# DEBRIS SIZE INFERENCE FROM STATISTICS OF RADAR CROSS SECTION SAMPLES

**S. N. Anfinsen[1,2], T. Grydeland[1], J. Vierinen[2], D. Kastinen[3], R. Ricker[1], I. Arntzen[1], J. Kero[3], and K. A. Høgda[1]**

[1]*NORCE Norwegian Research Centre, 9019 Tromsø, Norway*
[2]*UiT The Arctic University of Norway, 9037 Tromsø, Norway*
[3]*Swedish Institute of Space Physics, 98128 Kiruna, Sweden*

## ABSTRACT

The physical size (largest linear dimension) is a key parameter when evaluating the risk associated with a particular piece of space debris. There is information about physical size in radar observations of space debris objects, but this information is not easily accessible. The number of available radar cross section (RCS) estimates of such objects is small, and the number of physically relatable parameters that can be estimated is therefore extremely limited. Detailed EM modeling is possible, but it depends on a multitude of parameters, and such modeling can therefore only be used to inform and validate approaches that characterize unknown objects in lower dimensional parameter spaces. The well-known Swerling models have long been used to characterize the probability distribution function (PDF) for an object's RCS, in two broadly applicable classes. We suggest a refinement of the total scattering PDF in terms of a mixed scatterer model, where the PDF is a linear combination of several separate distributions from the same family but with unique parameters. We also propose to use regression modeling to map distribution parameters and other statistics from RCS measurement samples of a single space debris object to physically interpretable parameters for size and in a limited sense shape. Public databases of space debris objects with their size and shape will be used to train and evaluate the performance of these models.

Keywords: space debris; size estimation; radar cross section; statistical regression; machine learning.

## 1. INTRODUCTION

Space Debris is a hazard for all human activities in space, manned and unmanned. Precise observations of the orbiting population are necessary, both for characterization of the debris population in a statistical sense and for the precise estimation of orbits and object properties. The former is used to assess risk associated with a given mission profile, and the latter is of critical importance for conjunction analysis and for collision warnings and the planning of collision avoidance manoeuvres. For both purposes, it is vitally important to know the physical dimensions of the debris objects, as size can determine both how large a manoeuvre is necessary and how much damage a collision can be expected to cause.

Radar beam-park experiments have been very successful in characterizing the distribution of space debris objects, both in terms of orbital parameters but also in terms of limiting the estimates of their radar cross section, or RCS. A recent paper [1] used the EISCAT UHF radar to observe range and range rates and refine orbit estimates by matching up the observed SNR curve to that predicted by simulations. This gives good estimates of RCS for objects whose RCS does not vary rapidly, i.e., objects that are isotropic or not tumbling.

For assessment of collision risk and avoidance manoeuvering, the physical size of the debris object is the key parameter. As a next step, we will in an upcoming project investigate the feasibility of estimating object size and shape from small samples of RCS measurements in order to:

- statistically characterise the debris population to determine the risk of a given mission profile;
- estimate object properties for conjunction analyses, collision warnings and planning of collision avoidance manoeuvres.

The object size can be directly related to the RCS only in cases that are either extremely simple or modelled in exquisite detail. In this paper we describe instead a project designed to infer physical size from statistics and predictors extracted from the sample of RCS estimates made for a single object by using regression models from classical statistics and machine learning. In order to prove the concept, interpret the regression models and gain knowledge about the relationship between RCS statistics and the dimensions and shape of the space debris objects, we will model the statistical distribution of the RCS estimates and correlate their parameters with known properties from ESA's DISCOS (Database and Information System Characterising Ob-

*Proc. 2nd NEO and Debris Detection Conference, Darmstadt, Germany, 24-26 January 2023, published by the ESA Space Safety Programme Office*
*Ed. T. Flohrer, R. Moissl, F. Schmitz (http://conference.sdo.esoc.esa.int, February 2023)*

jects in Space) database[1] and the US Space Surveillance Network's Space-Track database[2]. To this end, we will also apply cluster algorithms to group features extracted from the RCS samples and interprete the clusters in terms of information from the same databases.

