COMPRESSIVE SENSING AND TARGET FEATURES: AN INFORMATION PRESERVING APPROACH FOR MIMO SAR

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1 INTRODUCTION

An Automatic Target Recognition (ATR) system usually consists of a sensor and a set of tasks which are able to detect, discriminate and classify potential objects of interests based on gathered data. There are many systems which are able to collect data (e.g. radar sensor, electro-optic sensor, infra-red devices) which are commonly used to collect information and detect, recognise and classify potential targets. Generally speaking an ATR system tries to make a decision based on some parameters (termed features) defined by the designer (as shown in Figure 1, i.e. finding the optimal partition of feature space).

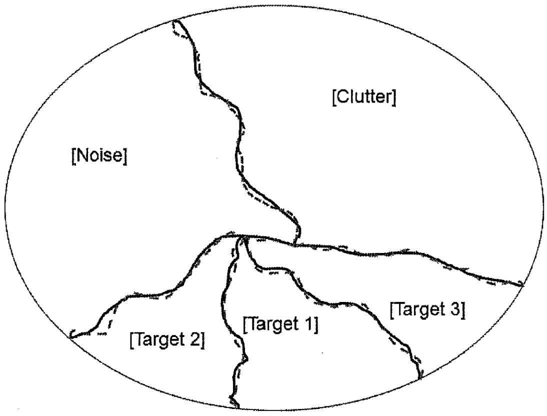


Figure 1: Problem description: the main goal of an ATR system is to 'build' boundaries between equivalence classes of the feature space, i.e. finding the partition of the feature space (solid black line). Unfortunately this is not possible; therefore a suboptimal solution has to be accepted (dashed red line).

In this paper a ground based MIMO SAR system will be considered as acquiring sensor of an ATR equipment.

MELISSA system is a new ground based MIMO SAR system developed by JRC [4]. By acquiring range profiles of scatters with multiple antennas, MELISSA is able to generate a 2-D image of the scene of interest. The processing indeed, based on a modified 2-D FFT algorithm [5], is able to create an image in azimuth and range, termed polar image. The application of this kind of system has succeeded in many security and surveillance tasks, such as avalanche, volcano eruption and landslip monitoring [4].

Recently, MELISSA has been adopted as early warning radar for monitoring the displacement of COSTA Concordia disaster [2]. Through interferometric techniques MELISSA system is able to determine the displacement and the deformation of the vessel successfully. However, despite the above-mentioned advantages, there are still many open questions, especially in case of image interpolation, *i.e.* the non-linear transform from a polar to a Cartesian grid (more readable for the user). Besides, the Cartesian image can be used for assessing the most important features of a target of interest easily. Indeed interpolation operation must be of extremely high quality to prevent the introduction of false or spurious targets into the region of interest.

Possible solutions can be 2D-sinc function operating into the polar domain, *i.e.* the classical signal recovery method based on the Nyquist-Shannons theorem or a sinc interpolator in range and a Lagrange polynomial in azimuth. The classical signal recovery method based on the Nyquist-Shannons theorem is affected by Gibbs phenomenon, whereas Lagrange interpolator is affected by the Runge's phenomenon. As a consequence distortions are introduced in the Cartesian image [3].
Since the features preservation is a crucial task for the classification of the potential targets of interest, it is important that the distortions introduced into the Cartesian image are minimized, for this reason we want to investigate the application of Compressive Sensing (CS) algorithms as an image enhancement technique for preserving the information of the target of interest.
CS theory defines a set of techniques which allow reconstructing a signal when Nyquist-Shannons theorem assumptions are not satisfied. It asserts that one can recover certain signals and images from far fewer samples or measurements than traditional methods use. The two most important principles of CS theory are: 1) Sparsity, which expresses the idea that the information rate of a continuous time signal may be much smaller than suggested by its bandwidth, or that a discrete-time signal depends on a number of degrees of freedom which is comparably much smaller than its (finite) length; 2) Incoherence, which extends the duality between time and frequency and expresses the idea that objects having a sparse representation in a domain must be spread out in the domain in which they are acquired, just as a Dirac or a spike in the time domain is spread out in the frequency domain. First experiments have allowed to understand the conditions under which CS is suitable as ground based MIMO SAR image interpolator (*i.e.* firstly because of the non-uniform cross-range sampling rate and secondly because the sparsity of cross-range sampling increases with the distance from the sensors).
In this article we investigate the performance obtained by adopting *Block matching pursuit* algorithm [1] as image interpolator. By comparing the scatters covariance matrix of a known target of interest, the assessing of the most important features (*i.e.* length and width of the potential target) is computed and an estimation of the distortion introduced by the interpolation algorithms is evaluated. First results have stressed the advantages and limitations of using CS with respect to back-projection algorithm [7] as image interpolator.
In section 2 an introduction of the system, the interpolation problem and the adopted algorithms will be given. In section 3 the results will be reported whereas in sections 4 and 5 the results discussion and conclusions will be described respectively.

