Radar Automatic Target Recognition based on Disjoint Multi-static K-space Coverage

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Abstract—This paper considers SAR image reconstruction from incomplete K-space coverage. In particular, the problem of image reconstruction from the type of disjoint K-space coverage that may arise from multi-static SAR systems is addressed. In previous work the effectiveness of reconstruction schemes were assessed in terms of their impact on automatic target recognition performance. It was found that a simple Fourier reconstruction, despite the significantly distorted point spread function that results, has advantages over a compressive sensing approach. In this paper, the idea of re-applying a SAR point spread function to the compressive sensing reconstruction is considered. It is found that this approach provides comparable performance to the use of the Fourier reconstruction. An interpretation of this behavior is provided in terms of a feature-based analysis.

Keywords—Compressive sensing, target recognition, ATR, K-space

I. INTRODUCTION

Synthetic aperture radar (SAR) is a radar imaging system in which the resolution in the range direction is determined by the bandwidth of the transmitted signal and the resolution in the cross-range (or azimuth) direction is determined by the Doppler bandwidth (i.e. the range of Doppler frequencies associated with a point on the ground as it enters and leaves the radar beam). After image formation, the SAR image contains complex-valued pixels. Taking the Fourier transform of this complex image will reveal the frequency content of the image with one axis associated with the radar frequencies and the other with the Doppler frequencies. This is known as K-space and the SAR data will occupy a delimited region within K-space defined by the radar bandwidth and the Doppler bandwidth.

Ideally, a SAR sensor would gather data that fully populates the delimited K-space region. However, there are occasions when this cannot be achieved. For example, if there is radio frequency interference (RFI) over the operating bandwidth of the SAR system, then it may be necessary to notch out some of the radar frequencies. Also, if imaging is being performed by a multi-function radar system, the beam may be steered onto other tasks during the collection of the SAR aperture and so there will be gaps in the Doppler bandwidth. An alternative scenario is provided by multi-static SAR operation in which multiple receivers are used that are not collocated with the transmitter. In this case, the data gathered can occupy a number of disjoint regions of K-space. This is illustrated conceptually in Figure 1. The top image shows an idealised simulation of a SAR image containing a number of random point scatterers (which have associated phase values). The Fourier transform of this will result in a fully populated region of K-space. However, use of a multi-static SAR system may result in only disjoint regions of K-space being measured as illustrated in the image at the bottom of Figure 1.

Fig. 1. Idealised simulation of a SAR image of a number of random point scatterers (top) and the K-space that, conceptually, might be obtained by a multi-static SAR system (bottom).

It is important to understand how to most effectively produce a SAR image when there is disjoint coverage of K-space and an initial investigation into this was presented in [1]. In that paper, the effectiveness of the SAR image formation
was assessed in terms of the performance of automatic target recognition (ATR) when applied to the images formed from disjoint K-space. Underlying this was an understanding that an ATR system should only need to be trained once and then be able to be applied to imagery from various different sources, e.g. both when full K-space coverage is available and when the coverage is only partial. Thus a consideration was how the performance of the ATR system varied when it was trained and tested on these different image types.

In [1] two approaches to dealing with disjoint K-space were considered. The first was to simply take the Fourier transform (FT) of the K-space data which will result in imagery with a significantly distorted point spread function (PSF). The second was to use a compressive sensing (CS) technique (basis pursuit de-noising [2], [3]) to perform image reconstruction.

The classification problem which was considered was to classify between SAR chips of targets and clutter objects. An ideal data set for this is provided by the publically available MSTAR data set [4] which was collected by AFRL in the 1990’s to support target recognition research. In particular, the target and clutter chips of dimension 128x128 at 15 degrees depression angle have been used which comprise the BMP2, BTR60, BTR70, T72 & clutter. One thousand examples of both targets and clutter were used for training and twenty-five examples of each were used for testing.

