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Linking Persistent Scatterers to the Built Environment Using Ray Tracing on Urban Models

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Abstract—Persistent scatterers (PSs) are coherent measurement points obtained from time series of satellite radar images, which are used to detect and estimate millimeter-scale displacements of the terrain or man-made structures. However, associating these measurement points with specific physical objects is not straightforward, which hampers the exploitation of the full potential of the data. We have investigated the potential for predicting the occurrence and location of PSs using generic 3-D city models and ray-tracing methods, and proposed a methodology to match PSs to the pointlike scatterers predicted using RaySAR, a ray-tracing synthetic aperture radar simulator. We also investigate the impact of the level of detail (LOD) of the city models. For our test area in Rotterdam, we find that 10% and 37% of the PSs detected in a stack of TerraSAR-X data can be matched with point scatterers identified by ray tracing using LOD1 and LOD2 models, respectively. In the LOD1 case, most matched scatterers are at street level while LOD2 allows the identification of many scatterers on the buildings. Over half of the identified scatterers easily correspond to identify double or triple-bounce scatterers. However, a significant fraction corresponds to higher bounce levels, with approximately 25% being fivefold-bounce scatterers.

Index Terms—Level of detail (LOD), persistent scatterers (PSs), ray tracing, simulation, synthetic aperture radar (SAR).

I. INTRODUCTION

PERSISTENT scatterer (PS) interferometry (PSI) [1] is a geodetic technique to measure surface displacements using multiepoche synthetic aperture radar (SAR) images.

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PSI estimates the displacement parameters from phase observations from selected coherent points, known as PSs, with millimeter-level precision. Using advanced high-resolution SAR satellite systems, such as TerraSAR-X and COSMO-SkyMed, this technology can be used to monitor individual structures [2]–[6].

However, PSs differ from traditional well-defined geodetic benchmarks. It is not clear that whether the observed signal stems from one dominant reflector, like a corner reflector, or from the effective summation of several reflectors within the resolution cell. Moreover, even if the PS is one dominant reflector, its precise localization remains a challenging task. Obviously, the capability to link PSs to (locations on) particular objects would enhance PSI analyses, for example, by reducing the uncertainty in the interpretation of the observed displacements in relation to specific driving mechanisms.

The relevance of establishing a one-to-one link between PSs and specific objects is most obvious when there are different driving mechanisms involved. For example, points may represent deep and/or shallow deformation, e.g., due to gas production and groundwater-level changes, respectively. Consequently, nearby PSs may show different deformation signals. In other cases, different parts of a building or infrastructure may deform differently, which may be a precursor of a partial or full collapse of the structure. In these complex scenarios, linking PSs to the objects in the built environment would not only help identifying the local deformation in the object but also facilitate the interpretation of the deformation signals.

Using the precise geolocalization of each PS seems to be the most straightforward approach to link the scatterer to an object. In fact, the geolocalization accuracy of PS for high-res (meter resolution) SAR data is shown to be in the order of centimeters in azimuth and range [7], and several decimeters up to 1.8 m for cross range [8]. This positioning uncertainty can be described with a variance–covariance (VC) matrix and visualized with an error ellipsoid [9], [10]. This way, the relatively poor cross-range precision of radar scatterers could be improved by intersecting the scaled error ellipsoid with 3-D models [9], [10]. Alternatively, an improvement of positioning precision could be obtained by using the SAR data from different viewing geometries [11], [12], albeit only for a selected number of targets, such as lamp posts.

Yet, these methods all consider only the *geometry* of the problem and are not based on physical scattering mechanisms. Consequently, the estimated positions may be geometrically optimal but physically unrealistic. For example, for a perfect corner reflector, it is known that the effective scattering center is at the apex of the reflector, even though the pure geometric position estimate may turn out to be at different positions. As a result, understanding the *physical* scattering mechanisms may help in the realistic physical positioning of scatterers.

Physical understanding of scattering mechanisms can be supported by SAR simulation methods. However, this requires, at the least, a 3-D geometrical representation of the scene (i.e., a 3-D city model) [13]. If this 3-D representation is realistic with sufficient detail, the observed SAR scene should be very similar to the simulated one. Subsequently, if there is sufficient similarity, we will know which scattering mechanism produced the observed scatterers and understand what caused the observed displacements.

A list of current SAR simulators includes, but is not limited to, SARAS [14], [15], Pol-SARAS [16], CAS [17], Xpatch 4 [18], GRECOSAR [19], CohRaS [20], SARViz [21], and RaySAR [22]. SARAS and CAS are oriented to ocean applications and do not consider multiple scattering for complex targets [14], [15], [17]. Pol-SARAS is the polarimetric version of SARAS, and it allows the simulation of natural scenes [16]. Xpatch 4 is an object-oriented version of Xpatch, which provides 0-D radar cross section, 1-D range profile, 2-D SAR image, and 3-D scattering center signatures, based on the shooting and bounces rays with the support of parallel computation [18]. Xpatch has been widely used in studies of the vehicle, typically an airplane or a ground vehicle [23]–[25]. GRECOSAR can generate polarimetric SAR and polarimetric inverse SAR images of complex targets and is used extensively for vessel classification studies [19]. CohRaS is an SAR simulator based on ray tracing, mainly for small scenes with high resolution, and only supports geometries made up of convex polygons [20]. SARViz is an SAR image simulation system that only simulates single- and double-bounce reflections and does not include coherent addition of multiple echos [21]. Finally, RaySAR is based on ray tracing, oriented toward the simulation of salient features in SAR images [26]–[28]. Despite the natural limitations resulting from the ray-tracing approach, it has some key advantages that motivated its use for the research presented in this paper: 1) it can handle an arbitrary number of bounces; 2) it keeps track of individual scatterers; 3) providing their 3-D location and bounce level; and 4) it is computationally inexpensive, which allows the simulation of relatively large and complex urban scenes.

Here, we investigate the potential for predicting the occurrence and location of SAR scatterers (i.e., potential PS) based on physical scattering mechanisms, using generic 3-D city models. In particular, we analyze the influence of the *level of detail* (LOD) of these city models on this prediction. The LOD is a generic metric describing the degree of adherence of the data set to its real-world counterpart [29]. This paper focuses on the urban environment, where we are limited by the short supply of high-resolution 3-D city models. We use

the ray-tracing SAR simulator RaySAR [22] to predict the radar scattering by illuminating the 3-D scene with an SAR sensor. The *rays* can follow multiple reflections within the object scene, yielding a collection of pointlike multiple-bounce scatterers that represent potential PS candidates. The use of ray-tracing algorithm implies that a significant part of the radar signal is not correctly modeled. Nevertheless, city models with an LOD that allows a full electromagnetic solution are not available nor expected to become available in the foreseeable future.

Section II introduces the 3-D ray-tracing simulation as well as the methodology to match the detected PSs with the simulated point scatterers (SPSs). Results corresponding to a test area in Rotterdam are presented and analyzed in Section II-C. Finally, Section IV presents our conclusions and future work.

II. METHODOLOGY

A. Point Scatterer Simulation With RaySAR

Ray tracing is a rendering method used to create an image by following the path of a ray through a 3-D model and simulating the reflections on the surfaces it encounters. Ray tracing is based on geometrical optics, which is valid for surfaces that are large and smooth relative to the wavelength. RaySAR is one of the several SAR data simulators based on ray tracing. It is built on the open source Persistence of Vision Ray-tracer (POV-Ray) [30], using the PoV-Ray basic algorithms for ray tracing, intersection tests between rays and objects, the estimation of intensities, and shadow calculations [22].

RaySAR generates a set of scattering centers positioned in 3-D SAR coordinates, i.e., azimuth, range, and cross range. RaySAR subsequently projects and interpolates these scatterers on the 2-D range-azimuth grid, adding different contributions coherently in order to generate a simulated SAR image. In this paper, however, we are mostly interested in the intermediate set of individual scatterers.

The set of scattering centers is provided by RaySAR as a list of signal vectors V

$$V = [a_i \ r_i \ c_i \ I \ b \ f] \quad (1)$$

where $[a_i \ r_i \ c_i]$ gives the position of the scattering phase center in azimuth, range, and cross range, I is a relative intensity normalized between 0 and 1, b specifies the number of bounces (trace level), and f is a Boolean indicating a specular reflection [0 or 1]. The signals V are referred to as contribution signals. These signals are the basis for the simulated image generation and point scatterers identification.

Fig. 1 sketches the localization of the phase center of a radar echo by RaySAR for a double-bounce signal. Starting from the virtual sensor plane, a primary ray for each pixel is followed along its path until intersection with the modeled scene is found. At the intersection point, a reflected ray is spawned in the specular direction and traced until the next intersection with the model, and so on. The azimuth, cross-range, and range coordinates of the double-bounce signal are

TABLE I
SURFACE PARAMETERS

Parameters	Impact on Radar Scattering	Value range	Low Roughness	Medium Roughness
Weight F_w	Weights the specularly reflected signal on a surface (loss of signal strength) of multiple reflections and works with a specular coefficient.	0 - 1	0.7	0.5
Specular F_s	Resembles specular reflection and provides a spreading of the highlights occurring near the object horizons.	0 - 1	0.7	0.5
Roughness F_r	Defines the width of a cone where a specular highlight occurs from 1(very rough) to 0(very smooth).	0 - 1	$8.5 \cdot 10^{-4}$	$3.3 \cdot 10^{-3}$

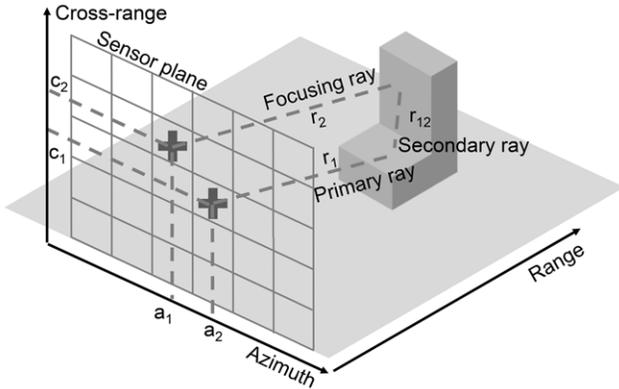


Fig. 1. Sketch of how RaySAR localizes a double-bounce signal and projects it in the sensor plane.

scene, which has to be specified in RaySAR as a position of the sensor with respect to the center of the scene.

2) *3-D Scene Model*: In this paper, the building model is reconstructed with 3dfier [31] by combining the large-scale topographic data set of the Netherlands, *Basisregistratie Grootschalige Topografie* in Dutch data set and the laser altimetry, *Actueel Hoogtebestand Nederland* in Dutch data sets. The acquisition of 3-D models can be constructed directly with a text editor or software, which can assist in visual controlling modeling (e.g., CAD). Importing available 3-D model into the POV-Ray format is an option considering there are a lot of city models available.

The 3-D object model has to provide sufficient geometric detail for SAR simulation. The amount of detail and spatial resolution of a 3-D city model is specified as LOD, denoting the abstraction level of a model as opposed to the real-world object [29]. The LODs have been described by CityGML [32], a prominent standard for the storage and exchange of 3-D city models. LOD1 is a model in which buildings are represented as blocks (usually obtained by extruding their footprint to a uniform height). LOD2 is a more detailed model including roof shapes [32], [33]. As it is the case with many other applications of 3-D city models [34], it is to be expected that the LOD and quality of the used 3-D model will have an influence on the performance of the simulation of radar signals, a topic that we investigate in this paper.

3) *Surface Parameters*: The scattering properties of the scattering surfaces in the 3-D model are specified by the parameters described in Table I. The first parameter, F_w , controls multiple scattering by setting the fraction of the ray intensity that is specularly reflected. Thus, setting $F_w = 0$ will completely suppress multiple scattering.

The second parameter, F_s , controls the relative intensity of the first reflection, counting from the illumination source. The roughness parameter, F_r , controls the angular width of the first reflection. Values of low roughness and medium roughness surfaces are given based on a constant relative permittivity of $5.7 + j \cdot 1.3$ for man-made objects [22].

Fig. 2 shows four images simulated with varying (F_w, F_s, F_r) values according to Table I. The parameter F_r works with specular coefficient F_s [see Fig. 2(a) and (b)]. With increasing roughness, the number of features shown in the simulated images increases. Fig. 2(c) and (d) illustrates the results of a combination of three parameters. With the weight factor F_w , the strong multiscattering is clearly described. The intensity of a multireflected signal is weighted with F_w . In this paper, we use the medium roughness $F_w = 0.5, F_s = 0.5,$

given by

$$\begin{aligned} a_i &= \frac{a_1 + a_2}{2} \\ c_i &= \frac{c_1 + c_2}{2} \\ r_i &= \frac{r_1 + r_2 + r_3}{2}. \end{aligned} \quad (2)$$

The trace level is the number of bounces of the signal.

To select potential PS candidates (simulated point scatterers), contribution signals with specular multiple scattering characteristics ($I > 0, b > 1,$ and $f = 1$) are chosen. The selection criteria are based on the premise that many PSs are physically associated with multiple specular reflections of the radar signal on relatively large surfaces.

B. Definition of a 3-D Scene for RaySAR

The input to RaySAR is a 3-D scene model including: 1) a virtual SAR system; 2) 3-D building models, and 3) surface parameters.