2 SYSTEM AND PROBLEM DESCRIPTION

2.1 Introduction of MELISSA GB MIMO SAR system

The concept of a ground based MIMO SAR (termed MELISSA) has been introduced by Tarchi et al. [4] and it is able to create a two-dimensional image by processing the returns of multiple signals transmitted by different antennas.
Getting into details, MELISSA is an FMCW radar with switches on the TX and RX antennas in order to allow time-separation of the signals in the receiver. MELISSA consists of a 10 elements ULA (**Uniform Linear Array**) as transmitter and two 6 elements ULA as receiver. As described in [4], an equivalent virtual array consisting of 120 elements with inter-element displacement equal to $\lambda/2$ (λ is the radar wavelength) as requested by Nyquists criterion is electronically created.

2.1.1 Image interpolation problem and adopted algorithms

Once the data have been acquired, images are created by applying the algorithm defined by Fortuny in [5]. The processing of raw data produces an image in the polar coordinates (ρ,θ) (i.e. range and azimuth), therefore an interpolation is necessary to convert the data in a Cartesian system of reference (x,y). The interpolation stage is important in order to making understandable pictures for the user and easier the assessing of the potential target features. As mentioned in Munson et al. in [6], the polar-to-Cartesian interpolation operation must be of extremely high quality to prevent aliasing into the original image of reflectors lying outside the terrain patch of interest. Besides poor interpolators can produce false or spurious targets that are associated with targets that lie within the Region Of Interest (**ROI**), hence the non-linear transform of the acquired sampled data to obtain a Cartesian image is a crucial step for two reasons: Firstly because the acquired data usually do not cover the complete range of interest of the Cartesian (x,y) reference system and secondly it is crucial to preserve geometric and radiometric information of the scene as well as avoid introducing artefacts in ROI.