The rest of the paper proceeds as follows: Section 2 provides background theory on RCS measurements of space debris. The statistical and machine learning methodology applied to infer space debris size and shape information and the statistical modelling used to understand and interpret the relations between RCS measurements and object properties are described in Section 3. A brief discussion of limitations and assumptions is given in Section , before Section concludes the paper.

## 2. THEORY

Radar observations for various studies of space debris have been made by a range of different radar systems, as described in [7, 8, 5, 6]. We focus on monostatic radar measurements with a stationary antenna beam pointing direction, referred to as beam-park observations. These will be performed with the EISCAT UHF radar, which was previously used in [1, 9, 10, 11].

The radar measures signal to noise ratio (SNR) for a given target. With precise information on the orbit of an object and a detailed model of the radar antenna pattern, it is possible to estimate the radar cross section, or RCS, of that target. In most cases the RCS will vary with the orientation of the target with regard to the radar's pointing direction, as illustrated in figure 1. Rotation (tumbling) of the target means that RCS will vary even if the target can be held in a known position or transit of the radar beam.

Even more complicated is the association of RCS with physical dimensions of a particular object. Well-known expressions for computing RCS exist only for the simplest cases of canonical geometric objects such as ellipsoids and cylinders, but debris from collisions or other fragmentation events are rarely of simple shape, and they can also vary greatly in their material properties. When an object is composited of more than one geometric objects, so that radio waves can experience multiple reflections, the RCS of the composite cannot be represented by simply adding up the RCS of each constituent part, known as the superposition principle.

Instead, the result will in all but the simplest cases be very sensitive to the exact configuration of the object, that is, the relative sizes, distances and angles between the constituents, and also their material properties. Therefore, the statistical distribution of its RCS measurements can only be obtained through detailed EM simulations, which are typically done using computer-aided design (CAD) models of the object and ray tracing techniques. By repeating this for every orientation of the object, a realistic

[1] https://discosweb.esoc.esa.int/

[2] https://space-track.org

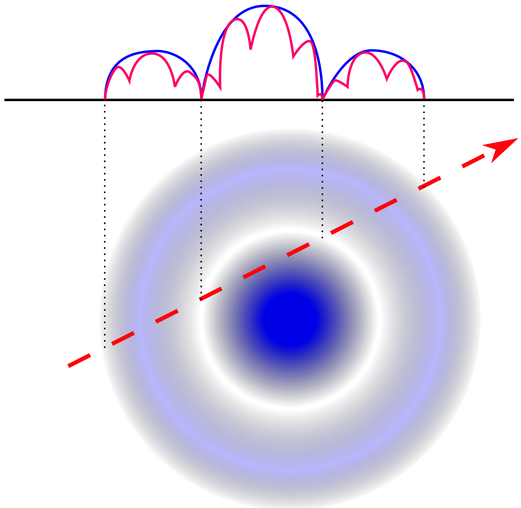

*Figure 1. The exact observed SNR curve (red line) depends on both the object's variable RCS, as well as details of how an object passes through the beam pattern of the radar (dashed red arrow over blue shading pattern). Matching up the observed SNR with the envelope curve of the beam lets us determine the scaling of the RCS as well as a parameter which characterizes the offset between the object's path and one that passes through the radar's boresight direction.*

and detailed RCS distribution can be obtained. There is however little chance of solving the inverse problem of obtaining the geometry and/or material properties of an orbiting composite object from its RCS distribution. The parameter space is vast, and even under the most favorable conditions the object will only be observed from a limited subset of all possible orientations.

Since we do not see a way of linking the distribution model and the physical properties of a composite object, we will in the following methodology section use a regression model approach to size inference and use clustering to infer shape information. This will link the statistics computed from RCS observation samples to known properties of space debris objects, and should be able to do so for both composite and simple objects, unaffected by the superposition principle. Given the limited number of observations, we will select our candidate algorithms among simple and well-known regression models from statistics and machine learning, and these will not have any immediate interpretative power. We should also emphasise that the approach will not be able to infer detailed information about shape, only numbers that indicate the deviation from spherical objects and point targets, and possibly a clustering that may be interpreted by comparison with DISCOS database classifications in terms of canonical objects.