1) *Virtual SAR System*: The virtual SAR system is described by the observation geometry and the system resolution. The geometry is defined using an orthographic projection and a parallel ray approximation. This parallel ray approximation makes the observation geometry azimuth invariant, as it should. However, it also makes the geometry elevation (hence range) invariant, which is not entirely correct. We will, nevertheless, assume that this approximation is good enough for a small scene. Thus, the observation geometry is defined by an incident angle and an azimuth angle with respect to the

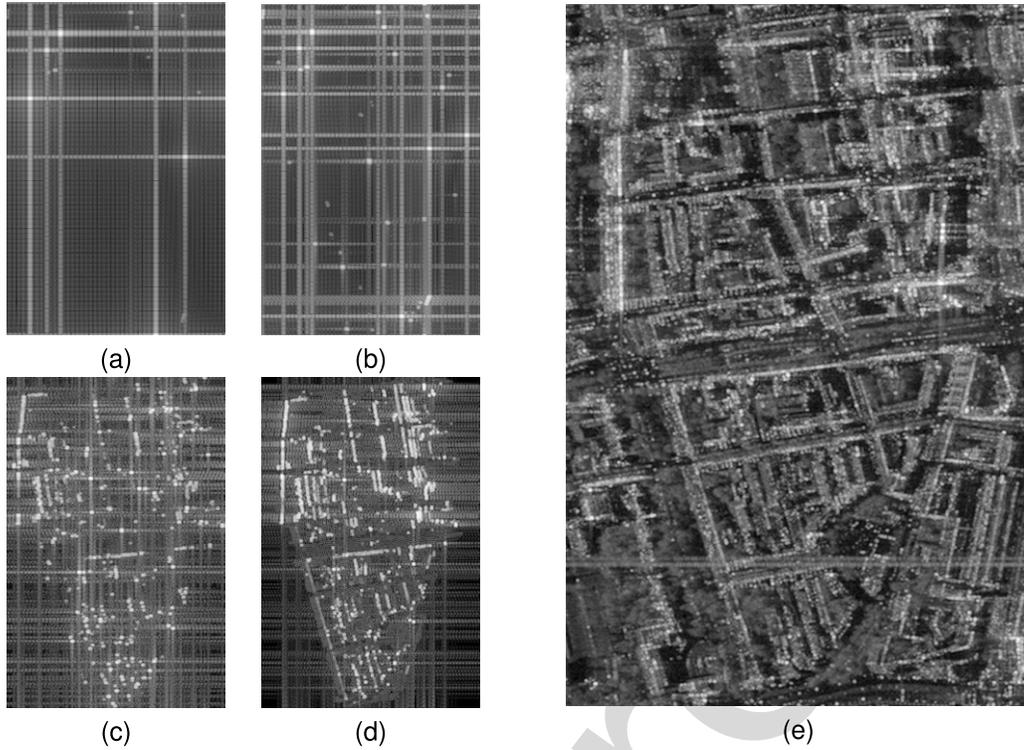


Fig. 2. Parameters function on SAR image simulation. (a) Image with $F_w = 0$, $F_s = 0.7$, $F_r = 8.5 \cdot 10^{-4}$. (b) Image with $F_w = 0$, $F_s = 0.5$, $F_r = 3.3 \cdot 10^{-3}$. (c) Image with $F_w = 0.7$, $F_s = 0.7$, $F_r = 8.5 \cdot 10^{-4}$. (d) Image with $F_w = 0.5$, $F_s = 0.5$, $F_r = 3.3 \cdot 10^{-3}$. (e) Mean intensity map of 49 TerraSAR-X images.

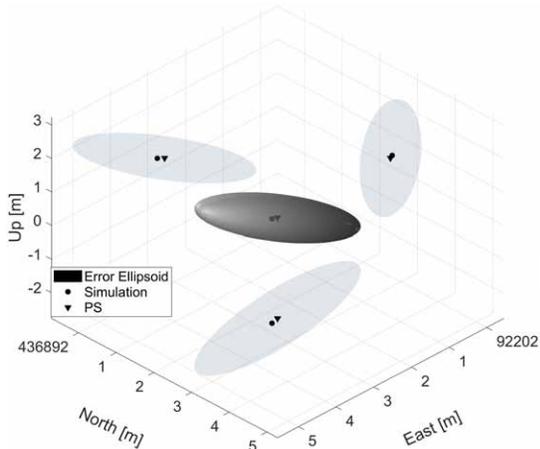


Fig. 3. Example of finding the corresponding simulation point of a PS based on the 3-D error ellipsoid. The position of the PS is indicated by a black triangle. A cigar-shaped error ellipsoid with a ratio of axis lengths 1/2/35 (with $\sigma_r = 0.019$ m) illustrates the PS position uncertainty. The corresponding SPS is located inside of the error ellipsoid and indicated by a black dot. The ellipsoid and PS are projected in east-north, north-up, and up-east planes to illustrate their intersection with the SPS.

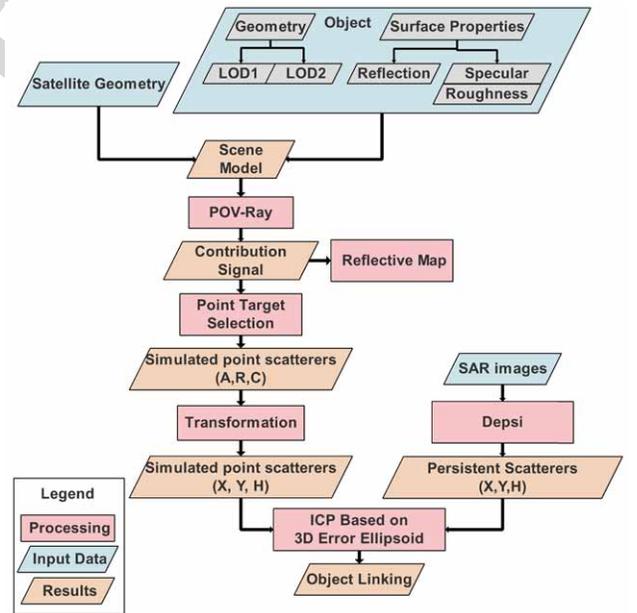


Fig. 4. Schematic of the methodology.

256 $F_w = 3.3 \cdot 10^{-3}$, compared to low roughness parameter
 257 setting, medium roughness parameters are closer to the reality
 258 using the X-band data [see Fig. 2(e)]. It is important to
 259 emphasize that the phase-center location of the simulated
 260 scatterers does not depend on the surface parameters. In the
 261 following, we focus solely on the phase-center location of
 262 multiple-bounce SPSs.

C. Linking of Simulation Points With PSs

263
 264 One of the main steps in the work presented is the matching
 265 of the SPSs with the PSs identified in the InSAR time series.
 266 The matching is done by evaluating the weighted Euclidean
 267 distances between the positions of the simulated point scatter-
 268 ers and the positions of the PSs. The weighting reflects the

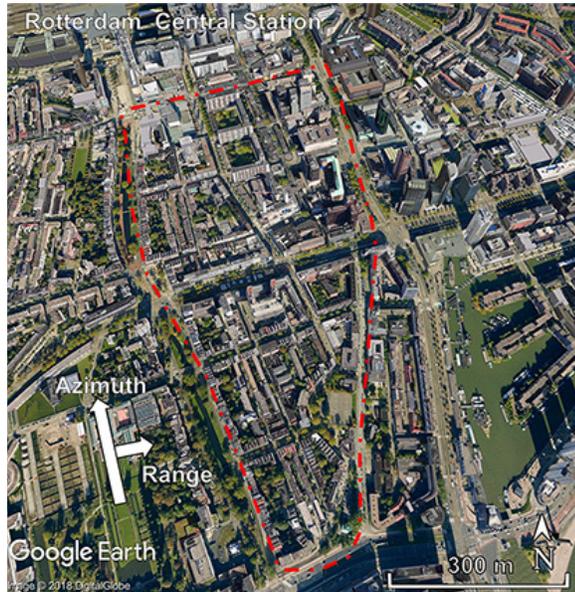


Fig. 5. Google Earth overview image of test site; azimuth and range directions indicate the view of the TerraSAR-X data.

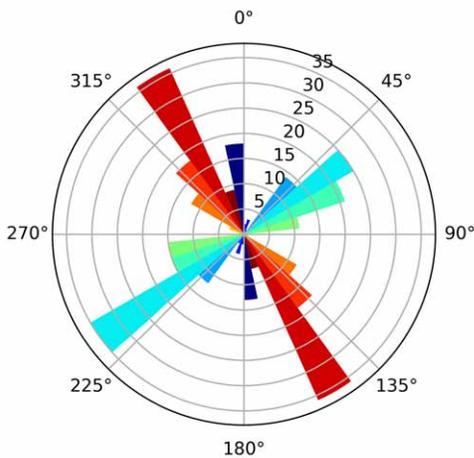


Fig. 6. Street orientation map of the AOI. Each bar represents the compass bearing of the streets and its length indicates the frequency of streets with those bearings. There are two main directions at 336° and 60°.

3-D position error ellipsoids, as defined by the positioning VC matrices, of the PSs [9]. For each PS, the positioning uncertainty in the local reference frame (East, North, and Up/Height) is given by

$$\mathbf{Q}_{\text{enh}} = \mathbf{R}_{3 \times 3} \cdot \mathbf{Q}_{\text{rac}} \cdot \mathbf{R}_{3 \times 3}^T = \begin{bmatrix} \sigma_e^2 & \sigma_{en}^2 & \sigma_{eh}^2 \\ \sigma_{en}^2 & \sigma_n^2 & \sigma_{nh}^2 \\ \sigma_{eh}^2 & \sigma_{nh}^2 & \sigma_h^2 \end{bmatrix} \quad (3)$$

where \mathbf{R} is the rotation matrix from radar geometry to local reference frame, \mathbf{Q}_{rac} is the positioning VC matrix in 3-D radar geometry with diagonal component variances (σ_r^2 , σ_a^2 , and σ_c^2) in range, azimuth, and cross range, the diagonal (σ_e^2 , σ_n^2 , and σ_h^2) and nondiagonal (σ_{en}^2 , σ_{eh}^2 , and σ_{nh}^2) are the variances and covariances in east, north, and up coordinates. For each PS, from the eigenvalues of \mathbf{Q}_{enh} , a 3-D error ellipsoid is drawn with the estimated position as its center. The semiaxis lengths of the ellipsoid are described by the

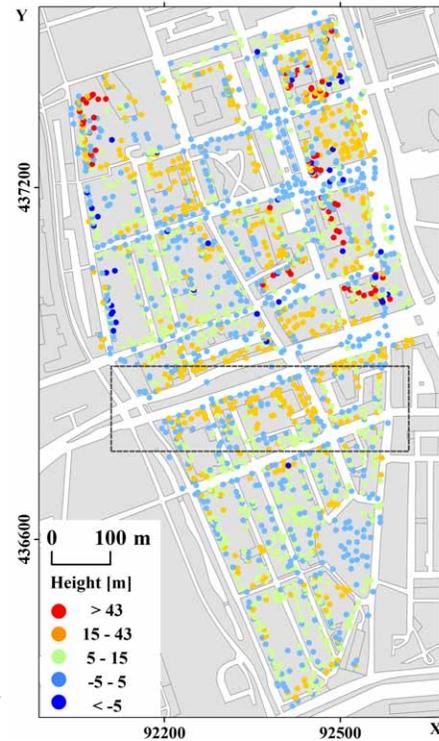


Fig. 7. PS identified in TerraSAR-X data stack overlaid on TOP10NL map. TOP10NL is the digital topographic base file of the Land Registry, the most detailed product within the basic registration topography. Colors: estimated PS heights (blue-low; red-high).

eigenvalues of \mathbf{Q}_{enh} , which are σ_r^2 , σ_a^2 , and σ_c^2 . The shape of ellipsoid is derived from the ratio of their axis lengths, given by $(1/\gamma_1 / \gamma_2)$, where $\gamma_1 = \sigma_a \cdot \sigma_r^{-1}$ and $\gamma_2 = \sigma_c \cdot \sigma_r^{-1}$. The orientation of ellipsoid is dependent on the local incidence angle of the radar beam at the PSs.

Fig. 3 illustrates the matching of an SPS with a PS based on the 3-D error ellipsoid. The position uncertainty of a PS is illustrated by 3-D error ellipsoid with 0.01 level of significance. The PS is matched to the corresponding SPS, which has to be inside the error ellipsoid.

As part of the matching process, it is necessary to consider and remove potential systematic positioning errors. The systematic errors may be the result of an oversimplified geometry (e.g., the already mentioned range invariance) or errors in the knowledge of the acquisition SAR geometry.

A fine coregistration is performed using the iterative closest point (ICP) algorithm [35], [36], which minimizes the sum of the weighted Euclidean distance between SPSs and PSs by least square estimation in an iterative way. Each iteration of the 3-D error ellipsoid-based ICP includes two steps: matching pairs of SPS and PSs based on the 3-D error ellipsoid; and finding the transformation that minimizes the weighted mean squares distance between pairs of points. The transformation results are applied to the point cloud of PSs, thereby changing the correspondence.

D. Simulation Assessment

A quantitative evaluation of the matching between the PS and the SPS is given by the confusion matrix \mathbf{M} described in Table II. Three performance ratios are considered as follows.