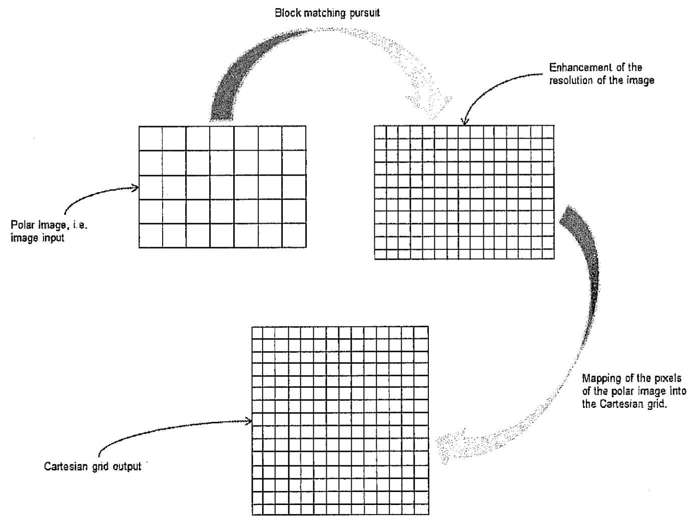


Figure 2: Processing block scheme

As mentioned in [3], there are many algorithms available for interpolating the polar image into a Cartesian grid, such as bilinear interpolation algorithm, two-dimensional *sinc* interpolation or a nonlinear approach for instance. In this article we want to investigate the performance of the mentioned technique by adopting *Block matching pursuit* algorithm [1] as image interpolator. Mallat and Yu indeed introduced a class of inverse problem estimators computed by mixing adaptively a family of linear estimators corresponding to different priors. Sparse mixing weights are calculated over blocks of coefficients in a frame providing a sparse signal representation. They minimize an ℓ_1 -norm taking into account the signal regularity in each block. Adaptive directional image interpolations are computed over a wavelet frame with an *O(N logN)* algorithm. As reported in Figure 2, the proposed image processing method for a GB MIMO SAR system consists in feeding the polar image into the iterative version of the algorithm described in [1]. The *Block matching pursuit* algorithm produces a super-resolved image (such as image processing paradigm, i.e. the resolution is enhanced in terms of pixels. It is important to note the difference with respect to classical radar super-resolution approach: in the latter the radar parameters are used in order to reduce the sidelobe and speckle artefacts, whereas in our case the super resolution consists in attempting to generate a single high resolution image from one or more low resolution images of the same scene) and the pixels of the super-resolved polar image are mapped into the desired Cartesian grid. The results of the algorithm [1] are compared with a classical Back-projection approach [7].
In order to estimate the distortions introduced by the algorithms, the dimensions (length and width respectively) of a known object are compared with the estimated ones from the interpolated data by computing the eigenvalues of the covariance matrix of a set of selected pixels of the ROI.

3 METHODS

As above mentioned, a known target has been adopted in order to assess the distortion introduced by interpolation process. In our experiment a VW Golf (length 4.204 m width 1.759 m) (see Figure 3a) placed in front of the sensor (at a distance of 6m approximately) has been considered.
As reported in Figure 3b representing the processing chain reported in [4], the target image is computed by applying the algorithm described in [5], whereas in Figure 4 the target image processed by using Back-projection algorithm reported in [7] is represented. The main difference between the pictures consists in the coordinate system. Figure 4 is in the (ρ,θ) domain (i.e. range

and azimuth), however Figure 5 is in a Cartesian grid, i.e. (x,y). Once the polar image is defined, it is processed, iteratively, by using the algorithm defined in [1]. In our experiments the algorithm has been applied 5 times and the outcomes has been used for mapping the pixels in a Cartesian grid defined as x=[-3,3] m, y=[5,12] m.
The Cartesian images have been then processed in order to define the ROI, fed to the CFAR processor in order to determine the binary image of the target, as reported in Figure 6-7.
The final step consists in computing the eigenvalues of the covariance matrix of a set of selected pixels of the ROI, as defined in [9]. Once the eigenvalues have been estimated, by using the Singular Value Decomposition factorization (**SVD**), the length and the width are estimated by considering the pixel geometrical distribution as Normal, therefore the eigenvalues coefficients are multiplied by a factor 3 in order to consider almost 99% of scatters in both directions.

4 RESULTS

Figure 3a: Target of the experiment

As for the CFAR, it has been simulated by considering the intensity image values and three different thresholds, i.e. 0.5E4 (the binary images are reported in Figure 5 and 6), 1E4 (Figure 8 and 9) and 1.5E4 (Figure 10 and 11). Since the intensity of the outcomes was different, the interpolated image with Super Resolution algorithm was scaled so that the maximum value of the image was the same in both images.
Other experiments consisted in estimating the optimal threshold which minimizes the error of target features assessment in case of the Back-projection image output. The computed value is a threshold equal to 0.5284E4. The corresponding binary images are reported in Figure 12 and 13.
As for the estimated parameters, they are reported in Table 1.
Finally in Figures 14-17, the distortions introduced by *Block matching pursuit* are presented.

