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Spread Spectrum Code Design for MIMO Radar Estimation Using Compressive Sensing Modeling

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Abstract

We consider the problem of multiple-target estimation using a collocated multiple-input multiple-output (MIMO) radar system. We employ sparse modeling to estimate the un-known target parameters (delay, Doppler) using a MIMO radar system that transmits frequency-hopping waveforms. We formulate the measurement model using a block sparse representation. We adaptively design the transmit waveform parameters (frequencies, amplitudes) to improve the estimation performance. Firstly, we derive analytical expressions for the correlations between the different blocks of columns of the sensing matrix. Using these expressions, we compute the block coherence measure of the dictionary. We use this measure to optimally design the sensing matrix by selecting the hopping frequencies for all the transmitters. Secondly, we adaptively design the amplitudes of the transmitted waveforms during each hopping interval to improve the estimation performance. Further, we employ compressive sensing to conduct accurate estimation from far fewer samples than the Nyquist rate.

Key words: Multiple input multiple output RADAR, Multiple targets, Compressive sensing and frequency-hopping codes.

I. INTRODUCTION

CONVENTIONAL monostatic single-input single- output (SISO) radar transmits an electro-magnetic (EM) wave from the transmitter. The properties of this wave are altered while reflecting from the surfaces of the targets towards the receiver. The altered properties of the wave enable estimation of unknown target parameters like range, Doppler, and attenuation. However, such systems offer limited degrees of freedom. Multiple-input multiple-output (MIMO) radar systems have attracted much attention in the recent past due to the additional degrees of freedom they offer MIMO radar is commonly used in two different antenna con- figurations: widely-separated (distributed) and collocated. Distribute MIMO radar exploits spatial diversity by utilizing multiple uncorrelated looks of the target. Collocated MIMO radar systems offer performance improvement by exploiting Wave form diversity. Each antenna has the freedom to

transmit a waveform that is different from the wave-forms of the other transmitters.
In this paper, MIMO radar refers to collocated MIMO radar.

Sparse modeling and compressive sensing have been a hot research topic as they enable accurate estimation from sub-
Nyquist rates. Since most real-world systems have sparsity in some basis representation, these tools have been used in many fields, such as engineering and medicine.

Also, there has been recent interest in applying them to the field of radar by exploiting sparsity in the target delay-Doppler space. In this paper, we employ sparse modeling to estimate the unknown target parameters using a pulsed MIMO radar system that transmits frequency-hopping waveforms. More specifically, we formulate the measurement model using a block sparse representation. Further, we adaptively design the parameters of the transmitted waveforms to achieve improved performance. First, we derive analytical expressions for the correlations between the different columns of the sensing matrix. Next, we use this result for optimal design by computing the block coherence measure of the sensing matrix and selecting the hopping frequencies of all the transmitters. Finally, we transmit constant modulus waveforms using these selected frequencies to estimate the radar cross section (RCS) values of all the targets. We use these RCS estimates to adaptively design the amplitudes of the transmitted waveforms during each hopping interval for achieving improved sparse recovery performance.

II. SYSTEM MODEL

Once some knowledge of radar theory had been gained, we began the task of designing a radar signal processor. First, the type of waveform to be used in the system had to be chosen. An impulse would be optimum for range resolution, but, aside from being impractical, it would also fail to yield any range rate resolution. A complex exponential, on the other hand, would yield optimum range rate resolution while leaving a great deal of ambiguity in the range resolution. A compromise between the two was needed. A good test of potential waveforms is to examine the nature of the ambiguity function. The ambiguity function is essentially an autocorrelation of a waveform with a delayed and/or phase-shifted version of itself. Plotting this function versus delay and phase shift yields a convenient visual gauge of a waveform's potential performance in a radar system. It turned out that a linear FM chirp offered acceptable resolution in range and in range rate. A program, dtFMchirp, was written to generate a discrete LFM chirp for a given time-bandwidth product (TW) and oversampling factor (p). Thus the output was essentially a continuous-time chirp sampled at a rate of p*W. An LFM chirp has a constant magnitude of one, but its phase varies quadratically with respect to its displacement from the time origin. After becoming familiar with the characteristics of the LFM chirp, we worked on range processing. In order to get good range resolution, a high signal-to-noise ratio is needed. Thus, large time-bandwidth chirps were used to increase the energy initially in the signal. This alone is not enough to make target detection possible. Some filtering of the signal must also be done. By examining the equation for the SNR, it is clear that to maximize SNR, the numerator must be maximized. The Cauchy-Schwartz inequality defines the upper bound of the numerator. The equality holds if the filter is the conjugate of the output signal with a reversed time axis. This type of filter is referred to as a matched filter and results in the optimum SNR. Another property of the matched filter is that it compresses the pulse into a narrow peak. As a result, radar systems using matched filtering are often referred to as pulse-compression radar.