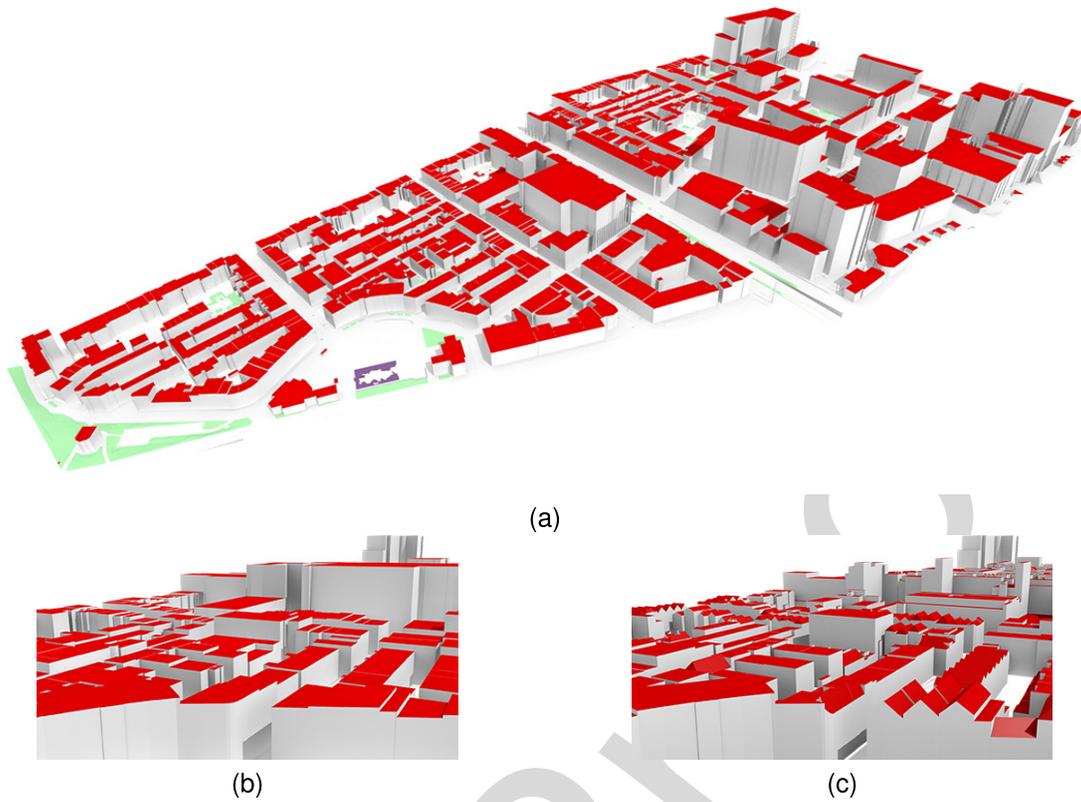


Fig. 8. (a) Overview of the used 3-D city model, (b) closer look on the LOD1 variant of the data set, and (c) its more detailed (LOD2) counterpart including roof shapes. Source of data: BGT, AHN, and City of Rotterdam.

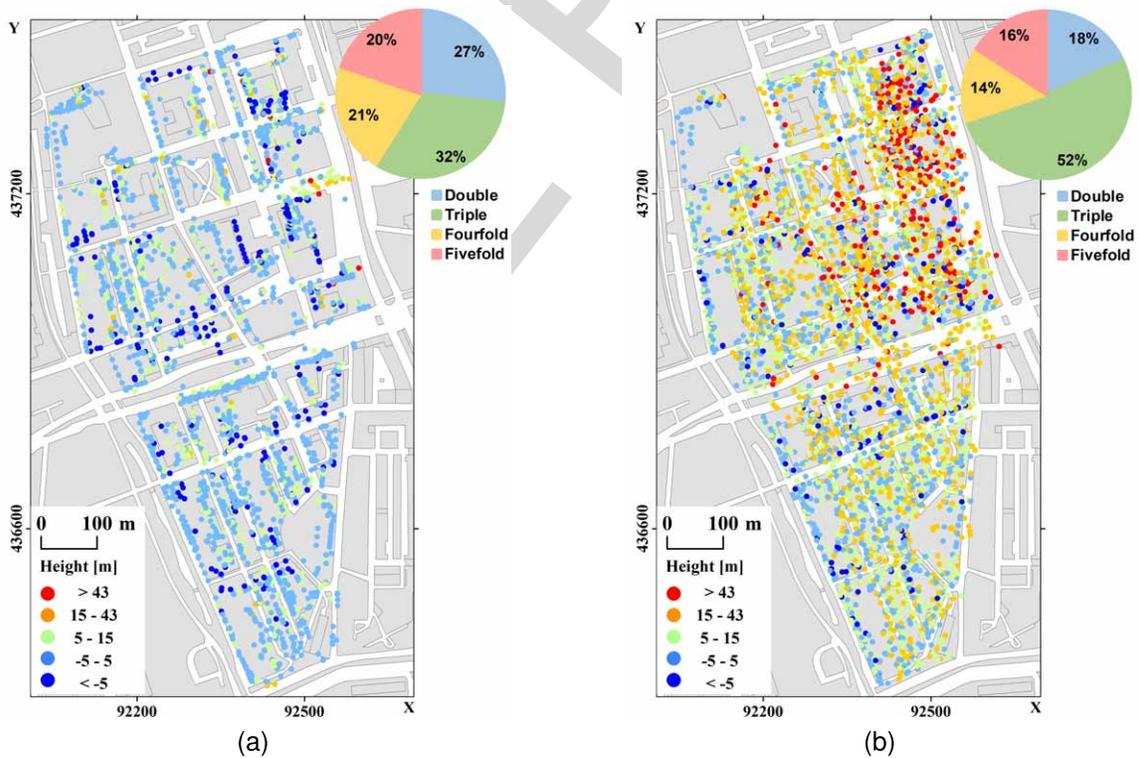


Fig. 9. (a) Point scatterers simulated based on the model of LOD1 with color represents height. (b) Point scatterers simulated based on the model of LOD2 with color represents height. The background image is TOP10NL map.

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1) *True Positive Rate (TPR)*: The ratio of the PSs that are matched to SPSs, with regards to the total number of PSs.

2) *False Negative Rate (FNR)*: The ratio of the PSs that have not been matched to an SPS, with regards to the total number of PSs,

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316
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TABLE II
CONFUSION MATRIX **M** BETWEEN SPS AND PS

Total		SPSs	
		Match	Non-Match
PSs	Match	True Positive Rate(TPR) $= \frac{\sum TP}{\sum PPSs}$	False Positive Rate(FPR) $= \frac{\sum FP}{\sum SPSs}$
	Non-Match	False Negative Rate(FNR) $= \frac{\sum FN}{\sum PPSs}$	

also known as miss rate. For FNR, we have $FNR = 1 - TPR$.

3) *False Positive Rate (FPR)*: The ratio of the SPSs that have not been matched, with regards to the total number of SPSs.

Hereby, the metric **TPR** describes the matching ratio between simulation points and PSs and is the primary evaluation indicator of simulation scatterers. **FPR** also an important indicator for describing the ratio of redundant simulation points.

Note that the PS or SPS selection criteria will have an impact on the performance metrics. For example, a low amplitude dispersion threshold may lead to selecting less actual point scatterers and lead to a higher FPR. Since the final goal of our research is to improve our capability to analyze deformation signals, we focus on the group of PSs that are deemed reliable. PSs are chosen with an amplitude dispersion threshold set to 0.45 and further checked based on network phase consistency [37]. Here, SPSs are scatterers predicted by the simulator based on the geometry. Therefore, the final number of PSs is less than the SPSs from the simulator because we eliminated many points during the PSI processing, which increases the FPR.

E. Work Flow

The flowchart shown in Fig 4 outlines the work flow of this paper, which consists basically of three parts: generation of simulation points, detection of PSs, and the matching of two point cloud sets. The generation of simulation points consists of scene modeling, signals detection with Pov-Ray, and selection of SPSs. The SAR data stack is processed with the Delft implementation of PSI (DePSI) [37], which is based on the Delft framework of geodetic estimation, testing, and quality control. DePSI detects PS with consistent reflection properties over time as input for time series deformation and height estimation. Then, matching of two point cloud sets is carried by ICP based on the 3-D error ellipsoid.

RaySAR is not demanding in terms of computational resources. It is built on POV-ray, an open source tool that traces rays in the reverse direction. In this paper, the calculation of 48 million contribution signals took about 10 min on a four-core workstation with 16 GB of RAM.

III. EXPERIMENT

A. Test Site and Data

The test area is located southeast of Rotterdam Central Station in the city of Rotterdam, the Netherlands. The size of

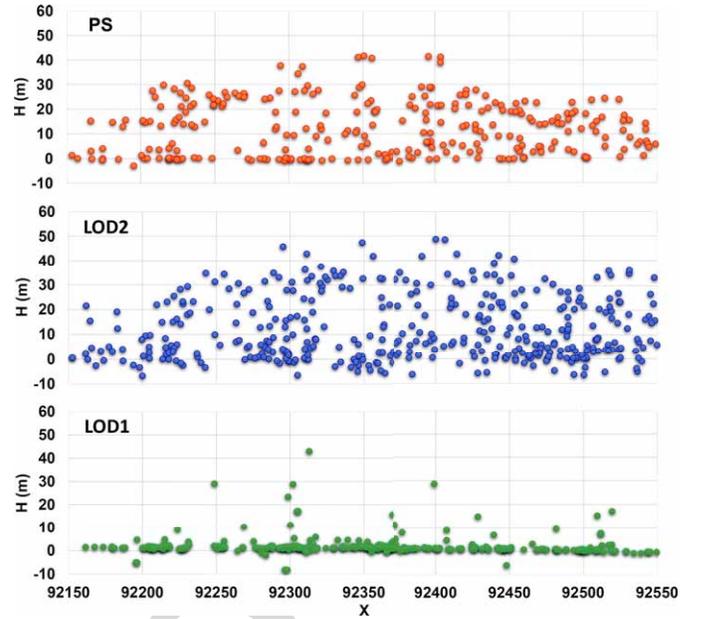


Fig. 10. Height profile of PSs, SPSs from LOD1 and LOD2, in the box indicated in Fig. 7 along the *x*-axis.

TABLE III
BASIC PARAMETERS OF TERRASAR-X DATA STACK

Satellite/Parameter	TerraSAR-X
Track	T025
Band(wavelength in cm)	X (3.1)
Start Date	2014.01.19
End Date	2017.02.14
Number of images	49
Acquisition mode	SM
Pass direction	Ascending
Polarization	HH
Pulse Repetition Frequency(Hz)	3790
Range Sampling Rate (MHz)	109.8
Incident angle (°)	39.3
Heading (°)	349.8
Slant range spacing (m)	1.36
Azimuth spacing (m)	1.86
Range Bandwidth (MHz)	100
Azimuth Bandwidth (Hz)	2765

the area of interest (AoI) is around $1 \times 0.5 \text{ km}^2$. Fig. 5 shows an overview of the test site, and its orientation with respect to the trajectory of TerraSAR-X. 49 TerraSAR-X strip-mode images are obtained from January 19, 2014 to February 25, 2017. Table III illustrates the basic parameters of TerraSAR-X data. Fig. 2(e) is the mean intensity map of 49 TerraSAR-X images over the AoI.

Fig. 6 shows a polar histogram describing the orientation of the streets within the AOI calculated based on OpenStreetMap [38]. The direction of each bar represents the compass bearings of the streets and its length indicates the relative frequency of streets with those bearings. In Fig. 6, two main orthogonal directions can be identified, one at about 336° (red bars), and another at about 60° (cyan).

The results of the PSI analysis are illustrated in Fig. 7: 2290 points are selected as PS in the AoI. The results are projected in the Dutch National Reference System



Fig. 11. Correspondence between SPSs, shown as solid circles color-coded by bounce level, and matched PSs, shown as empty circles. (a) Left and (b) right correspond to simulations using the LOD1 and LOD2 models, respectively.

379 *Rijksdriehoeksstelsel* (RD) in Dutch and vertical *Normaal*
 380 *Amsterdams Peil* in Dutch reference system. The axes shown
 381 in Fig. 7 show X (RD) and Y (RD) in meters, in East and North
 382 directions, respectively. The estimated heights are indicated by
 383 colors, showing some higher buildings in the northwest and
 384 northeast corner of the AoI, which can be found in Fig. 5.

385 Two 3-D city models with different LODs were employed
 386 to simulate scatterers using RaySAR. Fig.8 displays the
 387 3-D models at LOD1 and LOD2 of the AoI. In LOD1 model,
 388 buildings are represented as boxes with flat roof structures
 389 [Fig. 8(b)], opposed to buildings in LOD2 (Fig. 8c), which
 390 have differentiated roof structures with varying heights, pro-
 391 viding a more realistic representation of the reality.

392 From the enlarged partial picture of the LOD1 model
 393 [Fig. 8(b)] and the LOD2 model [Fig. 8(c)], it is clear that
 394 buildings in LOD2 include many different parts with varying
 395 roof shapes and heights. Data sets with LOD1 and LOD2 are
 396 the most common instance, in practice, because it is possible to
 397 obtain them automatically, e.g., from LiDAR data by automatic
 398 building reconstruction [33].

399 B. Simulated Point Scatterer

400 POV-Ray/RaySAR detects all contributing signals within
 401 the AoI. The total number of received signals from the
 402 LOD1 and LOD2 models is about 50 million. We detect

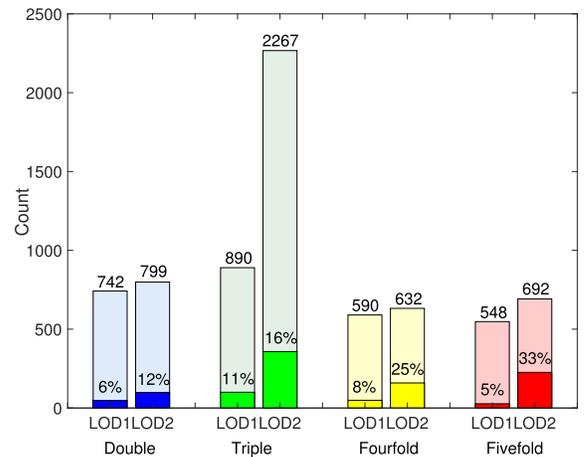


Fig. 12. Histograms of simulation points from LOD1 model and LOD2 model in double, triple, fourfold, and fivefold bounce. The X-axis is LOD1 and LOD2. The Y-axis is the count numbers from 0 to 2500. There were 742 and 799 double-bounce signals from LOD1 and LOD2 models. Among these signals, 6% and 12% points were linked to the PSs. Likewise, for triple-bounce signals, and fourfold-bounce signals and fivefold-bounce signals.

403 potential point scatterers and consider these as signals that
 404 exhibit the characteristics of PS ($I > 0$, $b > 1$, and $f = 1$)
 405 from the contribution signals.