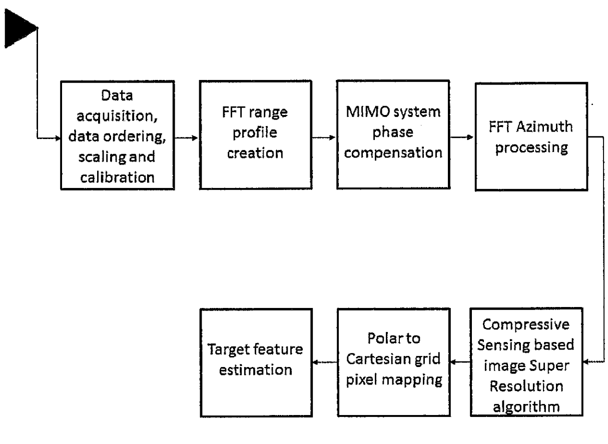


Figure 3b: MELISSA Processing chain

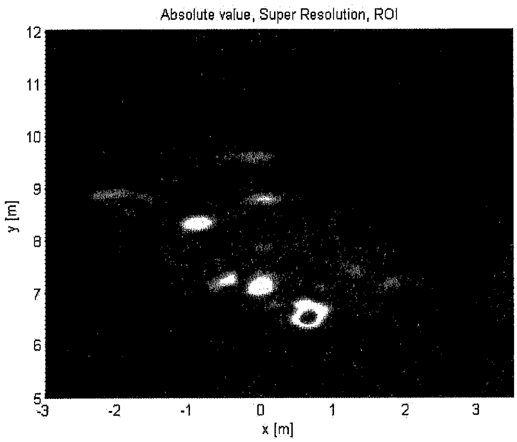


Figure 4: ROI of the polar super-resolved image

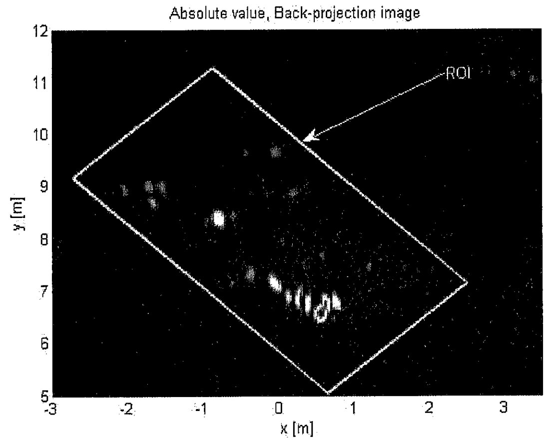


Figure 5: ROI of the BP projection image

5 DISCUSSION

The analysis of the images and the data allowed stressing some important issues of classification when a ground based MIMO SAR system is used. Firstly, the operating geometry of the sensor affects deeply the estimation of features of the system. As reported in Table 1 and in binary images, the estimation of the target width is difficult because of the orientation of the target with respect to the centre of the radar, which is not able to illuminate entirely the target, as a consequence part

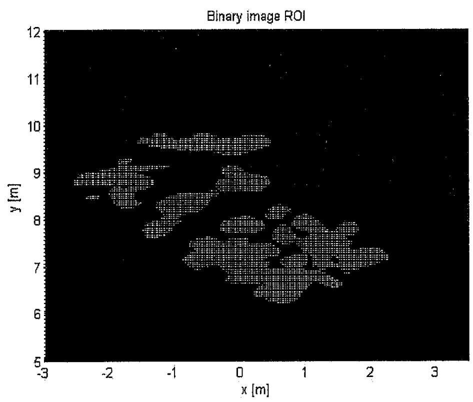


Figure 6: target binary image after application of the Super Resolution algorithm to the interpolated image. CFAR threshold 0.5E4