In order to help with the discussion in this paper, it is convenient to reproduce from [1] the test examples which are shown in Figure 2, the Fourier reconstructions which are shown in Figure 3 and the compressive sensing reconstructions which are shown in Figure 4.
An ATR scheme based on a convolutional neural network (CNN) [5] was implemented in [1] and the results are reproduced in Figure 5 for comparison with what follows. This table shows the proportion of incorrect classifications so that 0.0 would be perfect classification and 0.5 would be essentially random assignment to the two classes. The label Mg indicates the original magnitude image, Cs indicates the compressive sensing reconstruction and Ft indicates the Fourier transform reconstruction.

![Classification performance results for CNNs trained on one image type and tested on a second image type.](image)

The conclusion from this was that an ATR scheme trained on the Fourier reconstructions could be applied successfully to both the original magnitude images and to the compressive sensing reconstructions. This was not the case when training was performed in the other image types. Hence, use of the Fourier reconstruction is preferable to use of the compressive sensing reconstruction.

In this paper, the approach of re-applying a SAR point spread function (PSF) to the compressive sensing reconstruction is considered. This is discussed in Section II. In [1], the results were interpreted in terms of the impact of the reconstruction schemes on the occupancy of feature space for the different classes. In Section III, a similar analysis is performed to include the new approach of re-applying a point spread function. Conclusions are presented in Section IV.

**II. APPLYING A PSF TO THE CS RECONSTRUCTION**

**A. Rationale**

The compressive sensing reconstruction is based on the assumption that the scene is sparse. For SAR images, it may be considered that the important information in the scene is contained in a few dominant scatterers and so, in this sense, the scene is indeed sparse. However, this means that the reconstruction will essentially consist of a number of individual scatterers rather than something that has the characteristics of a SAR image. It is thus not surprising that classification performance is not transferrable between this and more standard image formation techniques.

One approach to retrieve a reconstruction based on compressive sensing that has the nature of a SAR image is to impose a SAR point spread function (PSF) onto the dominant scatterer representation produced by compressive sensing. In this way the energy contained in the dominant scatterers will be spread out in the same way as in the SAR imaging process but with a standard PSF rather than the one associated with a disjoint K-space. This may have advantages for target classification.

Figure 6 shows the Fourier transform of the PSF associated with the SAR image formation for the MSTAR data set which uses Taylor weighting. Once this is applied to the CS reconstructions, the images shown in Figure 7 are obtained. (These will be referred to as the “Pf” images.) Visually, these are much more characteristic of traditional SAR images than the raw CS reconstructions shown in Figure 4.

![Fourier transform of PSF for MSTAR data set which uses Taylor weighting.](image)

![Reconstructions of test chip images using compressive sensing followed by application of the MSTAR SAR PSF](image)

**B. Classification results**

New CNN classifiers were trained using the training data for all the reconstruction approaches, including Pf, and tested against the test data for all reconstruction approaches. The resulting performance values are given in Figure 8 where again it is the proportion of incorrect classifications is shown. (Note
that 0.0 is perfect classification and that random classification would give a figure of approximately 0.5.)

It can now be seen that, when a CNN is trained on the Pf images, it gives good performance against all the other image modalities. This is in sharp contrast to the performance observed when training is performed on the Cs reconstructions from which the Pf reconstructions are formed. It can thus be seen that, by imposing a SAR PSF onto the Cs reconstructions, a more robust performance, similar to the provided by the Ft reconstruction, is obtained.

III. FEATURE-BASED ANALYSIS

A. Feature space representation

It would be instructive to be able to interpret how the reconstruction schemes adopted may influence classification performance. One way of doing this is to think in terms of “feature space”. Features are values that characterize some aspect of the images under consideration. The simplest feature representation is to consider each pixel value as a feature value. Each image can then be interpreted as a point within a multi-dimensional space of dimension equal to the number of pixels. This is, however, not a particularly convenient representation to support visualization.