## 3. METHOD

### 3.1. Regression modelling

Our overall goal is to develop an algorithm that can accurately predict the size of a space debris object and give some indication of its shape and geometry. For this purpose, we hypothesise that the size of the radar target will correlate with its mean RCS and that deviations from this general behaviour can be related to contributions from multi-bounce scattering, which can be identified by inspecting RCS statistics. Under these assumptions, we will extract statistical features from the RCS samples and use them in regression models that shall predict size. By use of methods from clustering and dimensionality reduction, we also want to study the grouping of the same predictors to see if they reveal information about object shape.

To obtain statistics suitable for the regression and clustering tasks, we will compute a combination of linear and logarithmic moments. These are known from statistical analysis of synthetic aperture radar (SAR) images to have complementary strengths in retrieval of location parameters and shape parameters, respectively, of the statistical distribution [14, 13]. We will also extract model parameters from distribution models that capture the effect of mixed scattering from complex and composite objects. This mixture model [4] is explained in more detail in Section 3.2. In addition, we will extract other features considered to hold relevant information about potential fluctuations and correlations in measurement series of tumbling objects. Feature engineering is in this case seen to be more appropriate than a modern machine learning approach, where predictors for the regression model are learnt from the data, due to the limited amount of training data. Candidate regression models are both classical statistical models, like multilinear regression with lasso or ridge regularisation, and popular machine learning methods, such as random forest, ensemble methods implementing boosting, and kernel regression techniques.

To test the assumptions and hypotheses underlying the regression approach, we will use theoretical models for the RCS distribution of canonical objects such as ellipsoids, cones, cylinders and plates to generate RCS samples. We will study the correlation between the selected statistics computed from these samples and the object dimensions that we specify in these simulations. This data could potentially be used to train the regression models, but could also introduces biases that we would like to avoid. Regression models aimed for operational use on real data will therefore be developed on training data consisting of real RCS measurement, regressors computed from these, and regressands taken from databases that hold information on the dimensions and shape of the corresponding objects, such as the DISCOS database and the Space Track catalogue.

Characterisation of a common target will be based on a small sample of observations of the RCS, rarely exceeding 10–20. For such targets, whose geometry is unknown and whose RCS cannot be simulated, the detailed reconstruction of its shape and geometry is not possible. Due to the small observation samples, the parametrisation of object shape and geometry must have a low dimension. Expectations of what can be realistically retrieved should consider previous work on statistical modelling of radar targets, such as the well-known Swerling target models [2] and the more extensive work in [3] on physical characterisation of radar targets from their statistical distribution and moments.

### 3.2. Distribution modelling

The statistical distribution model for samples of RCS measurements will explicitly model mixtures of scattering sources, as first described in [4], and later used in [3] for similar modelling of SAR measurements. This model will encompass the classical Swerling target models from [2], but is more general and extends to non-standard RCS distributions. The mixture model is able to fit the distribution of objects with a mixture of scattering effects, for instance a composite object where the constituent parts contribute scattering of different intensity. Let the RCS measurement of a given object be denoted as $X$ and assume that it can be modelled as $X = X_1 + X_2$, that is, the additive combination of two scattering from two constituent parts, whose RCS contribution are $X_1$ and $X_2$. Then the probability density function (pdf) of $X$ is modelled by the mixture model as:

$$\begin{aligned} p_X(x) &= \pi_1 p_{X_1}(x; \boldsymbol{\theta_1}) + \pi_2 p_{X_2}(x; \boldsymbol{\theta_1}) \\ &= \pi p_{X_1}(x) + (1-\pi) p_{X_2}(x) \,, \end{aligned} \tag{1}$$