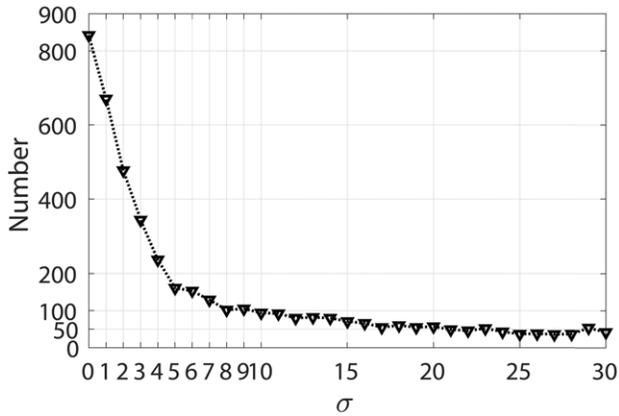


Fig. 13. Number of matched PSs as a function of the standard deviation of the disturbance added to the position of the simulated scatterers. The rapid decrease in matched pairs supports the assumption that the vast majority of matches is correct.

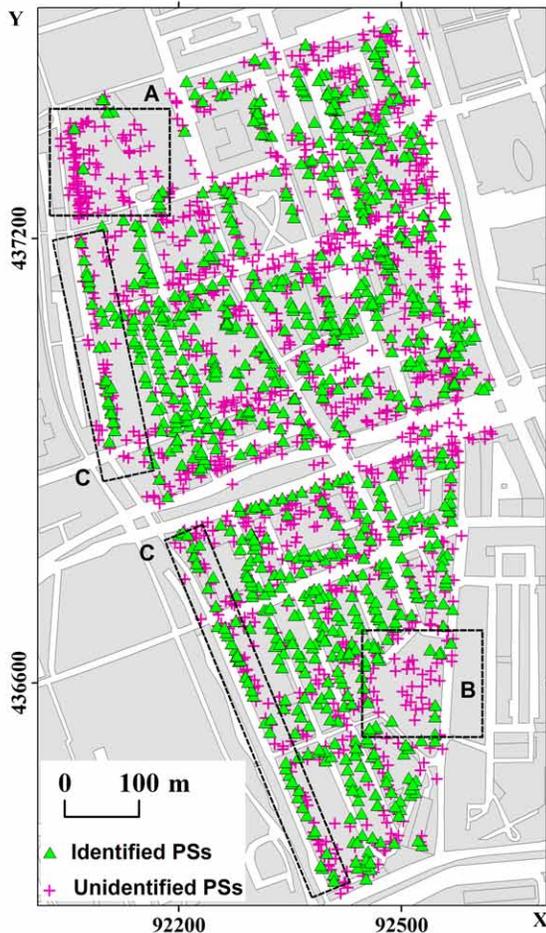


Fig. 14. Matched and unmatched PSs. A-labeled area: new building absent in the LOD2 model. B-labeled area: green-area free of buildings, where the PPs correspond to urban structures not included in the model. C-labeled areas: examples of predicted PSs at the linear structures of buildings and identified as triple bounce.

406 We identify 2770 potential point scatterers from the model
 407 at LOD1, as described in Section II. Fig. 9(a) shows the
 408 distribution of simulated points in the LOD1 model. The colors

TABLE IV
 CONFUSION MATRIX BETWEEN MEASURED PSS AND PREDICTED
 SCATTERERS BASED ON LOD1 MODEL AND LOD2 MODEL

	SPSs-LOD1 (2770)		SPSs-LOD2 (4390)	
	Match	Non-Match	Match	Non-Match
PS (2290)	223	2547	842	3548
	TPR	FPR	TPR	FPR
	10%	92%	37%	80%
	FNR		FNR	
	90%		63%	

409 indicate the height of simulation points. In comparison to
 410 the real radar results shown in Fig. 7, the height values
 411 of the SPSs is mainly below 15 m. The simulation points
 412 include 742 double bounces, 890 triple bounces, 590 fourfold
 413 bounces, and 548 fivefold bounces [see the pie chart in the top
 414 right of Fig. 9(a)]. Most signals correspond to triple-bounce
 415 scatterers, followed by double-bounce ones.

416 Using the LOD2 model results in 4390 potential point
 417 scatterers, as illustrated [see Fig. 9(b)]. Compared to the
 418 real PS data, see Fig.9(b), more points, and with higher
 419 heights are detected. Spatial distribution in height values of
 420 SPSs from the LOD2 model is similar to the measured PS
 421 [see Fig. 9(b)]. PSs with higher heights are clustered in the
 422 northeast corner of the test site, which is also predicted by
 423 the simulation. The height of simulation points in the corner
 424 of the northwest is lower than PSs shown in Fig. 7 because
 425 the buildings in the corner of the northwest are missed in
 426 the LOD2 model(equal to LOD1). The Google Earth image
 427 shown in Fig. 5 also indicate the newly built in the corner
 428 of the northwest. Simulated points from the LOD2 model
 429 include 799 double bounce, 2267 triple bounce, 632 fourfold
 430 bounce, and 692 fivefold bounce [see the pie chart in the top
 431 right of Fig. 9(b)]. More than half of the points are the triple
 432 bounces.

433 Fig. 10 shows the height profile of PSs, the SPSs of
 434 LOD1 and LOD2, in the box indicated in Fig. 7 along the
 435 *x*-axis. The height profile of PSs and SPSs from LOD2 is
 436 similar while the SPSs from LOD1 missed points with higher
 437 height.

438 *C. Linking of PSs and SPSs*

439 Following Section II-C, PSs (Fig. 7) were matched to the
 440 point scatterers predicted using the LOD1 [Fig. 9(a)] and
 441 LOD2 [Fig. 9(b)] models. Fig. 11(a) and (b) shows the spatial
 442 distribution of PSs and the corresponding SPSs. The dark
 443 circle indicates the location of PSs that have been matched
 444 to SPSs. The dots represent the corresponding SPSs, color
 445 coded by bounce level (see legend on the figure).

446 Table IV shows the confusion matrix between SPSs based
 447 on LOD1 and LOD2 models and PSs. Scatterers from the
 448 model of LOD1 predicted 10% PSs correctly (correspondingly,
 449 around 90% PSs were missed). The 92% simulation points
 450 have not been matched to a PS. By using the LO2 model,
 451 the amount of PSs matched with simulated scatterers increased
 452 to 37%. Naturally, the number of predicted point targets not
 453 matched to PSs also increased. However, it is noteworthy, that,



Fig. 15. Rendering of matched scatterers overlaid on the LOD2 city model.

454 in relative terms, the number of scatterers matched to PSs grew
 455 much stronger than the overall amount of predicted scatterers.
 456 Moreover, the ratio of simulation points that have not match
 457 to a PS is decreased to 80%.

458 Fig. 12 shows a quantitative overview of the number of
 459 point scatterers predicted for the LOD1 and LOD2 models,
 460 segregated by bounce level. In each of the bars, it is also
 461 indicated which fraction of the SPSs was matched to a PS. Not
 462 surprisingly, the increase in the LOD leads to a very strong
 463 growth (close to a factor 3) of the predicted triple-bounce
 464 scatterers. The fraction of predicted triple-bounce scatterers
 465 matched to actual PSs increased from 11% to 16%.

466 For the other bounce levels considered, the increase in
 467 predicted scatterers was quite modest. However, the fraction
 468 of these scatterers that was matched to PSs increased by a
 469 factor two for double-bounce scatterers, a factor three for
 470 fourfold-bounce scatterers, and by more than a factor six for
 471 fivefold-bounce scatterers.

472 The total number of matched scatterers increased from
 473 223 in the LOD1 case to 842 with the LOD2 model.
 474 Triple-bounce scatterers, 100 and 358, respectively, remained
 475 dominant. However, 226 of the LOD2-model scatterers,
 476 or about one-fourth of the total, corresponded to
 477 fivefold-bounce signals.

478 The number of predicted point scatterers for the
 479 LOD1 (2770) and LOD2 (4390) models was larger than the
 480 number of detected PSs. This can be explained by considering
 481 that PS selection is done based on the amplitude stability of
 482 individual resolution cells in the interferometric data stack.
 483 Typically, the amplitude will be stable if a single pointlike
 484 scatterer is a dominant factor in the radar echo for that
 485 resolution cell. Thus, even if we know for sure that we have a
 486 stable pointlike target within our resolution cell, as this does
 487 not exclude contributions from other scattering mechanisms,
 488 it does not imply that it will result in a PS. Moreover, as stated
 489 in Section II-D, the selection criterion also contributes to the
 490 fact that the number of simulation points was larger than the
 491 number of PSs.

D. Target Matching Validation

492 A potential pitfall in the matching process is that if the
 493 local density of either PSs or SPSs is higher, the amount of
 494 random matches increases as well (false positives). However,
 495 the amount of random matches should be insensitive to their
 496 exact position. Hence, while some pairs would be disassoci-
 497 ated roughly the same number is expected to appear.

498 Following this reasoning, we added random disturbances
 499 with Gaussian distribution to the coordinates of the simulated
 500 points and performed the PS matching, following the proce-
 501 dure discussed in Section II. In order to consider the worst
 502 case, the random disturbances are aligned along the dominant
 503 orientation of the buildings. The x -, y -, and z -coordinates of
 504 the simulated points with random disturbances are given by
 505

$$\begin{aligned} \tilde{x}_{\text{sim}} &= x_{\text{sim}} + \Delta x \\ \tilde{y}_{\text{sim}} &= y_{\text{sim}} + \Delta y \\ \tilde{z}_{\text{sim}} &= h_{\text{sim}} + \Delta z \end{aligned} \quad (4)$$

506 where x_{sim} , y_{sim} , and z_{sim} are the original coordinates of
 507 the SPSs, $\Delta x = n_1 \cdot \sin(t)$, $\Delta y = n_1 \cdot \cos(t)$, and $\Delta z = n_2$.
 508 The angle $t = 336^\circ$ is the main orientation angle of the
 509 streets and buildings as presented in Fig. 6. n_1 and n_2 are
 510 the zero-mean Gaussian-distributed random disturbances with
 511 a standard derivation of σ meter.
 512
 513
 514

515 Fig. 13 shows the number of matched PSs as a function
 516 of σ . The number of matched pairs decreases rapidly as the
 517 position disturbance σ increases. Introducing a position error
 518 with $\sigma = 4$ m, which is close to the spatial resolution of
 519 TerraSAR-X in stripmap mode, reduces the amount of matches
 520 by a factor 4 while a further increase in the positioning error
 521 has only a limited effect on decreasing the amount of matches.
 522 As less than 10% of the number of matches remains if the
 523 positioning error is increased to an unrealistically high value,
 524 this analysis suggests that the vast majority of matched pairs
 525 is physically correct.

526 Fig. 14 shows all PSs detected in the AoI, with iden-
 527 tified PSs represented by green triangles and unidentified

528 PSs indicated by magenta plus signs. The area labeled A, 529
 529 where most PSs were missed by the simulation, correspond 530
 530 to a newly built building not present in the LOD2 model. 531
 531 Moreover, the building model did not include the public 532
 532 facilities, like the flower boxes in the area labeled B. Most 533
 533 predicted PSs are located at linear structures of buildings and 534
 534 identified as triple bounce, such as the points in the area 535
 535 labeled C. Those scatterers originated from the roof and ghost 536
 536 corners, e.g., the corner of the wall and the ground, which is 537
 537 in agreement with the previous research [28].

538 Simulation points have precise locations in the model. The 539
 539 object snap of PSs can be achieved by the correlation of PSs 540
 540 and SPSs. Fig. 15 displays an overview of matched simulation 541
 541 points in the LOD2 model. The supplementary file of this 542
 542 paper includes a movie that is a 360° view of model and 543
 543 simulation points that matched to measured PSs.

544 IV. CONCLUSION

545 PSI can yield deformation with an accuracy of millimeter 546
 546 order by exploiting PSs. As discussed in the Introduction, two 547
 547 key issues in PSI are the precise geolocation of the scatterers in 548
 548 the 3-D space, and the association of the scatterers to specific 549
 549 physical features. In this paper, we have investigated the use of 550
 550 ray-tracing tools to address the second issue by illuminating 551
 551 3-D city models with different levels of detail (LOD1 and 552
 552 LOD2 according to the CityGML standard). As expected, 553
 553 the results obtained depend strongly on the LOD of the 554
 554 3-D model given as input to the ray-tracing tool.

555 For our area of study in Rotterdam, we were able to 556
 556 associate 37% of the PSs identified in a stack of TerraSAR-X 557
 557 data with simulated scatterers using a LOD2 city model. 558
 558 Using LOD1 models not only reduced the fraction of identified 559
 559 PSs to around 10% but also put most of them on the ground. 560
 560 We did not have models for real cities with a higher LOD. 561
 561 Nevertheless, from the observation of high-resolution SAR 562
 562 data, it is generally understood that many pointlike scatterers 563
 563 result from features, such as windows, which are not captured 564
 564 in LOD2. It is expected that using higher LOD models might 565
 565 further increase the fraction of identified scatterers.

566 Considering the details of the results, it worth noting that 567
 567 roughly one-fourth of the identified PSs were associated with 568
 568 fivefold bounces. These types of scatterers cannot be linked 569
 569 to physical objects by simply intersecting their location with 570
 570 the 3-D models.

571 LOD2 models can be produced automatically from, for 572
 572 example, laser-scanning data. Therefore, it should be expected 573
 573 that the LOD2 city models may become commonplace in the 574
 574 near future. The positive results of this paper underpin the 575
 575 usefulness of integrating this information in the PS processing.