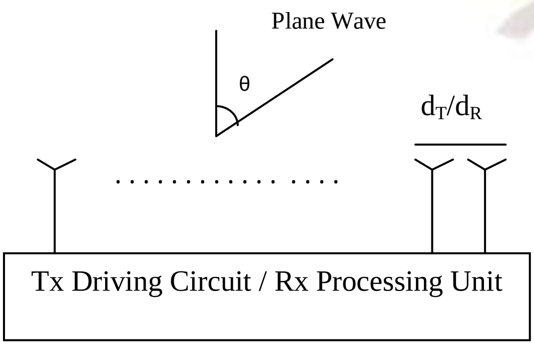

Fig.1.Transmit – Receive Antenna

Some chirps were generated and white Gaussian noise was added to test our ability to detect and resolve a target in noise. The matched filter results in a large peak in the time domain at the point where the entire pulse has returned. The location of the output peak from the matched filter is used to calculate the range by the following formula:

range = (peak location - length of chirp)*(c / 2) / (p*W)

The length of the chirp must be subtracted from the peak location in order to get the delay from the time the signal was sent out until the time the return signal was received since the peak location indicates the time at which the entire signal has been received, not the time at which it first started to arrive. Once the accuracy of this algorithm was confirmed, modifications were made in order to handle multiple targets. This requires the ability to locate multiple peaks in the filtered signal. For this, the program pkpicker , taken from CBESP, was used. Given a signal, a threshold, and a maximum number of peaks, pkpicker returns two vectors, one containing the peak values and the other containing the corresponding indices of the peaks. After experimenting with the threshold, it was determined that a threshold of .6 times the length of the chirp would be adequate. The length of the chirp is equal to the maximum peak in an autocorrelation of a chirp and so corresponds to the energy of a target in the absence of interference such as noise and clutter. The factor of .6 was found through trial and error to be the largest factor that would not result in a failure to detect a target. Experiments with multiple targets also gave us some notion of the degree of resolution that could be obtained with multiple targets (ie, how close could targets be before they could no longer be resolved separately. Having established an accurate target detection and range finding algorithm, we were ready to attempt range rate processing. Unless the target is moving at an extremely high speed relative to the speed of light, the Doppler shift will be small and very difficult to detect from one pulse. The solution to this problem is to transmit a burst waveform containing repeated pulses. Initially, for simplicity, boxcars were used as the pulse so that some insight into how the parameters of the pulse affect the Doppler shift might be gained. It was determined that the inter pulse period affected the width of the main lobe of the DTFT, the height of the main lobe was related to the number of pulses, and the magnitude of the side lobes depended upon the pulse length. Next, measurement of the Doppler shift from samples of the bursts was attempted.

This allows range rate processing with significantly less data and thus faster computation. The sampling was done as follows. Range processing is done with the first burst alone since the additional bursts do not provide any extra range information. For each of the targets detected, each filtered burst is sampled at the location corresponding to the peak location of that target. The Doppler shift for each target is then measured from the peak location of the DTFT of the corresponding sampled waveform. Range rate is then determined by the following formula:

$$(fd / fc)*(c / 2)$$

where f_d is the Doppler shift in Hz and fc is the center frequency of the radar in Hz. Range rate calculations will obviously be limited since shifts of the peak that are greater than pi will wrap around, resulting in incorrect calculations. Adjusting the center frequency allows the range of velocities that can be correctly calculated to change. As f_c is decreased, larger speeds can be calculated, but accuracy of these velocities suffers somewhat. Conversely, as fc increased, accuracy increased, but high velocities could not be detected due to aliasing. Next, LFM chirps were used as pulses and our ability to detect Doppler shifts of these waveforms was tested. Finally, a complete range and range rate analysis was performed. Once we were satisfied with the performance of this algorithm, it was time to try and analyze a signal that was not arbitrarily generated.

III. SPARSE RECONSTRUCTION

In this section, we present a reconstruction algorithm to recover the sparse vector from the noisy measurement vector. Ideally, in a noiseless scenario, we need to solve the following optimization problem to recover the sparse vector

$$\min_{z} z \;\; s.t \; y = \varphi_z$$

However, this problem is NP hard. Therefore, this problem is relaxed to one that involves the norm, and several approaches have been proposed in the literature to solve it. In a heuristic iterative approach called matching pursuit (MP) is presented. **Approaches such as basis pursuit (BP) and basis pursuit denoising (BPDN) are popular in this category.**

However, these algorithms do not exploit the fact that the non-zero entries of the sparse vector appear in blocks. Using the knowledge of block sparsity will improve recovery performance. This algorithm is a direct extension of the conventional MP, and is used when the columns within the blocks of the dictionary matrix are orthogonal.

Note that in the above expressions for sparse support recovery, we assumed that all the columns of φ have unit norm. When all of them are scaled by the same constant factor (non-unit norm), the update equations change by an appropriate scale factor corresponding to this norm.