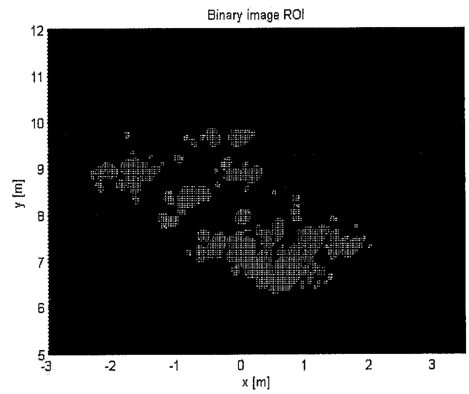


Figure 7: target binary image after application of the Back-projection image. CFAR threshold 0.5E4

of the transmitted energy is reflected in different directions and therefore part of the signal is not detected by receivers, as in case of classical SAR systems, creating blind zones.
By observing the binary images of the Super Resolution algorithm, it seems that the proposed algorithm tends to smooth the images much more than Back-projection algorithm. Figures 15-17 confirm this suggestion, indeed the Signal-to-Clutter ratio, is slightly reduced, when the number of iterations is increased. Consequently the CFAR processing could produce a higher number of false alarms which introduce distortions into the final feature space.

6 CONCLUSIONS

Polar-to-Cartesian interpolation process is a crucial step in GB MIMO SAR system in order to obtain an easier understanding of the scene, when the modified 2-D FFT algorithm [7] is adopted. When such kind of sensor is considered as ATR system, however, the feature extraction becomes very hard because of the degradation due to the interpolation algorithm used. As mentioned the trade-off

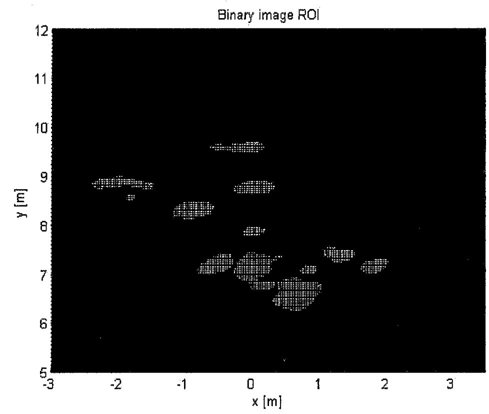


Figure 8: target binary image after application of the Super Resolution algorithm to the interpolated image. CFAR threshold 1E4

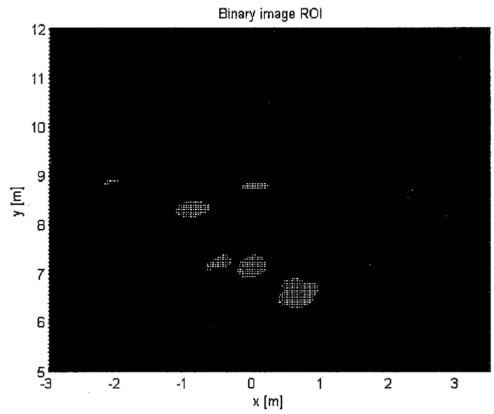


Figure 10: target binary image after application of the Super Resolution algorithm to the interpolated image. CFAR threshold 1.5E4

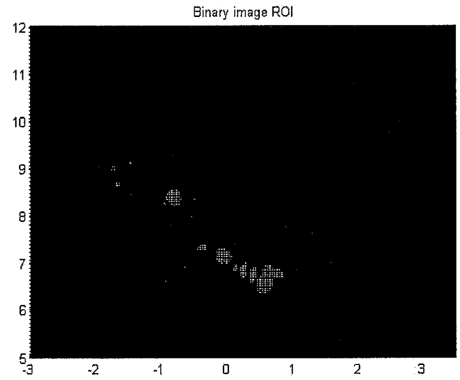


Figure 11: target binary image after application of the Back-projection image. CFAR threshold 1.5E4

The approach was iterative. The algoriess.
consists in avoiding the introduction of artefacts into the final image and the removal of pixels belonging to the potential target. Hence, for a correct feature extraction it is important to create a high quality interpolated image.