576 Associating PSs to physical features is a necessary step if we 577
 577 want to fully exploit the InSAR signal of individual scatterers, 578
 578 for example, to detect deformation of specific sections of a 579
 579 building. In this paper, we have shown that this association 580
 580 can be made. Each simulated PS can be traced back one or 581
 581 multiple reflections on specific locations of the 3-D model. 582
 582 However, with the tools used, the bookkeeping necessary 583
 583 to trace scatterers back to individual features in the model

(specific walls, roofs, and floors) is still missing. A logical next 584
 584 step in our research is to implement this bookkeeping, which 585
 585 includes identifying practical approaches to label features and, 586
 586 in particular, visualizing the results. 587

588 Another important intermediate objective is to investigate, 589
 589 with the support of simulations, how different deformation 590
 590 sources translate to individual PS deformation signals. For 591
 591 example, in the case of a fivefold-bounce scatterer, structural 592
 592 deformation may produce a signal with the opposite sign than 593
 593 for a triple-bounce scatterer. As already indicated, the long- 594
 594 term goal of the work presented is to improve the interpreta- 595
 595 tion of deformation signals in complex environments, where 596
 596 the observed deformation signals may have different causes. 597
 597 This relies on the anticipated increased availability of high 598
 598 resolution city models.

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IEEE PROOF

Linking Persistent Scatterers to the Built Environment Using Ray Tracing on Urban Models

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Abstract—Persistent scatterers (PSs) are coherent measurement points obtained from time series of satellite radar images, which are used to detect and estimate millimeter-scale displacements of the terrain or man-made structures. However, associating these measurement points with specific physical objects is not straightforward, which hampers the exploitation of the full potential of the data. We have investigated the potential for predicting the occurrence and location of PSs using generic 3-D city models and ray-tracing methods, and proposed a methodology to match PSs to the pointlike scatterers predicted using RaySAR, a ray-tracing synthetic aperture radar simulator. We also investigate the impact of the level of detail (LOD) of the city models. For our test area in Rotterdam, we find that 10% and 37% of the PSs detected in a stack of TerraSAR-X data can be matched with point scatterers identified by ray tracing using LOD1 and LOD2 models, respectively. In the LOD1 case, most matched scatterers are at street level while LOD2 allows the identification of many scatterers on the buildings. Over half of the identified scatterers easily correspond to identify double or triple-bounce scatterers. However, a significant fraction corresponds to higher bounce levels, with approximately 25% being fivefold-bounce scatterers.

Index Terms—Level of detail (LOD), persistent scatterers (PSs), ray tracing, simulation, synthetic aperture radar (SAR).

I. INTRODUCTION

PERSISTENT scatterer (PS) interferometry (PSI) [1] is a geodetic technique to measure surface displacements using multiepoche synthetic aperture radar (SAR) images.

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PSI estimates the displacement parameters from phase observations from selected coherent points, known as PSs, with millimeter-level precision. Using advanced high-resolution SAR satellite systems, such as TerraSAR-X and COSMO-SkyMed, this technology can be used to monitor individual structures [2]–[6].

However, PSs differ from traditional well-defined geodetic benchmarks. It is not clear that whether the observed signal stems from one dominant reflector, like a corner reflector, or from the effective summation of several reflectors within the resolution cell. Moreover, even if the PS is one dominant reflector, its precise localization remains a challenging task. Obviously, the capability to link PSs to (locations on) particular objects would enhance PSI analyses, for example, by reducing the uncertainty in the interpretation of the observed displacements in relation to specific driving mechanisms.

The relevance of establishing a one-to-one link between PSs and specific objects is most obvious when there are different driving mechanisms involved. For example, points may represent deep and/or shallow deformation, e.g., due to gas production and groundwater-level changes, respectively. Consequently, nearby PSs may show different deformation signals. In other cases, different parts of a building or infrastructure may deform differently, which may be a precursor of a partial or full collapse of the structure. In these complex scenarios, linking PSs to the objects in the built environment would not only help identifying the local deformation in the object but also facilitate the interpretation of the deformation signals.

Using the precise geolocalization of each PS seems to be the most straightforward approach to link the scatterer to an object. In fact, the geolocalization accuracy of PS for high-res (meter resolution) SAR data is shown to be in the order of centimeters in azimuth and range [7], and several decimeters up to 1.8 m for cross range [8]. This positioning uncertainty can be described with a variance–covariance (VC) matrix and visualized with an error ellipsoid [9], [10]. This way, the relatively poor cross-range precision of radar scatterers could be improved by intersecting the scaled error ellipsoid with 3-D models [9], [10]. Alternatively, an improvement of positioning precision could be obtained by using the SAR data from different viewing geometries [11], [12], albeit only for a selected number of targets, such as lamp posts.

Yet, these methods all consider only the *geometry* of the problem and are not based on physical scattering mechanisms. Consequently, the estimated positions may be geometrically optimal but physically unrealistic. For example, for a perfect corner reflector, it is known that the effective scattering center is at the apex of the reflector, even though the pure geometric position estimate may turn out to be at different positions. As a result, understanding the *physical* scattering mechanisms may help in the realistic physical positioning of scatterers.

Physical understanding of scattering mechanisms can be supported by SAR simulation methods. However, this requires, at the least, a 3-D geometrical representation of the scene (i.e., a 3-D city model) [13]. If this 3-D representation is realistic with sufficient detail, the observed SAR scene should be very similar to the simulated one. Subsequently, if there is sufficient similarity, we will know which scattering mechanism produced the observed scatterers and understand what caused the observed displacements.

A list of current SAR simulators includes, but is not limited to, SARAS [14], [15], Pol-SARAS [16], CAS [17], Xpatch 4 [18], GRECOSAR [19], CohRaS [20], SARViz [21], and RaySAR [22]. SARAS and CAS are oriented to ocean applications and do not consider multiple scattering for complex targets [14], [15], [17]. Pol-SARAS is the polarimetric version of SARAS, and it allows the simulation of natural scenes [16]. Xpatch 4 is an object-oriented version of Xpatch, which provides 0-D radar cross section, 1-D range profile, 2-D SAR image, and 3-D scattering center signatures, based on the shooting and bounces rays with the support of parallel computation [18]. Xpatch has been widely used in studies of the vehicle, typically an airplane or a ground vehicle [23]–[25]. GRECOSAR can generate polarimetric SAR and polarimetric inverse SAR images of complex targets and is used extensively for vessel classification studies [19]. CohRaS is an SAR simulator based on ray tracing, mainly for small scenes with high resolution, and only supports geometries made up of convex polygons [20]. SARViz is an SAR image simulation system that only simulates single- and double-bounce reflections and does not include coherent addition of multiple echos [21]. Finally, RaySAR is based on ray tracing, oriented toward the simulation of salient features in SAR images [26]–[28]. Despite the natural limitations resulting from the ray-tracing approach, it has some key advantages that motivated its use for the research presented in this paper: 1) it can handle an arbitrary number of bounces; 2) it keeps track of individual scatterers; 3) providing their 3-D location and bounce level; and 4) it is computationally inexpensive, which allows the simulation of relatively large and complex urban scenes.

Here, we investigate the potential for predicting the occurrence and location of SAR scatterers (i.e., potential PS) based on physical scattering mechanisms, using generic 3-D city models. In particular, we analyze the influence of the *level of detail* (LOD) of these city models on this prediction. The LOD is a generic metric describing the degree of adherence of the data set to its real-world counterpart [29]. This paper focuses on the urban environment, where we are limited by the short supply of high-resolution 3-D city models. We use

the ray-tracing SAR simulator RaySAR [22] to predict the radar scattering by illuminating the 3-D scene with an SAR sensor. The *rays* can follow multiple reflections within the object scene, yielding a collection of pointlike multiple-bounce scatterers that represent potential PS candidates. The use of ray-tracing algorithm implies that a significant part of the radar signal is not correctly modeled. Nevertheless, city models with an LOD that allows a full electromagnetic solution are not available nor expected to become available in the foreseeable future.

Section II introduces the 3-D ray-tracing simulation as well as the methodology to match the detected PSs with the simulated point scatterers (SPSs). Results corresponding to a test area in Rotterdam are presented and analyzed in Section II-C. Finally, Section IV presents our conclusions and future work.

II. METHODOLOGY

A. Point Scatterer Simulation With RaySAR

Ray tracing is a rendering method used to create an image by following the path of a ray through a 3-D model and simulating the reflections on the surfaces it encounters. Ray tracing is based on geometrical optics, which is valid for surfaces that are large and smooth relative to the wavelength. RaySAR is one of the several SAR data simulators based on ray tracing. It is built on the open source Persistence of Vision Ray-tracer (POV-Ray) [30], using the PoV-Ray basic algorithms for ray tracing, intersection tests between rays and objects, the estimation of intensities, and shadow calculations [22].

RaySAR generates a set of scattering centers positioned in 3-D SAR coordinates, i.e., azimuth, range, and cross range. RaySAR subsequently projects and interpolates these scatterers on the 2-D range-azimuth grid, adding different contributions coherently in order to generate a simulated SAR image. In this paper, however, we are mostly interested in the intermediate set of individual scatterers.

The set of scattering centers is provided by RaySAR as a list of signal vectors V

$$V = [a_i \ r_i \ c_i \ I \ b \ f] \quad (1)$$

where $[a_i \ r_i \ c_i]$ gives the position of the scattering phase center in azimuth, range, and cross range, I is a relative intensity normalized between 0 and 1, b specifies the number of bounces (trace level), and f is a Boolean indicating a specular reflection [0 or 1]. The signals V are referred to as contribution signals. These signals are the basis for the simulated image generation and point scatterers identification.

Fig. 1 sketches the localization of the phase center of a radar echo by RaySAR for a double-bounce signal. Starting from the virtual sensor plane, a primary ray for each pixel is followed along its path until intersection with the modeled scene is found. At the intersection point, a reflected ray is spawned in the specular direction and traced until the next intersection with the model, and so on. The azimuth, cross-range, and range coordinates of the double-bounce signal are

TABLE I
SURFACE PARAMETERS

Parameters	Impact on Radar Scattering	Value range	Low Roughness	Medium Roughness
Weight F_w	Weights the specularly reflected signal on a surface (loss of signal strength) of multiple reflections and works with a specular coefficient.	0 - 1	0.7	0.5
Specular F_s	Resembles specular reflection and provides a spreading of the highlights occurring near the object horizons.	0 - 1	0.7	0.5
Roughness F_r	Defines the width of a cone where a specular highlight occurs from 1(very rough) to 0(very smooth).	0 - 1	$8.5 \cdot 10^{-4}$	$3.3 \cdot 10^{-3}$

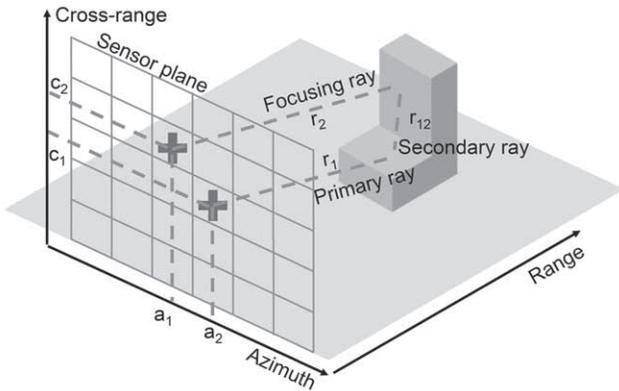


Fig. 1. Sketch of how RaySAR localizes a double-bounce signal and projects it in the sensor plane.

scene, which has to be specified in RaySAR as a position of the sensor with respect to the center of the scene.

2) *3-D Scene Model*: In this paper, the building model is reconstructed with 3dfier [31] by combining the large-scale topographic data set of the Netherlands, *Basisregistratie Grootschalige Topografie* in Dutch data set and the laser altimetry, *Actueel Hoogtebestand Nederland* in Dutch data sets. The acquisition of 3-D models can be constructed directly with a text editor or software, which can assist in visual controlling modeling (e.g., CAD). Importing available 3-D model into the POV-Ray format is an option considering there are a lot of city models available.

The 3-D object model has to provide sufficient geometric detail for SAR simulation. The amount of detail and spatial resolution of a 3-D city model is specified as LOD, denoting the abstraction level of a model as opposed to the real-world object [29]. The LODs have been described by CityGML [32], a prominent standard for the storage and exchange of 3-D city models. LOD1 is a model in which buildings are represented as blocks (usually obtained by extruding their footprint to a uniform height). LOD2 is a more detailed model including roof shapes [32], [33]. As it is the case with many other applications of 3-D city models [34], it is to be expected that the LOD and quality of the used 3-D model will have an influence on the performance of the simulation of radar signals, a topic that we investigate in this paper.

3) *Surface Parameters*: The scattering properties of the scattering surfaces in the 3-D model are specified by the parameters described in Table I. The first parameter, F_w , controls multiple scattering by setting the fraction of the ray intensity that is specularly reflected. Thus, setting $F_w = 0$ will completely suppress multiple scattering.

The second parameter, F_s , controls the relative intensity of the first reflection, counting from the illumination source. The roughness parameter, F_r , controls the angular width of the first reflection. Values of low roughness and medium roughness surfaces are given based on a constant relative permittivity of $5.7 + j \cdot 1.3$ for man-made objects [22].

Fig. 2 shows four images simulated with varying (F_w, F_s, F_r) values according to Table I. The parameter F_r works with specular coefficient F_s [see Fig. 2(a) and (b)]. With increasing roughness, the number of features shown in the simulated images increases. Fig. 2(c) and (d) illustrates the results of a combination of three parameters. With the weight factor F_w , the strong multiscattering is clearly described. The intensity of a multireflected signal is weighted with F_w . In this paper, we use the medium roughness $F_w = 0.5, F_s = 0.5,$

given by

$$\begin{aligned} a_i &= \frac{a_1 + a_2}{2} \\ c_i &= \frac{c_1 + c_2}{2} \\ r_i &= \frac{r_1 + r_2 + r_3}{2}. \end{aligned} \quad (2)$$

The trace level is the number of bounces of the signal.

To select potential PS candidates (simulated point scatterers), contribution signals with specular multiple scattering characteristics ($I > 0, b > 1,$ and $f = 1$) are chosen. The selection criteria are based on the premise that many PSs are physically associated with multiple specular reflections of the radar signal on relatively large surfaces.

