + \mathbf{e} \tag{1}$$

where $\boldsymbol{\alpha}\in\mathbb{R}^{N\times 1}$ is a vector with coefficients α_i's and $\mathbf{e}$ is the noise in the system. The design of $\mathbf{\Phi}$ affects the recovery success of $\boldsymbol{\alpha}$. In order to find the sparsest solution, an ℓ_1-norm of $\boldsymbol{\alpha}$ is minimized as

$$\hat{\boldsymbol{\alpha}} = \min_{\mathbf{x}} \|\boldsymbol{\alpha}\|_1 \qquad s.t. \quad \|\mathbf{y} - \mathbf{\Phi\Psi}\boldsymbol{\alpha}\|_{\mathbf{2}} \leq \varepsilon \tag{2}$$

where the threshold ε is related to the measurement noise as $\|\mathbf{n}\|_2 \leq \varepsilon$. Various alternatives have been formulated for equation (2) [20]. Here, we utilize an algorithm known as gradient projection for sparse reconstruction (GPSR) [21] which reconstructs the target space $\boldsymbol{\alpha}$ from the sensing matrix $\boldsymbol{A} = \mathbf{\Phi\Psi} \in \mathbb{R}^{M\times N}$ and the measurement vector $\mathbf{y}\in\mathbb{R}^{M\times 1}$

$$\min_{\boldsymbol{\alpha}} \frac{1}{2}\|\mathbf{y} - \boldsymbol{A\alpha}\|_2^2 + \mu\|\boldsymbol{\alpha}\|_1 \;\; with\; \mu = 0.1\left\|\boldsymbol{A}^T\boldsymbol{y}\right\|_\infty \tag{3}$$

When reconstruction of $\boldsymbol{\alpha}$ is done using time domain dictionary for a sizable spatial and velocity grid points, the computational burden becomes excessive and the reconstruction suffers much due to the extraordinary coherence of the dictionary atoms. Thus in the following section we explore the way to overcome such obstacles.

3. INCOHERENT DICTIONARY FORMULATION

Here we first look for a suitable dictionary in another domain other than the time-domain.

3.1. Spectral sparsity

If the dictionary $\mathbf{\Psi}$ is transformed in the frequency domain it will have limited/compressible information. This spectral compressibility can be utilized to reduce the computational burden of the CS reconstruction process. Thus, the spectral analysis of the dictionary $\mathbf{\Psi} = [\psi_1, \psi_2, \cdots, \psi_N] \in \mathbb{C}^{P\times N}$

is first performed via Fourier transform and power spectral density (PSD) calculations as

$$\tilde{\psi}_i = FFT\left(\psi_i\right) \Rightarrow \tilde{\psi}_i^{PSD} = {|\tilde{\psi}_i|^2}/{P} \tag{4}$$

where $i = 1, 2, \ldots, N$; P is the number of samples of each $\tilde{\psi}_i$. In figure (2), we show $\tilde{\psi}_i^{PSD}$ where we zoom out its dominant part. ψ_i has been selected randomly from the set of $\{\psi_i\}$ constituting the time-domain dictionary described in the simulation example (Section 4). Note that the spectral domain has dominant part with Q samples ($Q \ll P$). Therefore, these Q samples carrying ∼95% of the information can be selected to form a new dictionary, which we call here the *spectral dictionary*.

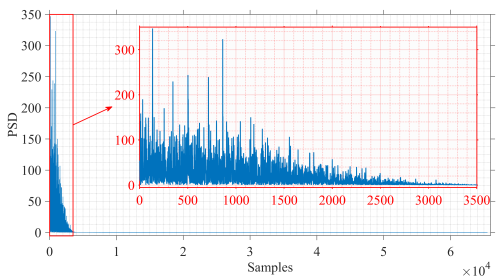

Fig. 2. Zooming out the dominant part of $\tilde{\psi}_i^{PSD}$.

3.2. Subspace transformation

The creation of the (truncated) spectral dictionary above reduces the computational burden. However, it still has high coherence, which makes the performance of CS reconstruction algorithms deteriorate. Thus, it is required to transform the spectral dictionary into another dictionary where the new dictionary becomes incoherent. This is achieved by implementing the PCA in combination with a whitening process [22, 23]. The resulting dictionary will have few uncorrelated samples with maximum variance among the data. First, the (truncated spectral) dictionary $\tilde{\mathbf{\Psi}} = \left[\tilde{\psi}_1, \tilde{\psi}_2, \cdots, \tilde{\psi}_Q\right]^T \in \mathbb{R}^{Q\times N}$ is mean centered as $\tilde{\psi}_j = \tilde{\psi}_j - E\left[\tilde{\psi}_j\right]$, where $j = 1, 2, \ldots, Q$. After which, the singular value decomposition (SVD) algorithm is applied to $\tilde{\mathbf{\Psi}}$ as

