TANDEM-L FOREST PARAMETER PERFORMANCE ANALYSIS

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ABSTRACT

Tandem-L is a satellite mission being currently studied at DLR. It foresees the deployment of two L-band SAR platforms that will fly in close formation enabling bistatic operations. The mission is intended to serve a number of different science objectives with applications in the lithosphere, biosphere and cryosphere. The variety of applications and their competition for the use of the system require that we develope performance models suitable for system and mission design. In this paper we present the main concepts developed for height structure retrieval and performance characterization considering the combination of single pass acquisitions. We use the Cramér-Rao bound for a layered model and we study the impact of the baseline number and distribution. We also describe simulations with the Covariance Matching and Polarization Coherence Tomography techniques and argue in favor of better modeling for forest vertical structure in the case of limited number of obervations.

1. INTRODUCTION

Tandem-L is a proposal for an innovative radar mission that enables the systematic monitoring of dynamic processes on the Earth surface. Important application areas are global forest structure and forest vegetation monitoring, measurements of Earth deformation due to tectonic processes, observation of 3-D structure changes in ice, and the monitoring of ocean surface currents. The mission goals will be achieved through the deployment of two satellite platforms with quad-polarimetric L-band SARs that will be operated for five years.

It is already clear that this mission is intended to serve many applications and on a global scale. At least 60 million square kilometers are involved for forest applications and some 35 millions for the global tectonic monitoring campaign. Moreover a high resolution is required. These factors make the mission design a difficult challenge in terms of instrument operation, fuel for orbit maneuvers, data rate and so on. It is therefore necessary to develope performance models for each of the main applications in order to optimize the instrument usage and mission acquisition scenario.

Forest height and forest structure are two important products that we plan to derive from multi-baseline and polarimetric acquisitions. They can be considered final products in their own right but also as precursors for above-ground biomass estimation.

2. FOREST HEIGHT AND STRUCTURE ESTIMATION WITH TANDEM-L

In the performance study our goal is to provide models that can predict the accuracy of our estimates from radar observables. Even if we could ignore the actual estimation algorithms, nonetheless we have to take into account the particular type of acquisitions the mission will be able to offer. In the case of Tandem-L we will have single-pass interferograms. Some acquisition will be fully polarimetric but some could be dual- or single-polarization acquisitions. We plan to visit a certain span of baselines so that tomographic techniques could be used. Due to feasibility constraints the number of different single-pass baselines for a given point on the ground will be limited. Currently we expect that this it will be in the order of 6-8 per year, or 3-4 per tomographic campaign. Temporal decorrelation concerns lead us to limit ourselves to the usage of single-pass interferograms, whereas additional interferograms between different passes could provide valuable information. In this respect, our evaluation will be a worst case assessment. In this paper we will discuss about the retrieval of the vertical scattering profile by mean of multi-baseline SAR tomography or model inversion [1], [3]. In this case forest height and ground reference (or phase calibration) are considered as inputs from indipendent sources, like Pol-InSAR inversion [5].

3. A BRIEF STUDY ON BASELINE SELECTION BASED ON A LAYERED MODEL AND THE CRAMÉR-RAO BOUND

We start evaluating the performance of vertical structure reconstruction as a function of the number and the distribution of the baselines. These parameters are very important for the mission because we will have a limited number of acquisitions (essentially because we aim at high resolution global coverage) and an ideal distribution of

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the baselines is potentially very expensive in terms of fuel for orbit adjustment. Indeed with a wavelength of 24cm (L-band) and a platform height of 760 km it is easy to see that we need a horizontal baseline around 20km (bistatic operation) to achieve a height of ambiguity of 10 meters at the equator for far range (45 degree incidence). This is particularly critical because the intended flight formation will cycle from small to large baselines and back several times during mission life.

We start by considering a simple model for the vertical profile. It comprises four layers described by cosines on a pedestal and a narrower cosine (ideally a delta) representing the ground return or the double bounce trunk-ground interaction. This model has fixed positions for the layers but free scattering powers, which are indeed the parameters that we want to estimate. A representation of the model is given in Fig. 1.