B. Definition of a 3-D Scene for RaySAR

The input to RaySAR is a 3-D scene model including: 1) a virtual SAR system; 2) 3-D building models, and 3) surface parameters.

1) *Virtual SAR System*: The virtual SAR system is described by the observation geometry and the system resolution. The geometry is defined using an orthographic projection and a parallel ray approximation. This parallel ray approximation makes the observation geometry azimuth invariant, as it should. However, it also makes the geometry elevation (hence range) invariant, which is not entirely correct. We will, nevertheless, assume that this approximation is good enough for a small scene. Thus, the observation geometry is defined by an incident angle and an azimuth angle with respect to the

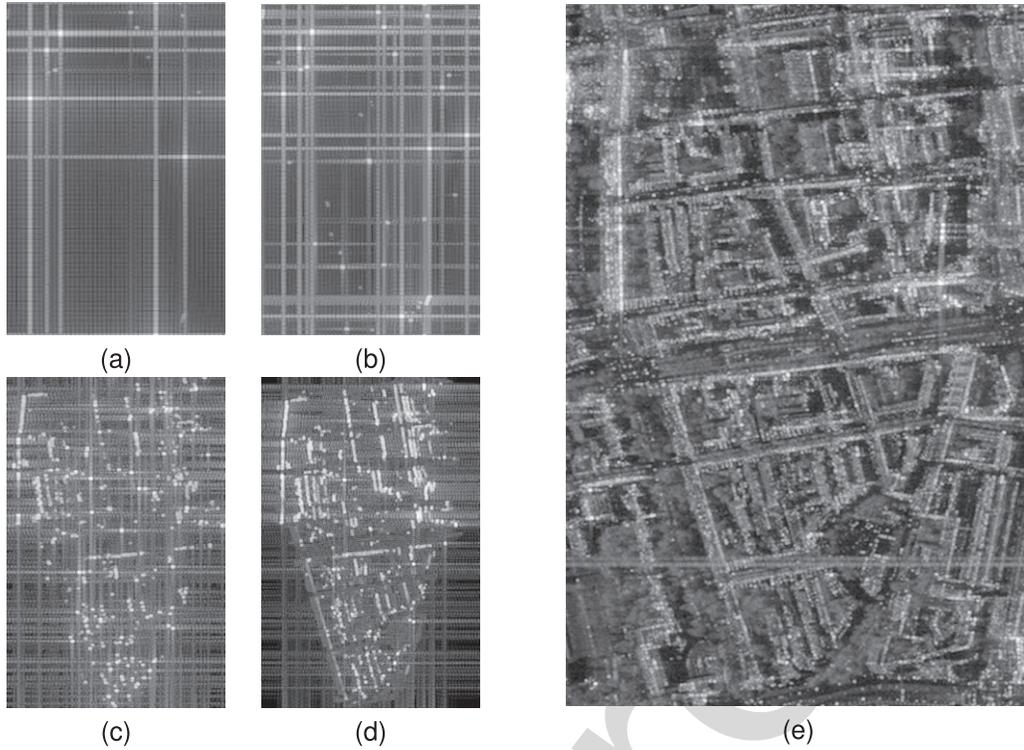


Fig. 2. Parameters function on SAR image simulation. (a) Image with $F_w = 0$, $F_s = 0.7$, $F_r = 8.5 \cdot 10^{-4}$. (b) Image with $F_w = 0$, $F_s = 0.5$, $F_r = 3.3 \cdot 10^{-3}$. (c) Image with $F_w = 0.7$, $F_s = 0.7$, $F_r = 8.5 \cdot 10^{-4}$. (d) Image with $F_w = 0.5$, $F_s = 0.5$, $F_r = 3.3 \cdot 10^{-3}$. (e) Mean intensity map of 49 TerraSAR-X images.

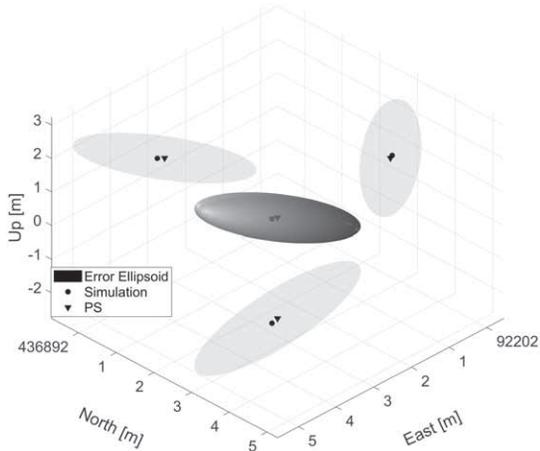


Fig. 3. Example of finding the corresponding simulation point of a PS based on the 3-D error ellipsoid. The position of the PS is indicated by a black triangle. A cigar-shaped error ellipsoid with a ratio of axis lengths 1/2/35 (with $\sigma_r = 0.019$ m) illustrates the PS position uncertainty. The corresponding SPS is located inside of the error ellipsoid and indicated by a black dot. The ellipsoid and PS are projected in east-north, north-up, and up-east planes to illustrate their intersection with the SPS.

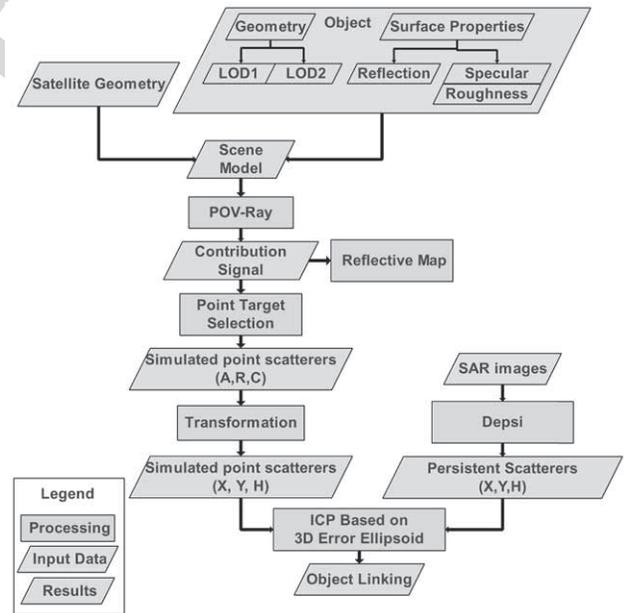


Fig. 4. Schematic of the methodology.

256 $F_w = 3.3 \cdot 10^{-3}$, compared to low roughness parameter
 257 setting, medium roughness parameters are closer to the reality
 258 using the X-band data [see Fig. 2(e)]. It is important to
 259 emphasize that the phase-center location of the simulated
 260 scatterers does not depend on the surface parameters. In the
 261 following, we focus solely on the phase-center location of
 262 multiple-bounce SPSs.

C. Linking of Simulation Points With PSs

263
 264 One of the main steps in the work presented is the matching
 265 of the SPSs with the PSs identified in the InSAR time series.
 266 The matching is done by evaluating the weighted Euclidean
 267 distances between the positions of the simulated point scatter-
 268 ers and the positions of the PSs. The weighting reflects the



Fig. 5. Google Earth overview image of test site; azimuth and range directions indicate the view of the TerraSAR-X data.

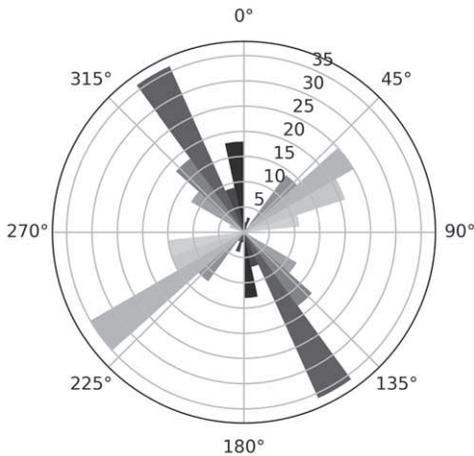


Fig. 6. Street orientation map of the AOI. Each bar represents the compass bearing of the streets and its length indicates the frequency of streets with those bearings. There are two main directions at 336° and 60°.

3-D position error ellipsoids, as defined by the positioning VC matrices, of the PSs [9]. For each PS, the positioning uncertainty in the local reference frame (East, North, and Up/Height) is given by

$$\mathbf{Q}_{\text{enh}} = \mathbf{R}_{3 \times 3} \cdot \mathbf{Q}_{\text{rac}} \cdot \mathbf{R}_{3 \times 3}^T = \begin{bmatrix} \sigma_e^2 & \sigma_{en}^2 & \sigma_{eh}^2 \\ \sigma_{en}^2 & \sigma_n^2 & \sigma_{nh}^2 \\ \sigma_{eh}^2 & \sigma_{nh}^2 & \sigma_h^2 \end{bmatrix} \quad (3)$$

where \mathbf{R} is the rotation matrix from radar geometry to local reference frame, \mathbf{Q}_{rac} is the positioning VC matrix in 3-D radar geometry with diagonal component variances (σ_r^2 , σ_a^2 , and σ_c^2) in range, azimuth, and cross range, the diagonal (σ_e^2 , σ_n^2 , and σ_h^2) and nondiagonal (σ_{en}^2 , σ_{eh}^2 , and σ_{nh}^2) are the variances and covariances in east, north, and up coordinates. For each PS, from the eigenvalues of \mathbf{Q}_{enh} , a 3-D error ellipsoid is drawn with the estimated position as its center. The semiaxis lengths of the ellipsoid are described by the

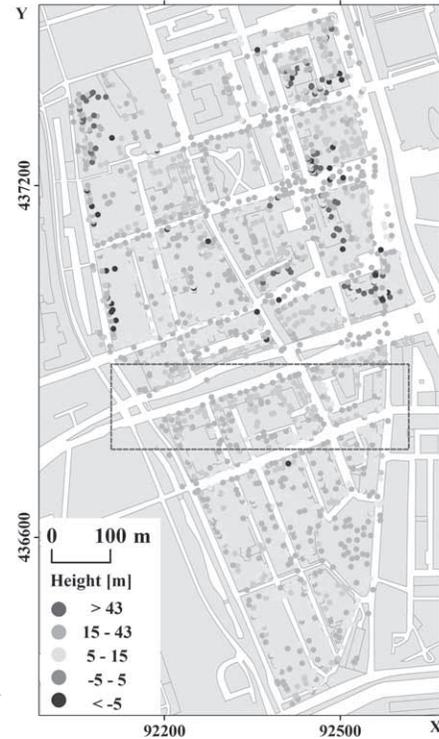


Fig. 7. PS identified in TerraSAR-X data stack overlaid on TOP10NL map. TOP10NL is the digital topographic base file of the Land Registry, the most detailed product within the basic registration topography. Colors: estimated PS heights (blue-low; red-high).

eigenvalues of \mathbf{Q}_{enh} , which are σ_r^2 , σ_a^2 , and σ_c^2 . The shape of ellipsoid is derived from the ratio of their axis lengths, given by $(1/\gamma_1 / \gamma_2)$, where $\gamma_1 = \sigma_a \cdot \sigma_r^{-1}$ and $\gamma_2 = \sigma_c \cdot \sigma_r^{-1}$. The orientation of ellipsoid is dependent on the local incidence angle of the radar beam at the PSs.

Fig. 3 illustrates the matching of an SPS with a PS based on the 3-D error ellipsoid. The position uncertainty of a PS is illustrated by 3-D error ellipsoid with 0.01 level of significance. The PS is matched to the corresponding SPS, which has to be inside the error ellipsoid.

As part of the matching process, it is necessary to consider and remove potential systematic positioning errors. The systematic errors may be the result of an oversimplified geometry (e.g., the already mentioned range invariance) or errors in the knowledge of the acquisition SAR geometry.

A fine coregistration is performed using the iterative closest point (ICP) algorithm [35], [36], which minimizes the sum of the weighted Euclidean distance between SPSs and PSs by least square estimation in an iterative way. Each iteration of the 3-D error ellipsoid-based ICP includes two steps: matching pairs of SPS and PSs based on the 3-D error ellipsoid; and finding the transformation that minimizes the weighted mean squares distance between pairs of points. The transformation results are applied to the point cloud of PSs, thereby changing the correspondence.

D. Simulation Assessment

A quantitative evaluation of the matching between the PS and the SPS is given by the confusion matrix \mathbf{M} described in Table II. Three performance ratios are considered as follows.

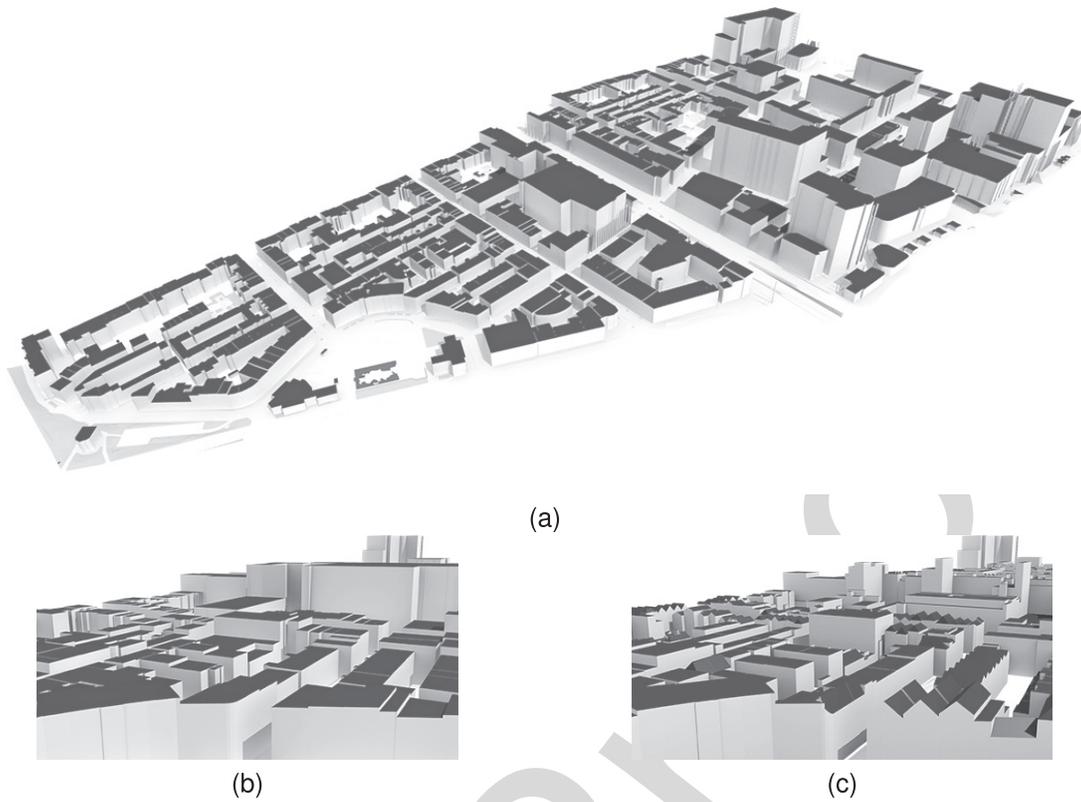


Fig. 8. (a) Overview of the used 3-D city model, (b) closer look on the LOD1 variant of the data set, and (c) its more detailed (LOD2) counterpart including roof shapes. Source of data: BGT, AHN, and City of Rotterdam.