where $\pi_1$ and $\pi_2$ are the mixing proportions of the mixture components $X_1$ and $X_2$, which can be simplified by setting $\pi_1 = \pi$ and $\pi_2 = (1-\pi)$, since $\pi_1 + \pi_2 = 1$ must hold. We assume that the pdfs of $X_1$ and $X_2$ come from the same distribution family, but have different parameter vectors $\boldsymbol{\theta_1}$ and ; $\boldsymbol{\theta_2}$, respectively, that typically contain a mean value and spread or shape parameter. The mixing proportion $\pi$ and the parameters of vectors $\boldsymbol{\theta_1}$ and ; $\boldsymbol{\theta_2}$ can be estimated from the RCS sample using methods derived in [4]. Notably, the theory in [4] and [3] is derived for synthetic aperture radar (SAR) intensity, which is a variable resulting from incoherent integration of measurements of the Earth surface. However, a similar theory for radar variables that represent coherent integration will be derived with inspiration from [12], where data on a coherently integrated SAR format known as single-look complex is modelled.

The adopted mixture model can easily be be related to the Swerling models, that can be conceptualized as either one dominant and several weaker scatterers (types 1 and 2) or several equally strong scatterers (types 3 and 4). The mixture model we will use considers scattering distribution to be a combination of multiple gamma distributions (of which the exponential form in Swerling types 1 and 2 is a special case), possibly with different weights as well

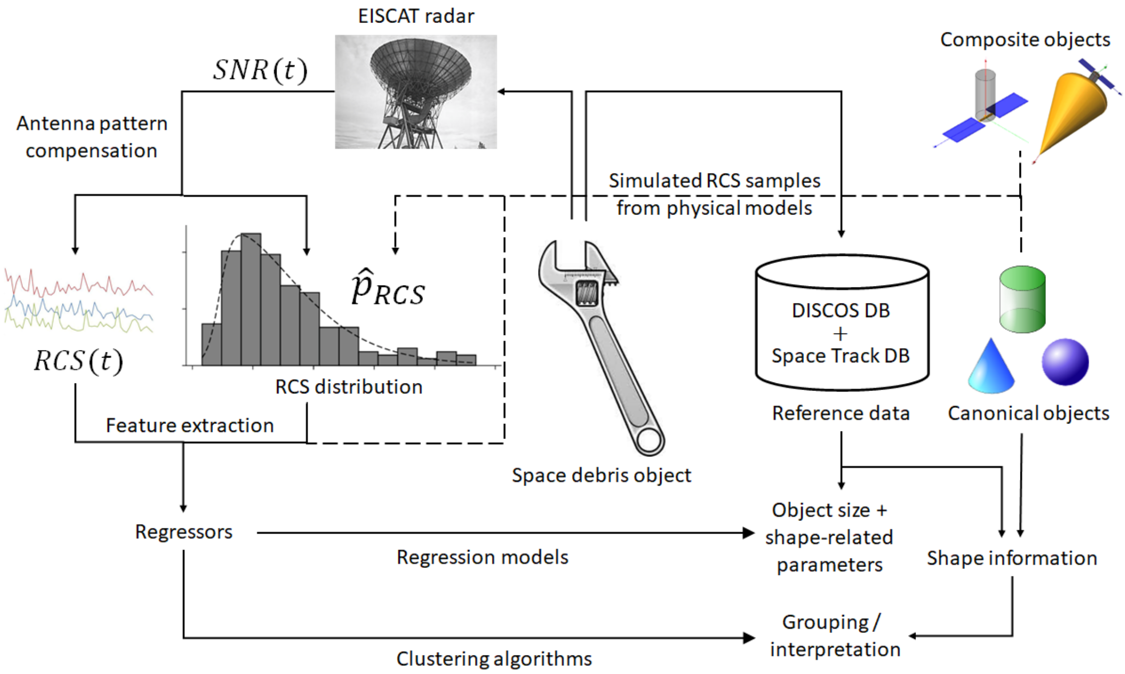


*Figure 2. Project overview showing that space debris objects will be tracked by the EISCAT radar; Time series of SNR measurements will be converted to RCS samples, which will be used to model the RCS distribution and extract RCS statistics that capture dimensional characteristics of the object; These will be use as regressors in a regression model for size and shape trained on databases of known object properties. Simulated RCS samples of canonical and composite objects will be run through the same regression model to verify the mappings. Machine learning algorithms will also be used to cluster the RCS statistics, and the grouping will be interpreted using shape information from the DISCOS and Space Track reference databases.*