The signal received at each angular position (after spectral-shift filtering) can be modeled as an integral of random contributions with phase shifts that depend on the height h:

$$y(n) = \int \xi(h) \exp(j k_h^n h) dh \qquad (1)$$

where k_h^n is the phase-to-height conversion for acquisition n and ξ is the stochastic scatterering profile. Collecting all the observations from the different angular positions in a single column vector $\mathbf{y}$ we can define the covariance matrix $\mathbf{R} = E[\mathbf{y}\mathbf{y}^H]$. In our case the matrix $\mathbf{R}$ will contain many zeros, as we assume total temporal decorrelation between different passes.

Actually we can define a covariance matrix $\mathbf{C}_k$ corresponding to each independent layer and rewrite $\mathbf{R}$ as a summation of these partial covariances like this:

$$\mathbf{R} = \sum \sigma_k^2 \mathbf{C}_k. \qquad (2)$$

Here the σ_k^2 represent the weighting of each layer and are exactly the parameters to be determined. The Cramér-Rao lower bound (CR) gives us a measure of the theoretical accuracy that can be achieved by our estimators. In this case (and assuming Gaussian statistics) the computation turns out to be quite easy. The covariances for the estimates (i.e. the average square errors on the estimation of the σ_k^2) are contained in the inverse of the Fisher information matrix and the variances can be read along the diagonal. The Fisher information matrix has the following expression

$$\mathbf{I}_{n,k} = \mathbf{E}\left[\frac{\partial}{\partial \sigma_n^2}\log(f)\frac{\partial}{\partial \sigma_k^2}\log(f)\right] \qquad (3)$$

for a probability density f whose parameters to be determined are the σ_k^2. For gaussian variables many simplifications occur and in our case one can obtain this simple expression:

$$\mathbf{I}_{n,k} = \{trace[\mathbf{R^{-1}C_nR^{-1}C_k}]\}. \qquad (4)$$

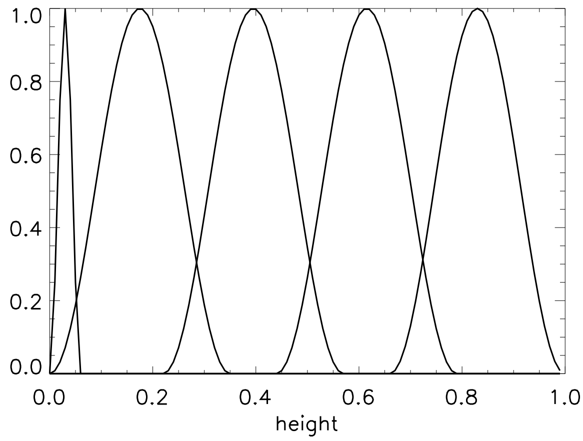

Figure 1. Layer model for performance of profile reconstruction.

In the next paragraphs we consider a simple measure of the total performance. We add together the errors on the reconstruction of each layer. This corresponds to taking the trace of the inverse of the Fisher information matrix:

$$ERR = trace(\mathbf{I}^{-1}) \qquad (5)$$

We will consider 50 looks for the performances. Since the CR is concerned with unbiased estimators, the performance is simply linearly scaled by the number of looks.

3.1. Equally spaced baselines

We compare the total error using two to five baselines equally spaced. The results are shown in Fig. 2. Since the performance depends on the particular profile, the performances of a thousand different random profiles have been averaged for each baseline choice. The baseline/height dependence is given as a normalized number, so that for a volume of height 1 the best spacing in terms of Fourier analysis would be $1, 2, 3$, etc. (Said with other words, the *abscissae* represent the volume height divided by the height of ambiguity) This allows an analysis independent of actual baselines and forest heights, since what matters is their combination. The same graph can be read both as the variation of the performance given a fixed forest height and different baseline spacing (when one wants to decide roughly the baselines suiting an average forest height), or as the variation of the performance given a baseline set and for different forest heights (which might occur in a scene after one has set the baselines).

Coming to the discussion of Fig. 2 the performance is limited from each side by two different factors. On the small baseline side the resolution is inadequate as the baselines are not enough spaced. On the other side the baselines are too stretched and ambiguity is the bottleneck. From this analysis two single pass pairs are not enough. They provide acceptable performance only for

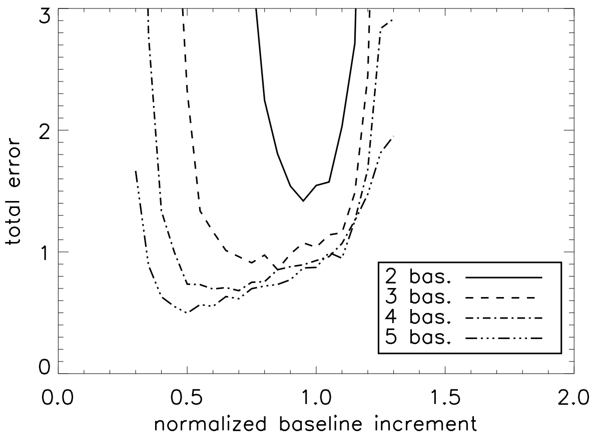

Figure 2. Performance for different baseline spacings.