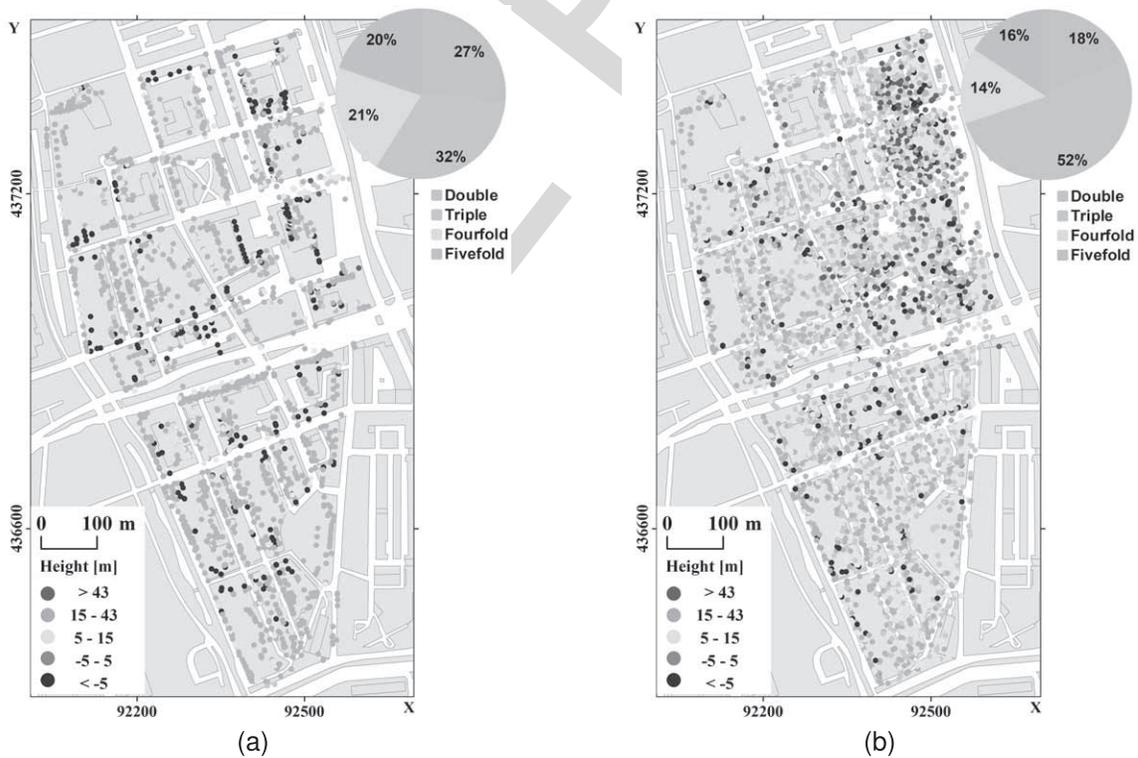


Fig. 9. (a) Point scatterers simulated based on the model of LOD1 with color represents height. (b) Point scatterers simulated based on the model of LOD2 with color represents height. The background image is TOP10NL map.

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1) *True Positive Rate (TPR)*: The ratio of the PSs that are matched to SPSs, with regards to the total number of PSs.

2) *False Negative Rate (FNR)*: The ratio of the PSs that have not been matched to an SPS, with regards to the total number of PSs,

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TABLE II
CONFUSION MATRIX **M** BETWEEN SPS AND PS

Total		SPSs	
		Match	Non-Match
PSs	Match	True Positive Rate(TPR) $= \frac{\sum TP}{\sum PPS}$	False Positive Rate(FPR) $= \frac{\sum FP}{\sum SPSs}$
	Non-Match	False Negative Rate(FNR) $= \frac{\sum FN}{\sum PPS}$	

also known as miss rate. For FNR, we have $FNR = 1 - TPR$.

3) *False Positive Rate (FPR)*: The ratio of the SPSs that have not been matched, with regards to the total number of SPSs.

Hereby, the metric **TPR** describes the matching ratio between simulation points and PSs and is the primary evaluation indicator of simulation scatterers. **FPR** also an important indicator for describing the ratio of redundant simulation points.

Note that the PS or SPS selection criteria will have an impact on the performance metrics. For example, a low amplitude dispersion threshold may lead to selecting less actual point scatterers and lead to a higher FPR. Since the final goal of our research is to improve our capability to analyze deformation signals, we focus on the group of PSs that are deemed reliable. PSs are chosen with an amplitude dispersion threshold set to 0.45 and further checked based on network phase consistency [37]. Here, SPSs are scatterers predicted by the simulator based on the geometry. Therefore, the final number of PSs is less than the SPSs from the simulator because we eliminated many points during the PSI processing, which increases the FPR.

E. Work Flow

The flowchart shown in Fig 4 outlines the work flow of this paper, which consists basically of three parts: generation of simulation points, detection of PSs, and the matching of two point cloud sets. The generation of simulation points consists of scene modeling, signals detection with Pov-Ray, and selection of SPSs. The SAR data stack is processed with the Delft implementation of PSI (DePSI) [37], which is based on the Delft framework of geodetic estimation, testing, and quality control. DePSI detects PS with consistent reflection properties over time as input for time series deformation and height estimation. Then, matching of two point cloud sets is carried by ICP based on the 3-D error ellipsoid.

RaySAR is not demanding in terms of computational resources. It is built on POV-ray, an open source tool that traces rays in the reverse direction. In this paper, the calculation of 48 million contribution signals took about 10 min on a four-core workstation with 16 GB of RAM.

III. EXPERIMENT

A. Test Site and Data

The test area is located southeast of Rotterdam Central Station in the city of Rotterdam, the Netherlands. The size of

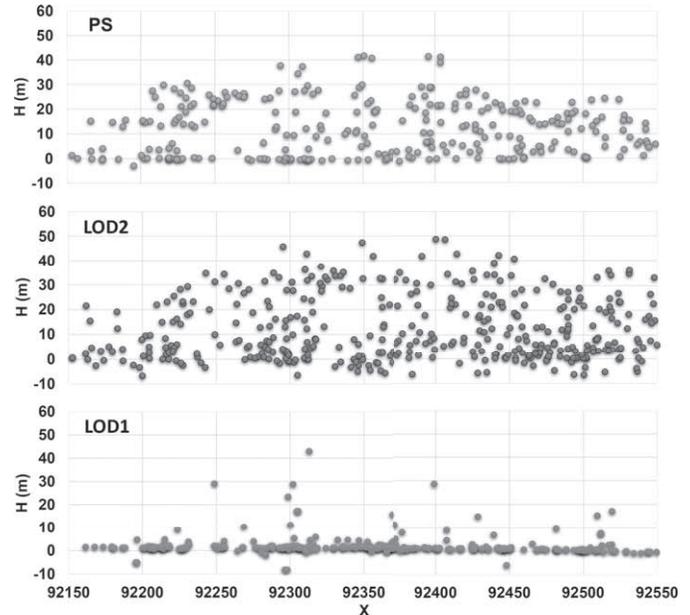


Fig. 10. Height profile of PSs, SPSs from LOD1 and LOD2, in the box indicated in Fig. 7 along the x-axis.

TABLE III
BASIC PARAMETERS OF TERRASAR-X DATA STACK

Satellite/Parameter	TerraSAR-X
Track	T025
Band(wavelength in cm)	X (3.1)
Start Date	2014.01.19
End Date	2017.02.14
Number of images	49
Acquisition mode	SM
Pass direction	Ascending
Polarization	HH
Pulse Repetition Frequency(Hz)	3790
Range Sampling Rate (MHz)	109.8
Incident angle (°)	39.3
Heading (°)	349.8
Slant range spacing (m)	1.36
Azimuth spacing (m)	1.86
Range Bandwidth (MHz)	100
Azimuth Bandwidth (Hz)	2765

the area of interest (AoI) is around $1 \times 0.5 \text{ km}^2$. Fig. 5 shows an overview of the test site, and its orientation with respect to the trajectory of TerraSAR-X. 49 TerraSAR-X strip-mode images are obtained from January 19, 2014 to February 25, 2017. Table III illustrates the basic parameters of TerraSAR-X data. Fig. 2(e) is the mean intensity map of 49 TerraSAR-X images over the AoI.

Fig. 6 shows a polar histogram describing the orientation of the streets within the AOI calculated based on OpenStreetMap [38]. The direction of each bar represents the compass bearings of the streets and its length indicates the relative frequency of streets with those bearings. In Fig. 6, two main orthogonal directions can be identified, one at about 336° (red bars), and another at about 60° (cyan).

The results of the PSI analysis are illustrated in Fig. 7: 2290 points are selected as PS in the AoI. The results are projected in the Dutch National Reference System



Fig. 11. Correspondence between SPSs, shown as solid circles color-coded by bounce level, and matched PSs, shown as empty circles. (a) Left and (b) right correspond to simulations using the LOD1 and LOD2 models, respectively.

379 *Rijksdriehoeksstelsel* (RD) in Dutch and vertical *Normaal*
 380 *Amsterdams Peil* in Dutch reference system. The axes shown
 381 in Fig. 7 show X (RD) and Y (RD) in meters, in East and North
 382 directions, respectively. The estimated heights are indicated by
 383 colors, showing some higher buildings in the northwest and
 384 northeast corner of the AoI, which can be found in Fig. 5.

385 Two 3-D city models with different LODs were employed
 386 to simulate scatterers using RaySAR. Fig. 8 displays the
 387 3-D models at LOD1 and LOD2 of the AoI. In LOD1 model,
 388 buildings are represented as boxes with flat roof structures
 389 [Fig. 8(b)], opposed to buildings in LOD2 (Fig. 8c), which
 390 have differentiated roof structures with varying heights, pro-
 391 viding a more realistic representation of the reality.

392 From the enlarged partial picture of the LOD1 model
 393 [Fig. 8(b)] and the LOD2 model [Fig. 8(c)], it is clear that
 394 buildings in LOD2 include many different parts with varying
 395 roof shapes and heights. Data sets with LOD1 and LOD2 are
 396 the most common instance, in practice, because it is possible to
 397 obtain them automatically, e.g., from LiDAR data by automatic
 398 building reconstruction [33].

399 B. Simulated Point Scatterer

400 POV-Ray/RaySAR detects all contributing signals within
 401 the AoI. The total number of received signals from the
 402 LOD1 and LOD2 models is about 50 million. We detect

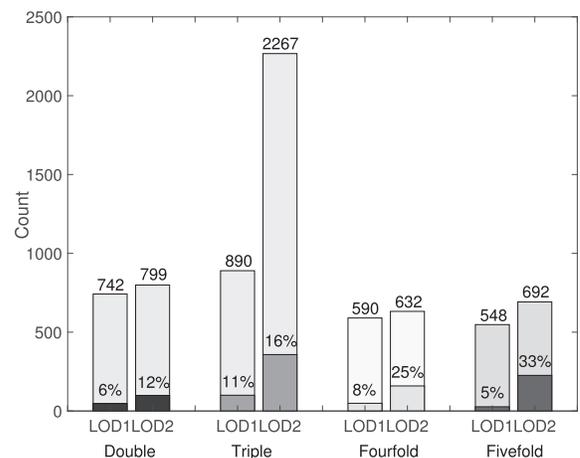


Fig. 12. Histograms of simulation points from LOD1 model and LOD2 model in double, triple, fourfold, and fivefold bounce. The X-axis is LOD1 and LOD2. The Y-axis is the count numbers from 0 to 2500. There were 742 and 799 double-bounce signals from LOD1 and LOD2 models. Among these signals, 6% and 12% points were linked to the PSs. Likewise, for triple-bounce signals, and fourfold-bounce signals and fivefold-bounce signals.

403 potential point scatterers and consider these as signals that
 404 exhibit the characteristics of PS ($I > 0$, $b > 1$, and $f = 1$)
 405 from the contribution signals.

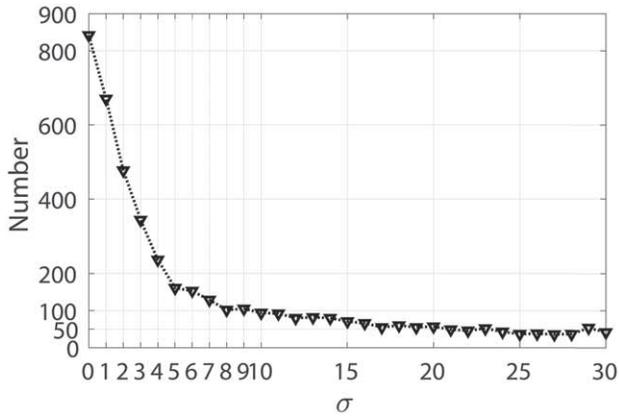


Fig. 13. Number of matched PSs as a function of the standard deviation of the disturbance added to the position of the simulated scatterers. The rapid decrease in matched pairs supports the assumption that the vast majority of matches is correct.