as shape and scale parameters. When applied to SAR imagery, the shape parameter is determined by the amount of multi-looking, or incoherent integration. We will have control over the raw data processing chain, and can experiment with different amounts of coherent and incoherent integration in the processing of raw data to see what is best suited for the purposes here.

The estimated parameters of the distribution models will be correlated with properties of the space debris object they represent to investigate their interpretative value.

## 4. USE OF SIMULATIONS

We aim to use the mentioned simulations of RCS distributions to study the identifiability of different geometrical objects from RCS samples and derived statistics. Simulated RCS distributions based on the geometric classification of targets in the DISCOS database will be used to check for consistency with the empirical distributions of the same targets.

In addition, a small number of fairly simple composite objects will be defined for the purpose of detailed EM simulations to obtain their RCS. This will serve to validate the approach, in the sense that we can see that composite objects are identified as consisting of multiple basic shapes, and hence not well modelled as a canonical distribution. It will also serve to validate the fundamental assumption that the overall size of an object correlates with the mean value of the distribution. These simulations will use CAD models for the selected objects and ray tracing for the RCS computations.

### 4.1. Measurement campaigns

EISCAT radars have been used for space debris measurement campaigns for several years already, resulting in a total of 500 hours of radar data, typically with around 2 000 hard targets detected per 24 hours.

A certain subset of EISCAT data taken in the past have recorded voltage-level data. In this project, we aim to collect and reprocess all of the available historic data using the hard target processing developed for space debris observations. Hard target echoes will be correlated to the catalogue at the time of observation, and detections can be collected for objects that appear multiple times. This lets us build up a catalogue of scattering histograms for different objects suitable for the statistical model development.

Planned activities in the project include new observation campaigns, both of the beam-park type with a fixed pointing for 24 hours, and observations where repeated observations will be attempted of particularly interesting targets from a pre-defined list.

Targets will be chosen to span over many different geometric shapes and sizes. In particular, orbiting calibration spheres will be included , likewise the large defunct satellite ENVISAT as well as objects down to a cubesat in size.

## 5. DISCUSSION

The purpose of this method is to come up with a more accurate assessment of the physical size of space debris objects from radar detections. While we expect to make improvements in such size estimates, it is important to also understand the limitations inherent in the problem formulation.

Firstly, measurements made with radar can only say something about objects that are visible to a radar in the first place. This seems an obvious point, but it can be easy to overlook. If an object comprises large parts made of fibreglass, these are not visible on radar and the size of the total structure is likely to be underestimated.

Secondly, we have no control over the orientation of the objects to be observed, and some simple geometries have RCS that render them undetectable in all but a very limited number of aspects (e.g. a flat plate has extremely small RCS in all aspects except broadside). An object with similarly restricted observability is unlikely to present its visible side to the observer on the ground. This means that its size will be underestimated, if indeed a detection is made at all.

## 6. CONCLUSIONS

We have presented a project that will attempt to infer size and shape information for space debris from radar cross section samples obtained from radar beam-park measurements with the EISCAT UHF radar. Background theory and methodology for statistical modelling and inference was introduced. As the main results, the project expects to produce a method to perform light curve matching to produce RCS estimates from SNR measurements given long enough tracklets of the objects. We will collect RCS statistics from multiple tracklets for single objects. Object size will be inferred from RCS statistics and accuracy will be reported. We hope to obtain some indication of shape from RCS regression in terms of a broad categorisation. We will further use the size estimates to assist with validation of the size distribution in debris models.