IV. COMPRESSIVE SENSING

In this section, we use compressive sensing to accurately reconstruct the sparse vector from far fewer samples when compared with the Nyquist rate. The theory of compressive sensing says that this is possible when the sensing matrix has minimal coherence with the dictionary matrix. Since random matrices to give a low coherence measure, we will generate the entries of the sensing matrix as realizations of independent and identically distributed (i.i.d.) Gaussian random variables. Let φ denote an $N_{CS} \times NM_R$ dimensional random Gaussian sensing matrix, where $N_{CS} < NM_R$. Define y_{CS} as the measurement vector after compressive sensing. Then, the measurement model in changes to

$$y_{CS} = \emptyset\varphi_x + \emptyset_{e.}$$

The sensors receive continuous data across all the pulses. This data is projected onto a finite lower dimensional space spanned by random continuous Gaussian noise sequences. The dimensions of this space are much smaller than the Nyquist rate. Therefore, we are actually sampling directly at a reduced rate. The above equation is just an equivalent way of representing the signal processing involved in this procedure. Now we need to recover x from the compressedmeasurement vector y_{CS} . The reconstruction algorithm and design schemes presented in the earlier sections of the paper are also valid for compressive sensing. We define the percentage of compression as

$$\delta = \frac{N_{CS}}{NM_R} \times 100\%$$

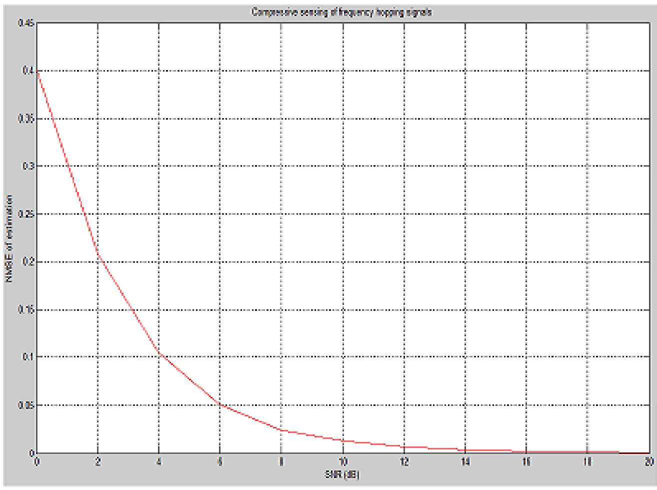

Fig.2. compressive sensing of frequency hopping signals

V. SIMULATION RESULTS

In this section, we present numerical simulations to demonstrate the performance of our proposed radar system.

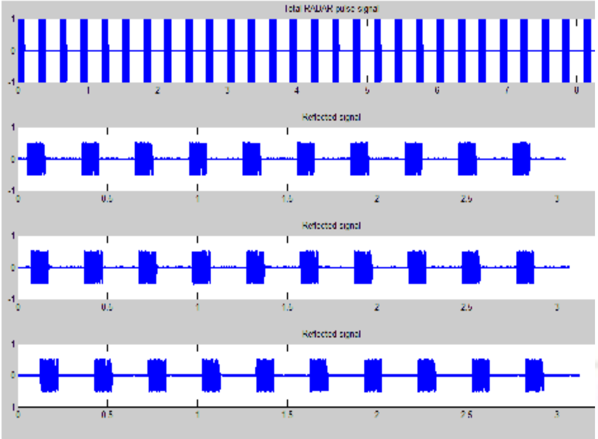

Fig.3. Pulses Emitted from 3-Transmitters

The above figure shows the pulses that are emitted from 3 transmitters. Each transmitter emits 10 pulses. Based on the returned signal we are calculating drift, velocity, Doppler shift, round trip time.

For transmitter1
round trip time
5.3300e-007
target range
79.9500
For transmitter2
round trip time
7.3300e-007
target range
109.9500
For transmitter 3
round trip time
1.2670e-006
target range
190.0500

VI. CONCLUDING REMARKS

We proposed a sparsity-based colocated MIMO radar system using frequency-hopping waveforms. We estimated the unknown target parameters using sparse support recovery algorithm. We derived an analytical expression for the block coherence measure of the dictionary matrix and, hence, studied the problem of selecting the hopping frequencies.We presented an iterative algorithm for designing an optimal code matrix. Further, we proposed an approach to optimally design the amplitudes of the transmitted waveforms during each hopping interval using the estimates of the target returns. We demonstrated the performance improvement due to the optimal design.

REFERENCES

[1] M. I. Skolnik, *"Introduction to Radar Systems"*. NewYork:McGraw-Hill, 1980.

[2] A. M. Haimovich, R. S. Blum, and L. J. Cimini, *"MIMO radar with widely separated antennas"*, IEEE Signal Process. Mag., vol. 25, pp. 116–129, Jan. 2008.

[3] S. Gogineni and A. Nehorai, *"Polarimetric MIMO radar with distributed antennas for target detection,"* IEEE Trans. Signal Process., vol. 58, pp. 1689–1697, Mar. 2010.

[4] J. Li and P. Stoica, *"MIMO Radar Signal Processing"*. Hoboken, NJ: Wiley, 2009.

[5] A. Hassanien and S. A. Vorobyov, *"Transmit/receive beamforming for MIMO radar with colocated antennas,"* in Proc. IEEE Int. Confe. Acoust., Speech, Signal Process., Taipei, Taiwan, Apr. 2009, pp. 2089–2092.