Fig. 14. Matched and unmatched PSs. A-labeled area: new building absent in the LOD2 model. B-labeled area: green-area free of buildings, where the PPs correspond to urban structures not included in the model. C-labeled areas: examples of predicted PSs at the linear structures of buildings and identified as triple bounce.

406 We identify 2770 potential point scatterers from the model
 407 at LOD1, as described in Section II. Fig. 9(a) shows the
 408 distribution of simulated points in the LOD1 model. The colors

TABLE IV
 CONFUSION MATRIX BETWEEN MEASURED PSS AND PREDICTED
 SCATTERERS BASED ON LOD1 MODEL AND LOD2 MODEL

	SPSs-LOD1 (2770)		SPSs-LOD2 (4390)	
	Match	Non-Match	Match	Non-Match
PS (2290)	223	2547	842	3548
	TPR	FPR	TPR	FPR
	10%	92%	37%	80%
	FNR		FNR	
	90%		63%	

409 indicate the height of simulation points. In comparison to
 410 the real radar results shown in Fig. 7, the height values
 411 of the SPSs is mainly below 15 m. The simulation points
 412 include 742 double bounces, 890 triple bounces, 590 fourfold
 413 bounces, and 548 fivefold bounces [see the pie chart in the top
 414 right of Fig. 9(a)]. Most signals correspond to triple-bounce
 415 scatterers, followed by double-bounce ones.

416 Using the LOD2 model results in 4390 potential point
 417 scatterers, as illustrated [see Fig. 9(b)]. Compared to the
 418 real PS data, see Fig.9(b), more points, and with higher
 419 heights are detected. Spatial distribution in height values of
 420 SPSs from the LOD2 model is similar to the measured PS
 421 [see Fig. 9(b)]. PSs with higher heights are clustered in the
 422 northeast corner of the test site, which is also predicted by
 423 the simulation. The height of simulation points in the corner
 424 of the northwest is lower than PSs shown in Fig. 7 because
 425 the buildings in the corner of the northwest are missed in
 426 the LOD2 model(equal to LOD1). The Google Earth image
 427 shown in Fig. 5 also indicate the newly built in the corner
 428 of the northwest. Simulated points from the LOD2 model
 429 include 799 double bounce, 2267 triple bounce, 632 fourfold
 430 bounce, and 692 fivefold bounce [see the pie chart in the top
 431 right of Fig. 9(b)]. More than half of the points are the triple
 432 bounces.

433 Fig. 10 shows the height profile of PSs, the SPSs of
 434 LOD1 and LOD2, in the box indicated in Fig. 7 along the
 435 *x*-axis. The height profile of PSs and SPSs from LOD2 is
 436 similar while the SPSs from LOD1 missed points with higher
 437 height.

438 *C. Linking of PSs and SPSs*

439 Following Section II-C, PSs (Fig. 7) were matched to the
 440 point scatterers predicted using the LOD1 [Fig. 9(a)] and
 441 LOD2 [Fig. 9(b)] models. Fig. 11(a) and (b) shows the spatial
 442 distribution of PSs and the corresponding SPSs. The dark circle
 443 indicates the location of PSs that have been matched to SPSs. The
 444 dots represent the corresponding SPSs, color coded by bounce level
 445 (see legend on the figure).

446 Table IV shows the confusion matrix between SPSs based
 447 on LOD1 and LOD2 models and PSs. Scatterers from the
 448 model of LOD1 predicted 10% PSs correctly (correspondingly,
 449 around 90% PSs were missed). The 92% simulation points
 450 have not been matched to a PS. By using the LO2 model,
 451 the amount of PSs matched with simulated scatterers increased
 452 to 37%. Naturally, the number of predicted point targets not
 453 matched to PSs also increased. However, it is noteworthy, that,

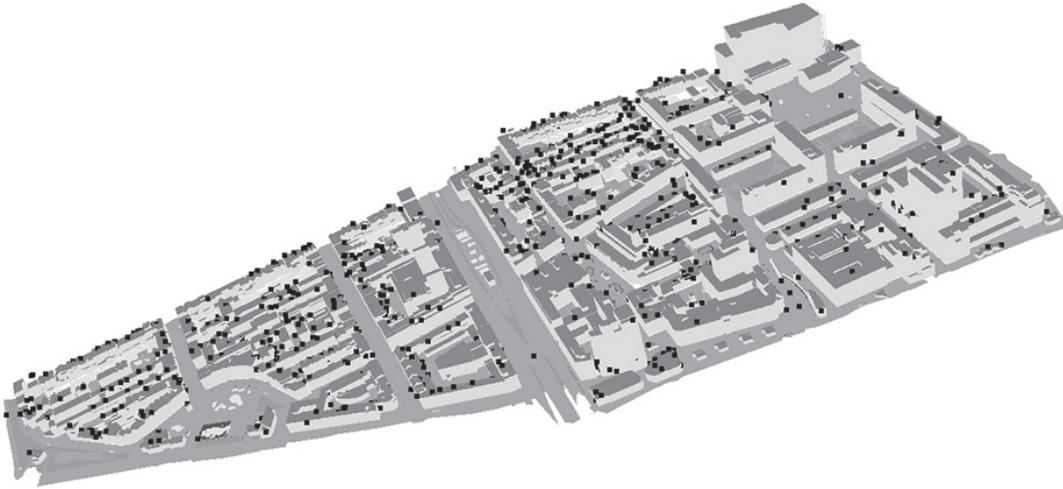


Fig. 15. Rendering of matched scatterers overlaid on the LOD2 city model.

454 in relative terms, the number of scatterers matched to PSs grew
 455 much stronger than the overall amount of predicted scatterers.
 456 Moreover, the ratio of simulation points that have not match
 457 to a PS is decreased to 80%.

458 Fig. 12 shows a quantitative overview of the number of
 459 point scatterers predicted for the LOD1 and LOD2 models,
 460 segregated by bounce level. In each of the bars, it is also
 461 indicated which fraction of the SPSs was matched to a PS. Not
 462 surprisingly, the increase in the LOD leads to a very strong
 463 growth (close to a factor 3) of the predicted triple-bounce
 464 scatterers. The fraction of predicted triple-bounce scatterers
 465 matched to actual PSs increased from 11% to 16%.

466 For the other bounce levels considered, the increase in
 467 predicted scatterers was quite modest. However, the fraction
 468 of these scatterers that was matched to PSs increased by a
 469 factor two for double-bounce scatterers, a factor three for
 470 fourfold-bounce scatterers, and by more than a factor six for
 471 fivefold-bounce scatterers.

472 The total number of matched scatterers increased from
 473 223 in the LOD1 case to 842 with the LOD2 model.
 474 Triple-bounce scatterers, 100 and 358, respectively, remained
 475 dominant. However, 226 of the LOD2-model scatterers,
 476 or about one-fourth of the total, corresponded to
 477 fivefold-bounce signals.

478 The number of predicted point scatterers for the
 479 LOD1 (2770) and LOD2 (4390) models was larger than the
 480 number of detected PSs. This can be explained by considering
 481 that PS selection is done based on the amplitude stability of
 482 individual resolution cells in the interferometric data stack.
 483 Typically, the amplitude will be stable if a single pointlike
 484 scatterer is a dominant factor in the radar echo for that
 485 resolution cell. Thus, even if we know for sure that we have a
 486 stable pointlike target within our resolution cell, as this does
 487 not exclude contributions from other scattering mechanisms,
 488 it does not imply that it will result in a PS. Moreover, as stated
 489 in Section II-D, the selection criterion also contributes to the
 490 fact that the number of simulation points was larger than the
 491 number of PSs.

D. Target Matching Validation

492 A potential pitfall in the matching process is that if the
 493 local density of either PSs or SPSs is higher, the amount of
 494 random matches increases as well (false positives). However,
 495 the amount of random matches should be insensitive to their
 496 exact position. Hence, while some pairs would be disassoci-
 497 ated roughly the same number is expected to appear.

498 Following this reasoning, we added random disturbances
 499 with Gaussian distribution to the coordinates of the simulated
 500 points and performed the PS matching, following the proce-
 501 dure discussed in Section II. In order to consider the worst
 502 case, the random disturbances are aligned along the dominant
 503 orientation of the buildings. The x -, y -, and z -coordinates of
 504 the simulated points with random disturbances are given by
 505

$$\begin{aligned}
 \tilde{x}_{\text{sim}} &= x_{\text{sim}} + \Delta x & 506 \\
 \tilde{y}_{\text{sim}} &= y_{\text{sim}} + \Delta y & 507 \\
 \tilde{z}_{\text{sim}} &= h_{\text{sim}} + \Delta z & 508
 \end{aligned} \tag{4}$$

509 where x_{sim} , y_{sim} , and z_{sim} are the original coordinates of
 510 the SPSs, $\Delta x = n_1 \cdot \sin(t)$, $\Delta y = n_1 \cdot \cos(t)$, and $\Delta z = n_2$.
 511 The angle $t = 336^\circ$ is the main orientation angle of the
 512 streets and buildings as presented in Fig. 6. n_1 and n_2 are
 513 the zero-mean Gaussian-distributed random disturbances with
 514 a standard derivation of σ meter.

515 Fig. 13 shows the number of matched PSs as a function
 516 of σ . The number of matched pairs decreases rapidly as the
 517 position disturbance σ increases. Introducing a position error
 518 with $\sigma = 4$ m, which is close to the spatial resolution of
 519 TerraSAR-X in stripmap mode, reduces the amount of matches
 520 by a factor 4 while a further increase in the positioning error
 521 has only a limited effect on decreasing the amount of matches.
 522 As less than 10% of the number of matches remains if the
 523 positioning error is increased to an unrealistically high value,
 524 this analysis suggests that the vast majority of matched pairs
 525 is physically correct.

526 Fig. 14 shows all PSs detected in the AoI, with iden-
 527 tified PSs represented by green triangles and unidentified

528 PSs indicated by magenta plus signs. The area labeled A,
 529 where most PSs were missed by the simulation, correspond
 530 to a newly built building not present in the LOD2 model.
 531 Moreover, the building model did not include the public
 532 facilities, like the flower boxes in the area labeled B. Most
 533 predicted PSs are located at linear structures of buildings and
 534 identified as triple bounce, such as the points in the area
 535 labeled C. Those scatterers originated from the roof and ghost
 536 corners, e.g., the corner of the wall and the ground, which is
 537 in agreement with the previous research [28].

538 Simulation points have precise locations in the model. The
 539 object snap of PSs can be achieved by the correlation of PSs
 540 and SPSs. Fig. 15 displays an overview of matched simulation
 541 points in the LOD2 model. The supplementary file of this
 542 paper includes a movie that is a 360° view of model and
 543 simulation points that matched to measured PSs.

544 IV. CONCLUSION

545 PSI can yield deformation with an accuracy of millimeter
 546 order by exploiting PSs. As discussed in the Introduction, two
 547 key issues in PSI are the precise geolocation of the scatterers in
 548 the 3-D space, and the association of the scatterers to specific
 549 physical features. In this paper, we have investigated the use of
 550 ray-tracing tools to address the second issue by illuminating
 551 3-D city models with different levels of detail (LOD1 and
 552 LOD2 according to the CityGML standard). As expected,
 553 the results obtained depend strongly on the LOD of the
 554 3-D model given as input to the ray-tracing tool.

555 For our area of study in Rotterdam, we were able to
 556 associate 37% of the PSs identified in a stack of TerraSAR-X
 557 data with simulated scatterers using a LOD2 city model.
 558 Using LOD1 models not only reduced the fraction of identified
 559 PSs to around 10% but also put most of them on the ground.
 560 We did not have models for real cities with a higher LOD.
 561 Nevertheless, from the observation of high-resolution SAR
 562 data, it is generally understood that many pointlike scatterers
 563 result from features, such as windows, which are not captured
 564 in LOD2. It is expected that using higher LOD models might
 565 further increase the fraction of identified scatterers.

566 Considering the details of the results, it worth noting that
 567 roughly one-fourth of the identified PSs were associated with
 568 fivefold bounces. These types of scatterers cannot be linked
 569 to physical objects by simply intersecting their location with
 570 the 3-D models.

571 LOD2 models can be produced automatically from, for
 572 example, laser-scanning data. Therefore, it should be expected
 573 that the LOD2 city models may become commonplace in the
 574 near future. The positive results of this paper underpin the
 575 usefulness of integrating this information in the PS processing.

576 Associating PSs to physical features is a necessary step if we
 577 want to fully exploit the InSAR signal of individual scatterers,
 578 for example, to detect deformation of specific sections of a
 579 building. In this paper, we have shown that this association
 580 can be made. Each simulated PS can be traced back one or
 581 multiple reflections on specific locations of the 3-D model.
 582 However, with the tools used, the bookkeeping necessary
 583 to trace scatterers back to individual features in the model

(specific walls, roofs, and floors) is still missing. A logical next
 step in our research is to implement this bookkeeping, which
 includes identifying practical approaches to label features and,
 in particular, visualizing the results.

Another important intermediate objective is to investigate,
 with the support of simulations, how different deformation
 sources translate to individual PS deformation signals. For
 example, in the case of a fivefold-bounce scatterer, structural
 deformation may produce a signal with the opposite sign than
 for a triple-bounce scatterer. As already indicated, the long-
 term goal of the work presented is to improve the interpreta-
 tion of deformation signals in complex environments, where
 the observed deformation signals may have different causes.
 This relies on the anticipated increased availability of high
 resolution city models.

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