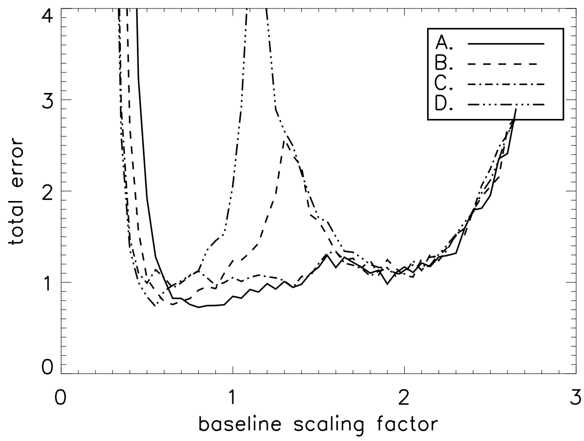

Figure 3. Performance for irregular baseline spacings. The four basic baseline combinations are detailed in Tab. 1 and scaled according to the horizontal axis.

Table 1. Different baseline patterns studied.

Case				
A	0.5	1.0	2.0	3.0
B	0.5	1.0	2.5	3.5
C	0.5	1.0	2.0	4.0
D	0.5	1.0	3.0	4.0

a specific normalized baseline spacing, whereas three to four baselines appear to cover a wider span of possible heights.

3.2. Irregularly spaced baselines

We want to analyse also the case of irregularly spaced baselines. This can arise for different reasons. One of them is the possible combination of the tomographic campaign with a Pol-InSAR campaign that will require two-three small baselines. We try different baseline patterns and spacings. The (normalized) patterns are detailed in Tab. 1 and then scaled similarly as for the regular baseline case. The effects on the left and right side are similar and can be interpreted as a product of lack of resolution or ambiguous energy. However a new phenomenon is present for certain baseline combinations, namely the cases B and D. A new intermediate peak appears and seems to be related to the missing sample at position 2. From this analysis it looks like that we must be careful in the sampling even if we are not strictly using a Fourier approach for tomographic reconstruction. On the other hand we can see the benefit of using even a single large baseline (case C) to improve the resolution.

4. COMET AND PCT

So far no estimator has been introduced in the discussion since we could rely on the Cramér-Rao theoretical predictions. Introducing an estimator allows us to check the predictions with simulations as a function of the number of looks. In this work we adopt the Covariance Matching Estimation Technique (COMET) whose description can be found in [2]. Its application to SAR tomography is described in [1]. Essentially it is derived from maximum-likelihood estimators with the aim of accounting for the statistics of the observables (i.e. the sample covariance matrix statistics). With maximum-likelihood estimators it shares the asymptotic efficiency. A particular advantage over maximum-likelihood estimators is that it provides a reduced computational cost for the estimation of so-called linear parameters, which in our case are the intensities of the different layers. If we wanted to introduce the layer positions in the estimate, the estimation of this part would be expensive and would need an exhaustive search in the parameter space. This estimator is attractive because could be used for quick simulations in situations when the CR limit is not enough.

The general form of the metric to be minimized for COMET is given here:

$$M = trace\left[\hat{\mathbf{R}}^{-1}(\hat{\mathbf{R}} - \mathbf{R})\hat{\mathbf{R}}^{-1}(\hat{\mathbf{R}} - \mathbf{R})\right] \quad (6)$$

where $\hat{\mathbf{R}}$ is the sample covariance matrix, and $\mathbf{R}$ is the modeled one, which depends on the parameters. Simplified versions hold for the mentioned linear parameters and in our case the cost is limited to a general linear system inversion that has as many unknowns as the number of layers.

Some simulations confirmed that even for a relatively small number of looks COMET performance is close to

Table 2. COMET performance and CR predictions.

