

Chapter 5

Conclusions and Future Work

5.1 Summary of the work

In this dissertation, the problems of refractivity retrieval from a networked of weather radars and reflectivity and velocity estimation using imaging radar are considered for the application of compressive sensing. Due to small number of measurements and noise contamination on the received signals, compressive sensing is an attractive method for the estimation, since it is robust to noise and well suited for underdetermined problems. CS has potential to achieve high quality images using random sampling scheme and so the various receiver configurations with different spacings in phased array radars are potential for CS application. One of the goal for this work was to develop a new method to obtained high resolution and high quality weather radar images by using compressive sensing theory.

In the first study, CS was proposed to improve the refractivity retrieval using a network of radars since the performance of conventional methods for refractivity retrieval can be limited by the limited number of high-quality ground returns and noise. CS has been applied to other fields and has shown promising image reconstruction with much fewer measurements than those used in the conventional sampling scheme. The application of CS to refractivity retrieval was formulated using a linear model and subsequently demonstrated using simulations in chapter 3. The modeled refractivity fields were obtained from a numerical weather prediction model. The performance of CS and CLS was quantified

using RMSE and was tested statistically as a function of noise, number of radars and refractivity models with different compressibility and smoothness. Note that both CS and CLS rely on the same linear model and can be implemented for a single radar. It is evident that both CS and CLS can grossly reconstruct the refractivity difference for most of times. Moreover, from the cases investigated, CS always provides better reconstruction than CLS, manifested by the lower RMSE. In addition, the results have shown that CS is also less susceptible to noise contamination, especially when the image for reconstruction is more compressible.

By taking advantage of networked radars, both CS and CLS performances are improved as the number of measurements and the viewing angles increase. However, the shape of the refractivity difference is better preserved in CS than CLS. The CS algorithm can be further improved by more carefully choosing penalty parameters between the DCT and TV terms. In CLS, the selection of the threshold level for the singular values may not be optimal. Based on the cases presented in this work, CS has the potential to perform better reconstructions than CLS given the same condition such as noise, number of radars, etc.

The second application of CS was conducted with imaging radar to image atmospheric reflectivity and velocity field. The performance of the digital beamforming algorithms such as Capon, Fourier, can be limited due to resolution limitation, calibration process, noise contamination, number of receivers. CS was proposed to improve the reconstruction of reflectivity and velocity structure by using phased array radars, as alternative to DBF techniques. The problem of DBF is posed as an inverse problem and formulated using a linear model for both reflectivity and velocity estimation. was formulated using a linear model for both reflectivity and velocity estimation and Subsequently, the application of CS to DBF was demonstrated using simulations, where the model reflectivity is obtained from Gaussian models and numerical weather prediction model in chapter 4. The performance of CS, CB and FB was quantified using RMSE, RES, DR and velocity interval and tested

statistically as a function of SNR, number of receivers, receiver spacings, number of samples and reflectivity models. Note that CS is relied on the linear model can be applied to two dimensional beamforming. It is obvious that CS, CB, FB can grossly reconstruct the reflectivity and velocity fields in most cases. Moreover, CS can provide better reconstruction for reflectivity and velocity than FB and also CB in some cases, for example, when the amount of noise increased, or the dynamic range of reflectivity relatively small , or using smaller number of samples. In addition, the results show that CS is less susceptible to noise contamination.

Increasing the number of receivers, the performance of CS, CB, and FB was improved. Moreover, CS and CB takes advantage of non-redundant and random spacing receiver configurations, where the redundancy in the receiver pairs are reduced significantly and so the number of independent measurements increases. CS is able to recover reflectivity structure accurately by using 17 receivers for the cases are considered in this work. The shape of the reflectivity structures preserved in CS and CB is comparable for the larger number of receivers and samples. CS overestimates the resolution when the dynamic range of reflectivity becomes larger, however, still provides reasonable result comparing to CB and FB. The impact of reflectivity on velocity estimation is studied in chapter 4. Again, when the dynamic range of reflectivity becomes larger, the accurately estimated velocity region for CS becomes narrower. This is also true for FB velocity estimates. However, CB can provide a reasonable velocity range by using high number of samples and number of receivers.