## REFERENCES


1. Kastinen, D., J. Vierinen, T. Grydeland, and J. Kero (2023). "Using radar beam-parks to characterize the Kosmos-1408 fragmentation event", *Acta Astronautica*, 202, 341–359, doi:10.1016/j.actaastro.2022.10.021.
2. Swerling, P. (1954). "Probability of detection for fluctuating targets", research note, 46 pp., RAND Corporation, Santa Monica, California, USA. `https://www.rand.org/pubs/research_memoranda/RM1217.html`.
3. Deng, X., C. Lopez-Martinez and E. M. Varona (2016). "A physical analysis of polarimetric SAR data statistical models," *IEEE Trans. Geosci. Remote Sens.*, 54(5), 3035–3048, doi:10.1109/TGRS.2015.2510399.
4. Anfinsen, S.N. (2016). "Statistical unmixing of SAR images", research note, 4 pp., Munin Open Research Archive, UiT The Arctic University of Norway, Tromsø, Norway. `https://hdl.handle.net/10037/8425`.
5. Braun, V., Lemmens, S., Reihs, B., Krag, H. and Horstmann, A. (2017). "Analysis of breakup events," in Proc. 7th European Conference on Space Debris, ESA Space Debris Office, Darmstadt, Germany, 13 pp.
6. Muntoni, G., Montisci, G., Pisanu, T., Andronico, P. and Valente, G. (2021). "Crowded Space: A review on radar measurements for space debris monitoring and tracking", *Appl. Sci.* 11(4), 1364.. `http://dx.doi.org/10.3390/app11041364`.
7. Jehn, R. and Klinkrad, H. (1997). "From measurement results to space debris environment models," in: IAA-97, Paris, France: The International Astronautical Federation, Torino, Italy, 9 pp.
8. Flegel, S. and Krisko, P. (2010). "Modeling the space debris environment with MASTER-2009 and ORDEM2010," in 38th COSPAR Scientific Assembly, Bremen, Germany, 14 pp. `https://www.researchgate.net/publication/239751139_Modeling_the_space_debris_environment_with_MASTER2009_and_ORDEM2010`.
9. Markkanen, J., Lehtinen, M. and Landgraf, M. (2005). "Real-time space debris monitoring with EISCAT," *Adv. Space Res.*, 35(7): 1197–1209. `http://dx.doi.org/10.1016/j.asr.2005.03.038`.
10. Vierinen, J., Markkanen, J., Krag, H. (2009). "High power large aperture radar observations of the Iridium-COSMOS collision," in Proc. 5th European Conference on Space Debris, ESA Space Debris Office, Darmstadt, Germany, 2009, 10 pp.
11. Vierinen, J., Kastinen, D., Markkanen, J., Grydeland, T., Kero, J., Horstmann, A., Hesselbach, S., Kebschull, C., Røynestad, E. and Krag, H. (2019). "2018 beam-park observations of space debris with the EISCAT radars," in Proc. 1st NEO and Debris Detection Conference, vol. 1, ESA Space Safety Programme Office, Darmstadt, Germany, 10 pp. `https://conference.sdo.esoc.esa.int/proceedings/neosst1/paper/480`.

12. Anfinsen, S. N., Tao, D. and Brekke, C. (2011). "Improved target detection in polarimetric SAR images by use of Mellin kind statistics," In Proc. Int. Workshop Sci. Appl. SAR Polarimetry Polarimetric Interferometry (PolInSAR 2011), Frascati, Italy, European Space Agency, 4 pp.,
13. Anfinsen, S. N. and Eltoft, T. (2011). "Application of the matrix-variate Mellin transform to analysis of polarimetric radar images," *IEEE Transactions on Geoscience and Remote Sensing*, 49(6), 2281-2295.
14. Anfinsen, S. N., Doulgeris, A. P. and Eltoft, T. (2009). "Estimation of the equivalent number of looks in polarimetric synthetic aperture radar imagery," *IEEE Transactions on Geoscience and Remote Sensing*, 47(11), 3795-3809.