Looks	mean (est.)	mean	var (est.)	var (CR)
50	0.47	0.5	0.0042	0.0045
	0.005	0.0	0.0023	0.0026
	0.92	1.0	0.0078	0.0077
36	0.45	0.5	0.0055	0.0063
	0.007	0.0	0.0031	0.0037
	0.90	1.0	0.0098	0.0107
25	0.44	0.5	0.0083	0.0091
	0.02	0.0	0.0047	0.0053
	0.85	1.0	0.0142	0.0154

the CR bound (the theory guarantees this for a large number of looks). The results from this simulations can be found in Tab. 2 comparing the last two columns. This example considers only three layers with fixed energies (1.0, 0.0 and 0.5), which are the only parameters to be estimated given the observables from 5 regularly-spaced baselines. It is possible to see that the bias is reduced as the number of looks increases.

In recent years an algorithm was proposed (Polarization Coherence Tomography - PCT[4]) to reconstruct vertical profiles starting from the complex coherences. It deals naturally with single-pass interferograms and we want to investigate the possible differences with COMET. This algorithm (PCT) reconstructs the profile using as a basis the Legendre polynomials. It establishes the linear relation between the polynomial coefficients and the complex coherences (which depend upon the baselines) and inverts it to find the coefficients.

In order to carry out the comparison with COMET we model the partial covariance matrices ($\mathbf{C}_k$ in section 3) as to represent each one a Legendre polynomial and we do the inversion feeding the COMET estimator with the normalized covariances, i.e. the complex coherences. The results, after a normalization to the first coefficient, are shown in Fig. 4 and 5. The two reconstructions are almost identical. Due to the stochastic nature of the scattering even 50 looks are not enough to perfectly reconstruct the profile. However, in all the simulations that we run, the two estimator were giving practically the very same results.

In this kind of problems we have to consider that we are on the border between tomography and model inversion, since we are dealing a very limited number of baselines. If we had many baselines we could adopt a large tomographic basis and the choice of the basis would not be so important. Here we want to reconstruct the profile with a few functions and we want to pick up the ones that explain quickly most of the observed energy. PCT, being based on Legendre polynomials, is not able to approximate high frequency components but after a large number of polynomials. A model based approach would fit better. For instance if we expected to see a strong ground or double-bounce component we could incorporate it easily in the model as a delta and avoid being blinded by it.

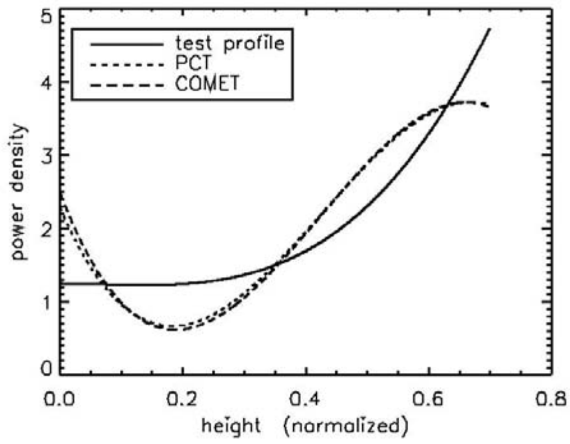

Figure 4. Example for COMET and PCT comparison.

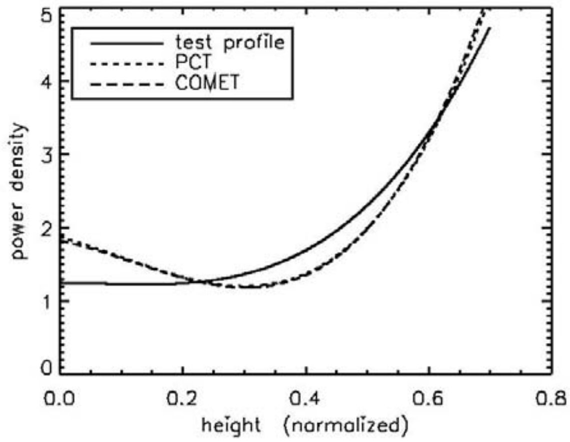

Figure 5. Another example for COMET and PCT comparison.

Generally speaking the best solution would be to adapt the basis or the model to the particular case at hand instead of relying on a particular basis that should fit all.