The article has been addressed in order to understand the suitability of *Block matching pursuit* algorithm, defined in [1], as image interpolator. It is based on the assumption that each point a Cartesian grid can be considered as a point into the polar image domain, therefore the application of a Super-resolution algorithm based on the CS algorithm can reduce the distortions introduced by

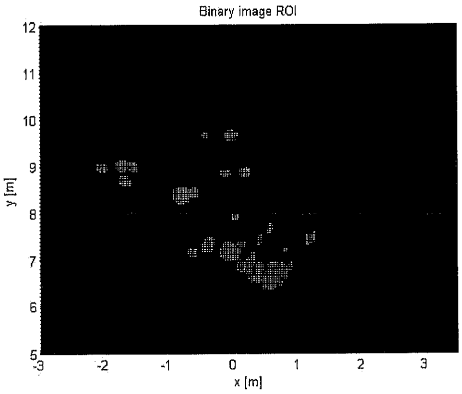


Figure 9: target binary image after application of the Back-projection image. CFAR threshold 1E4

Table 1: features assessing of the target reported in Figure 1. The values are in metres

	Back-Projection		[illegible]	
	Length	Wid[illegible]	[illegible]	[illegible]
Thr=0.5E4	4. 2559	1.06	[illegible]	[illegible]
Thr=1.0E4	4.0408	0.69	[illegible]	[illegible]
Thr=1.5E4	2.4084	0.1479	2.6564	0.3131
Thr=0.5284E4	4.2048	1.0496	4.6488	1.3345

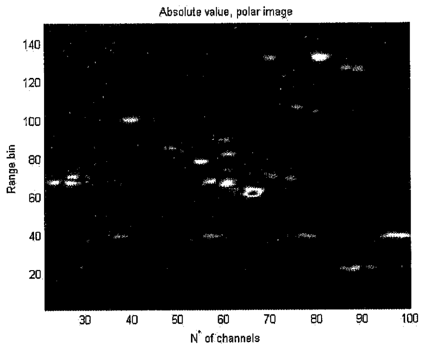


Figure 14: Super resolution with one iteration on the entire image. The algorithm has been applied once on the polar image. The image has doubled in size.

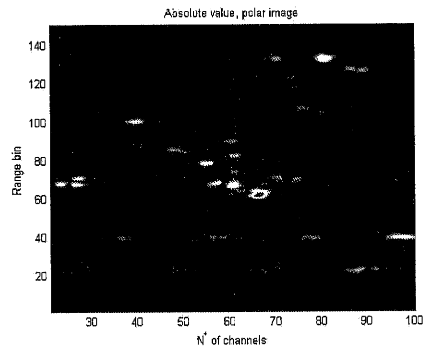


Figure 15: Super resolution with two iterations on the entire image. The algorithm has been applied twice on the polar image. The image is 4 times in size with respect to the original polar image.

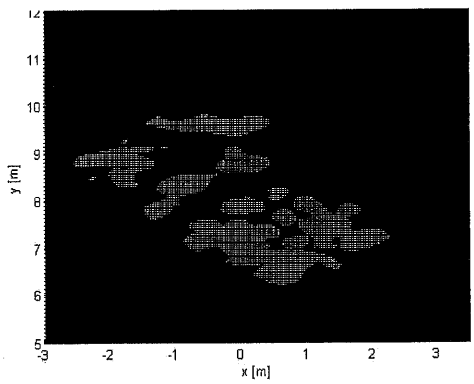


Figure 12: target binary image after application of the Super Resolution algorithm to the interpolated image. CFAR threshold 0.5284E4

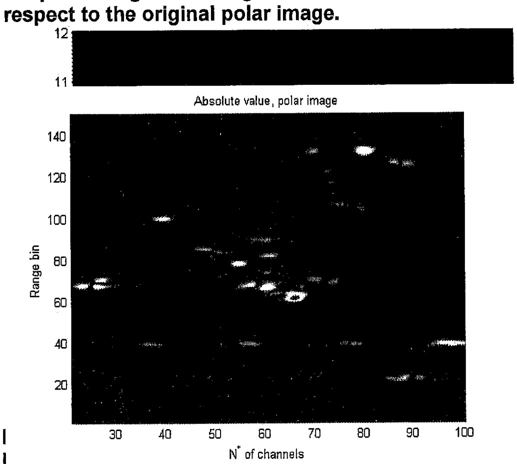
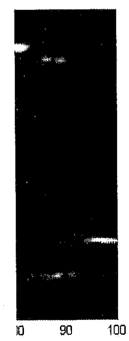