$$\tilde{\mathbf{\Psi}} = U \Sigma V^* \tag{5}$$

where $U \in \mathbb{R}^{Q\times Q}$ contains eigenvectors of the covariance matrix of $\tilde{\mathbf{\Psi}}$ and its eigenvalues (sorted in decreasing order) are given as $\boldsymbol{\lambda} = \sqrt{diag\left(\Sigma\right)} \in \mathbb{R}^{Q\times 1}$. The first M eigenvectors from matrix $U = \left[u_1, u_2, \cdots, u_M, \cdots u_Q\right]^T$ are selected in accordance with the first M eigenvalues from vector $\boldsymbol{\lambda} = \left[\lambda_1, \lambda_2, \cdots, \lambda_M, \cdots \lambda_Q\right]^T$ such that $\lambda_1 > \lambda_2 > \cdots > \lambda_M > \cdots > \lambda_Q$. Thus we have $\tilde{U} = \left[u_1, u_2, \cdots, u_M\right]^T \in \mathbb{R}^{M\times Q}$ and the new dictionary after PCA operation will be

$$\hat{\mathbf{\Psi}} = \tilde{U}\tilde{\mathbf{\Psi}} \tag{6}$$

Here, the M principle components are chosen such that the resultant data set in equation (6) has approximately 95% of data variance. After that, the data set is whitened (decorrelated) by the whitening transform matrix $W \in \mathbb{R}^{M\times M}$ such that $W = {E^T}/{\sqrt{D}}$, where matrix $E \in \mathbb{R}^{M\times M}$ is formed from the eigenvectors of the sample covariance matrix of $\hat{\mathbf{\Psi}} \in \mathbb{R}^{M\times N}$and $D \in \mathbb{R}^{M\times M}$ is a diagonal matrix whose elements are the eigenvalues $\hat{\boldsymbol{\lambda}} \in \mathbb{R}^{M\times 1}$. Consequently, the overall subspace transformation can be given as

$$\check{\mathbf{\Psi}} = W\hat{\mathbf{\Psi}} = W\tilde{U}\tilde{\mathbf{\Psi}} \tag{7}$$

where $W \in \mathbb{R}^{M\times M}$ is the whitening transformation matrix and rows of matrix $\tilde{U} \in \mathbb{R}^{M\times Q}$ are the first M eigenvectors for the covariance matrix of $\tilde{\mathbf{\Psi}} \in \mathbb{R}^{Q\times N}$.

Once this new *incoherent dictionary* $\check{\mathbf{\Psi}}$ is formed, the target scene recovery is done using the GPSR algorithm as discussed in Sub-section (2.3)

4. SIMULATION RESULTS

Here the generation of simulation scenarios and the results are discussed for a surveillance space comprising multiple ground moving or low flying targets.

4.1. Signals and target scenario generation

The GSM signals were generated using SystemVue simulation environment (from Agilent Technologies) for GSM-900 (935 - 960 MHz downlink) band. The target response is received due to a single channel GSM signal reflected from the point targets positioned at specific grid cells. The (time-domain) dictionary is formed utilizing the direct signal based on the discrete delay-Doppler gird and an observation time of 0.6554 seconds.

The proposed PBR reconstruction system is tested for a target scenario which is shown in figure (3). The target space has an area of $1km \times 1km$ with range resolution $\Delta R = 100m$, between two consecutive (possible) targets; thus, having a fine grid of 10×10 cells. Each possible target can have a velocity from 50 km/h to 250 km/h with a velocity resolution of 2 km/hr (~ 0.56 m/s). Of these possible 10,100 (=10x10x101) delay-Doppler combinations, it is assumed that only 18 targets are present, which makes the scenario quite sparse. In figure (3), for the purpose of clarity, spatial indices from x and y-directions are grouped together following a convention as shown in figure (1). The targets are placed in three clusters where some of the targets took same position/velocity values as their close neighbors. For example, the target-cluster in the bottom consists of 3 targets with the same location index and 4 targets with the same velocity value, and for this reason part of this cluster appears as a line. Moreover, a noisy environment with SNR level of 15 dB is considered.