5. DISCRIMINATION BETWEEN DIFFERENT PROFILE CLASSES

Another use of an estimator in the context of performance analysis is the simulation of a classification approach. In this case the performance is measured according to the ability to discriminate between different forest models. We simulate acquisitions with five different forest models and see which one is recognized. For each possible model we identified the parameters (intensities) with COMET and computed a likelihood. Finally we picked the model

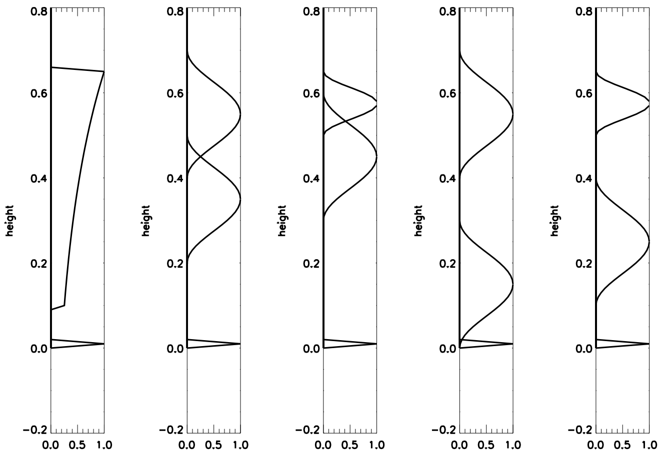

Figure 6. Test models for classification approach.

Table 3. Confusion matrix for a classification problem with 15 looks. Each column represents the results for a given model of those in Fig. 6

%	I	II	III	IV	V
I	49	15	3	4	4
II	27	80	19	1	2
III	4	2	72	0	0
IV	9	0	5	93	2
V	11	3	1	2	92
Total	100%	100%	100%	100%	100%

with the highest likelihood.

The five models are displayed in Fig. 6. They all have a delta at ground level and layers at different heights and with different thickness. As above, the intensities are left free to vary with a certain distribution.

The ability to distinguish between the five models can be interpreted as a resolution capability. The number of looks as well as the baseline distribution have influence on the performance. This simulation can be used to study which is the minimum number of looks required so that the performance will be acceptable and limited more by our ability to model the profile efficiently than by the stochastic character of the data themselves.

Some results for 15 looks are reported in Tab. 3. They were obtained simulating 1000 trials for every of the mentioned models. Each trial had random intensities for the layers, whose position and thickness was fixed.

Increasing the number of looks the confusion matrix resembles more and more a diagonal matrix. This can be seen in Tab. 4 where the same simulations were run for 50 looks (100 trials).

Table 4. Confusion matrix for a classification problem with 50 looks. Each column represents the results for a given model of those in Fig. 6

%	I	II	III	IV	V
I	83	3	0	1	0
II	14	97	7	0	0
III	0	0	93	0	0
IV	3	0	0	99	0
V	0	0	0	0	100
Total	100%	100%	100%	100%	100%

6. CONCLUSIONS

In this paper we have described some basic ideas about vertical profile reconstruction using single-pass interferograms that will be available with Tandem-L. We suggest that the Cramér-Rao bound can be used to predict the performances with a simple layered model (averaging on many profiles) or that a classification approach can be simulated at the cheap cost provided by COMET estimator.

From our simulations it appears that even with only three-four interferograms we can reconstruct some low-pass components of the profile and that might be enough to support biomass estimation. A minimum number of looks of 30-50 can be necessary to reduce the statistical variability of the observables so that the main limitation in the reconstruction comes from our ability to model the profile. A regular baseline sampling is not necessary but some care has to be taken in the baseline distribution choice.

Given the extremly reduced number of observations the choice of good models for the vertical profile becomes of great relevance. We think that this aspect should be further investigated with real data (and many baselines).

In this work we have omitted to consider the effect of additive noise (both thermal noise and ambiguity noise) and phase noise, to concentrate on the specific aspects of this reconstruction problem. Also, possible temporal correlation between different passes has to be considered more deeply. Indeed it can have some paradoxical effect in reducing the number of looks in the case of dense sampling in the angular domain.

Another effect that can potentially reduce the performance is the variation of the scattering profile between different passes, due to seasonal structural changes (e.g. leaves-on leaves-off effects) or scattering changes (e.g. due to moisture changes). To limit this effect we will have to try to schedule the acquisitions as close in time as possible.

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