An alternative is to select features that have some physically intuitive justification in terms of being suitable to characterize the images. Many such features exist, but for the purposes of this discussion, the “contrast” and “rank fill ratio” features will be considered. These are defined below where p is the pixel value and N is the number of pixels.

1. contrast = $N \frac{\sum p^2}{(\sum p)^2} - 1$

2. rank fill = $\frac{\sum p_{10\%}}{\sum p}$
   - (sum top 10% and divide by sum of all)

The contrast provides a measure of the degree of disparity between the brighter and darker pixels and is useful since metal objects in SAR images tend to be bright in comparison to the background. The rank fill ratio measures to what extent the energy within the image is concentrated into just a few pixels as this is characteristic of man-made vehicles in SAR images.

The values of contrast and rank fill can be plotted against each other in a feature-space scatter plot for all image examples in a particular class to provide a visualization of the spread of values associated with that class.

B. Behaviour of image reconstructions in feature space

The scatter plots using “contrast” and “rank fill” for targets (top) and clutter (bottom) are shown in Figure 9. A classifier will define regions within feature space designed to separate the classes. It can be seen that the regions occupied by features calculated for the Mg (red) and Ft (cyan) images overlap considerably for targets and for clutter. Thus any decision boundary formed to separate targets from clutter based on one of these modalities might be expected to provide reasonable performance on the other modality.

Fig. 9. Scatter plots of contrast against rank fill for targets (top) and clutter (bottom) for Mg (red), Cs (blue) and Ft (cyan).

However, the region of feature space occupied by features calculated for the Cs (blue) images lies far from the Mg (red) and Ft (cyan) regions. Thus any decision boundary formed on the basis of the Cs images will have no transfer of performance to the Mg or Ft images. Fundamentally, the Cs reconstruction does not have the characteristics of a standard SAR image and so the region of feature space occupied by the Cs reconstructions is not the same as that occupied by the Mg and Ft images.

If the Pf reconstructions are now introduced, the scatter plots shown in Figure 10 are obtained. It can be seen that the effect of imposing the SAR PSF has been to move the region of feature space associated with the Cs reconstruction to a position where it has considerably more overlap with the Mg and Ft regions. It might thus be expected that a classifier trained on the Pf reconstructions would provide more transferable performance than a classifier trained on the Cs reconstructions as has been observed.

![Feature Space Scatter Plots](image-url)
IV. CONCLUSIONS

This paper has built on the results of [1] to consider further the effect on classification performance of various schemes for image reconstruction applied to the disjoint K-space which would arise from multi-static SAR imaging. Of particular interest has been how well the performance of a classifier trained on one image type transfers to test data from a different image type.

In [1] it was been found that a classifier trained on the Cs image reconstructions has no transfer of performance to other image modalities. In contrast, a classifier trained on the Ft reconstructions provides good performance against all other modalities and is, in this sense, more robust. However, in the work reported here, it has been found that, if a SAR PSF is imposed on the Cs reconstruction, a classifier trained on the resulting (Pf) images also provides good performance against all other modalities.

An analysis in terms of the effect of reconstructions on feature space has provided a visual interpretation of this behavior. In essence, it seems that the use of a PSF makes the image reconstructions more characteristic of SAR images. The Cs reconstructions themselves consist only of dominant scatterers and are not of the same nature as images produced by Fourier techniques.

In terms of whether Ft or Pf reconstruction should be used to produce images from disjoint K-space, classification performance is only one factor. The Pf approach is very computationally intensive and irreversible although it may give a visually appealing reconstruction. The Ft approach is rapid and reversible but the resulting image will have a distorted PSF which may cause issues for further exploitation. There is perhaps a trade-off to be made between these approaches although, given similar performance in terms of classification, the speed and reversibility (the original data can always be retrieved) of the Fourier approach are significant advantages.

This paper has only considered two approaches to SAR image reconstruction from disjoint K-space but other approaches have been reported, e.g. [6], [7], [8]. Further work could consider assessing these approaches in terms of their effect on ATR performance.

ACKNOWLEDGMENT

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