For the smaller number of samples and receivers, CS is able to provide better estimation than CB using NRS and RS receiver configurations. One difficulty in CS estimation is the beta value selection. CS is sensitive to beta value and large or small tolerance for the noise, could lead to inaccurate estimation. Additionally, the CS performance can be improved by choosing penalty parameters carefully between the Wavelet and Laplace in the l_1 -norm minimization. Based on the cases presented in this work, CS has potential to perform better reconstructions than CB and FB for given the condition of noise, number of receivers,

number of samples, calibration, etc. In the present study, SVD was used to reduce the size of measurement matrix and potentially reduce the redundancy in the measurements. The beta value for the noise and statistical imperfections in the data is estimated by defining a threshold on the measurements associated with the smaller singular values. It is important to note that, incoherence and sparsity is fundamental for evaluating the quality of sparse approximation, however, in this work, incoherence was not too low (5.5 in the range of 1 to 11.3) for three receiver configurations by using Wavelet transformation. The incoherence value was too high with DCT, therefore, Wavelet transformation was selected for the study. In this work, the time series signals are generated by using three dimensional radar simulator. A thousands of scatters are randomly located within the simulation domain. The calibration of CS, FB power estimates is made by considering the transmitting and receiving antenna pattern in the simulation. It is important that CS can be calibrated by using uniform reflectivity or a point target structure for three receiver configurations based on the simulation results. The experimental imaging radar data was used to demonstrate the feasibility of CS in radar imaging. The data is obtained from one of the imaging radar AIR in April 2012. CS and FB qualitatively produced similar reflectivity and velocity estimation, where the recovered reflectivity from CB was noisy by using the number of samples 53 and number of receivers 36.

The coherence condition was studied to assess the probability of exact reconstruction using l_1 -norm minimization on sparse images. It is important to note that, while coherency is fundamental in evaluating quality of sparse approximation, the satisfaction of the restricted isometry property (RIP) enables more robust and stable reconstruction of sparse signals Duarte and Eldar (2011). RIP ensures that two sparse images with same transform coefficients at different locations cannot produce same measurement vector and thus guarantees unique solution Duarte and Eldar (2011). However, it is computationally expensive to check the RIP condition Baraniuk et al. (2010). On the other hand, coherency provides

an alternative way in checking the probability of robust recovery Tropp (2006). Additionally, coherency can be conservatively used to bound RIP and enables stable recovery via l_1 -norm minimization Potter et al. (June 2010). Furthermore, it is also important to note that compressible images can be reconstructed by approximating most significant transform coefficients, even when RIP is not satisfied Zhang (2008); Candès and Tao (2007). While, under such conditions, the recovery of images might not be exact, they are still valuable in solving practical problems. In the refractivity retrieval study, while the computed mutual coherence is relatively low (0.16 in a range of 0 to 1), such a value cannot be used to guarantee exact recovery (similar to conditions with unsatisfied RIP) unless sparsity property of signals to be recovered and transformation matrix are also considered Candès and Romberg (2006). On the other hand, the present simulation results demonstrate the proposed method based on the CS theory indicates better performance than CLS in reconstructing refractivity. In the DBF study, the coherence is computed for three receiver configurations (uniform, nonredundant, and random spacing) and the value is similar at about 0.5.

5.2 Suggestions for further research

In the radar refractivity retrieval study, the radar location are selected on the corners, and target locations are random for simplicity. Note that ground targets are likely to group together and sparsely distributed, which makes even more challenging to estimate the phase. This work is just the first step to tackle the problem and a more general and convenient setup was used. As such, the improvement in the overlap region of refractivity from additional radar can be easily observed and quantified. For the future study, a realistic radar configuration and target locations can be considered. One difficulty in the refractivity retrieval is to unwrapped the received signal phase accurately in the case of sparse and missing target distributions in the radar field of view. The phase unwrapping algorithm can be tested and implemented for refractivity field experimentation.

Another important issue in the framework of CS application is the choice of regularization parameters for the combination of multiple transformation matrix in the minimization. Further, the selection of the parameters can be effected by the choice of β value based on the discrepancy principle in the inverse problems and of the l_1 - norm solver. Additionally, l_p -norm regularizations can be considered for the favoring of sparsity, where p can be between 0 and 1.

Another research direction is the selection of β value for the error tolerance under various amount of noise and number of measurements. A good choice of β will lead to a good choice of regularization parameters and calibration value in chapter 4. It is also worth to note that the condition of incoherence can be further improved by designing a better transformation matrix, which can result in better sparsity of signals in the transformed domain and incoherence to measurement matrices.

For the digital beamforming study, the spatial continuity is considered only in one dimension (vertical direction) for CS estimation. Cross-range spatial continuity can be considered between the successive range gates by using the estimation from the pervious range in the current minimization. However, one drawback is that the error propagation from the previous estimation, if the initial estimation or previous estimation fails. Another possible way to estimate reflectivity in two dimension (estimation of RHI image at once) by concatenating the measurements in a vector form and creating new combined measurement matrix. However, the computational time will be increased significantly, since the size of measurement matrix and transformation matrix increase proportionally with the number of measurements and number of pixels to be reconstructed.