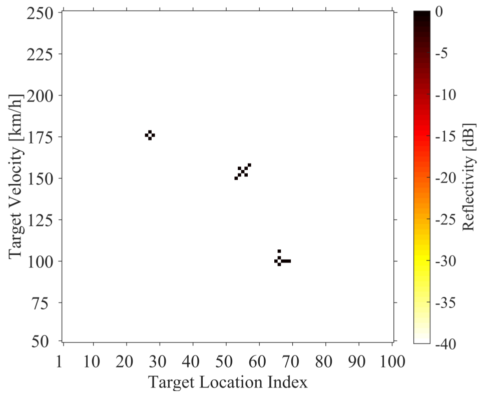

Fig. 3. Original scenario with multiple moving targets.

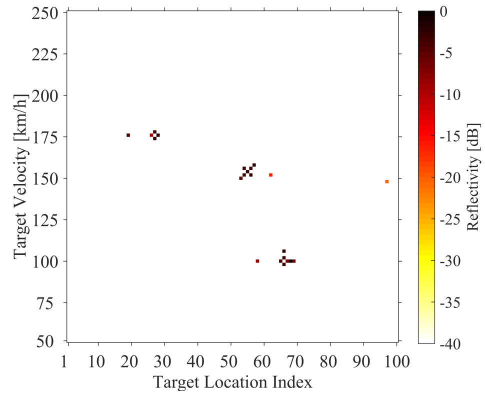

Fig. 5. Target scene reconstruction using $\check{\boldsymbol{\Psi}}$.

4.2. Reconstruction results

During the reconstruction process, both the location index and velocity of the target is reconstructed in a single step. The number of CS measurements was about 10% of the number of atoms in the dictionary. Also the elements of $\boldsymbol{\Phi}$ were drawn from Gaussian random matrices. Measurement noise with normal distribution was added to the CS measured signal. The target scene recovery is done using the GPSR algorithm as discussed in Sub-section (2.3). Figure (4) shows the reconstruction results for the target space when the truncated spectral dictionary $\tilde{\boldsymbol{\Psi}}$ is used, which turns out to be inaccurate.

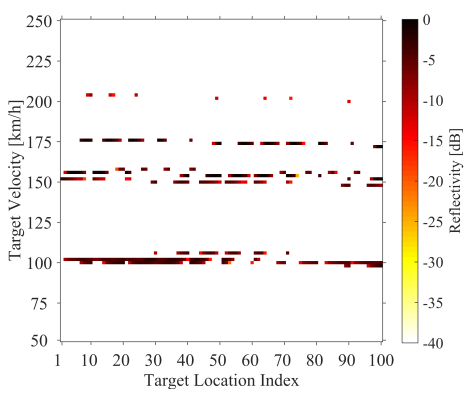

Fig. 4. Target scene reconstruction using $\tilde{\boldsymbol{\Psi}}$.

On the other hand, the PCA and whitening process when applied to the spectral dictionary does allow for excellent target space reconstruction. The dictionary $\check{\boldsymbol{\Psi}}$ was used in this case and the excellent recovery results are shown in figure (5). These results clearly show that the reconstruction via incoherent dictionary is far better than that via spectral dictionary. Also, both range and velocity resolutions achieved here are much better than what is achievable using classical matched filtering.

4.3. Reconstruction performance evaluation

An image quality metric, structural similarity index (SSIM), is employed here for the quantitative measure of the reconstruction process accuracy. This index measures the similarity between two images [24], with values 0 for minimum similarity and 1 for maximum similarity. Figure (6) shows the effect of SNR on SSIM when the reconstruction is performed using the incoherent dictionary. As noticed, the reconstruction accuracy remains fairly similar above $\sim$15 dB SNR.

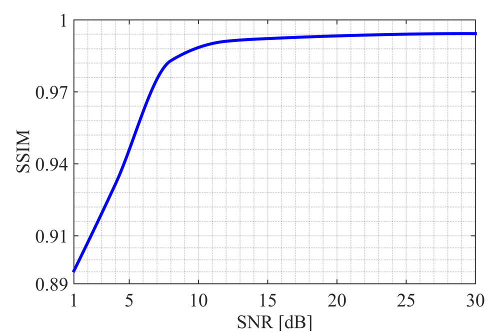

Fig. 6. Structural similarity index (SSIM) vs. SNR values.

5. CONCLUSIONS

A modified processing scheme is presented here for target detection using passive bistatic radar. A simplified but complete simulation scenario is generated to implement and test the GSM based PBR processing. To achieve high range resolution in GSM-PBR using single channel, compressive sensing (CS) has been implemented which makes use of dictionary generated by spectral transformation and PCA in combination with whitening. This allows for over-gridding the targets' scene to achieve finer delay-Doppler resolution. Simulation results have been presented to show the effectiveness of proposed algorithm in detecting targets separated by a distance as low as 100m using single GSM channel.

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