Figure 17: Super resolution with two iterations on the entire image. The algorithm has been applied twice on the polar image. The image is 32 times in size with respect to the original polar image.



iterations on the applied four times imes in size with

the polar-to-Cartesian interpolation process.
The approach was iterative. The algorithm indeed was modified because it only allows doubling the number of pixels. Once the desired Super Resolution is achieved the pixels of the super resolved image are mapped into the desired Cartesian grid. Once the Cartesian image is created [5], the ROI is defined and it is fed to the CFAR simulated processor, which creates the binary image [8]. The coordinates of non-null pixels are used in order to estimate the covariance sample matrix [9] and as a consequence to assess the target features.
Moreover the Super Resolution processing with respect to the Back-projection algorithm [7] reduces slightly the Signal-to-Clutter Ratio (i.e. the algorithm tends to smooth the final image), increasing the number of false alarms. Subsequently the distortions introduced into the feature space increase and the assessment of the target features is therefore decreased.
The estimation of the parameters by using:

$$\hat{\Sigma} = \frac{1}{N-1}\sum_{k=1}^{N}(X_k - \hat{M})(X_k - \hat{M})^T \qquad (1)$$

as reported in Table 1, stresses indeed that a part of the target is not visible from radar point of view because the bistatic angle of the system does not allow gathering some scatters which are reflected far-away from the radar receivers, therefore the parameter assessment is not correct, as in the case of the target width estimation.
Despite the radiometric distortion preservation is higher if Back-projection is adopted, the algorithm is inefficient in terms of necessary processing time. As a consequence, the trade-off between time consuming and radiometric distortion of the proposed processing can be improved if the Mallat's algorithm is rearranged in order to be processed in a parallel way. In this case moreover a real time classification approach can be also implemented.

7 REFERENCES

1. S. Mallat, G. Yu. Super-Resolution with sparse mixing estimators, IEEE Transactions on Image processing, Vol. 19, No. 11, November 2010, 2889-2899
2. J. Broussolle , V. Kyovtorov, M. Basso, G. Ferraro, J. Morgado, R. Giuliani, F. Oliveri, P.F.Sammartino,D. Tarchi. MELISSA, a new class of ground based InSAR system. An example of application in support to the Costa Concordia emergency, ISPRS Journal of Photogrammetry and Remote Sensing, Volume 91, May 2014, Pages 50-58.
3. G. Marino, D. Tarchi. MIMO radar imaging and geometrical target properties: a perspective from a classification point of view. EUSAR 2014, Berlin 2014.
4. D. Tarchi, F. Oliveri, P. F. Sammartino. MIMO Radar and Ground-Based SAR Imaging Systems: Equivalent Approaches for Remote Sensing, IEEE Trans. on Geoscience and Remote Sensing, Vol. 51, No. 1.
5. J. Fortuny. A Fast and Accurate Far-Field Pseudopolar Format Radar Imaging Algorithm. IEEE Trans. on Geoscience and Remote Sensing, Vol. 47, No. 4, April 2009.
6. D. C. Munson Jr., J. L. C. Sanz, W. Kenneth Jenkins, G. Kakazu and B. C. Mather. A comparison of algorithms for polar-to-Cartesian interpolation in spotlight mode SAR. IEEE International Conference on ICASSP, April 1985.
7. J. Fortuny, A. J. Sieber. Fast algorithm for near field synthetic aperture radar processor. IEEE Trans. on Antennas Propagation, Vol. 42, No. 10, pp. 1458-1460.
8. G. Marino, D. Tarchi. Compressive Sensing and MIMO radar image Polar-to-Cartesian interpolation. SET-213 Specialist Meeting on Compressed Sensing for Radar/SAR, Tallin 2014.
9. K. Fukunaga. Introduction to Statistical Pattern Recognition, 2nd Ed. Academic Press, 1990.