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Ground Movement Classification Using Statistical Tests Over Persistent Scatterer Interferometry Time Series

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Abstract

This study proposes modifications to an existing automatic classification method of Persistent Scatterers Interferometry (PSI) time series (TS) and a new procedure to classify ground movements into seven classes. We also represent a technique to detect TSs affected by phase unwrapping errors and a reclassification part to detect stable points, which are incorrectly classified as moving points using the original method. Around 60 km^2 of Catalunya were classified using Sentinel-1 images and a PSI technique. The proposed method classified 78359 PS TS. This study provided the spatial distribution of ground movement classes and detected several time series anomalies.

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Keywords: DInSAR; GMS; PSI; Classification; Sentinel; Remote Sensing

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1. Introduction

No-time and no-weather dependency turn the Synthetic Aperture Radar (SAR) a popular source of environmental sensing. The Ground Motion Services (GMSs) provide ground motion time-series information using SAR images. GMS application fields are broad and include natural and man-induced geohazard risk assessment, land management, urban planning, infrastructure development and management, mining and other natural resources extraction, dam, and groundwater monitoring, etc. [1]. Differential Interferometric SAR (DInSAR) techniques, such as Persistent Scatterer Interferometry (PSI), have been utilised for two decades. Deformation time series and velocity estimation at PS points are the PSI technique's main outcomes [2]. These outcomes are extracted from processing interferograms. Interferograms are the result of subtracting the phases of two coregistered SAR images over the same area [3]. PSI [2] methods can measure displacement over those available PSs, where are mostly over reflective targets, including infrastructures, outcrops, and exposed rocks. The PSI technique was introduced by [4,5]. [2] also extensively discussed a review of PSI, including the main PSI algorithms, several technical aspects of the PSI techniques, the validation of the PSI results, the main PSI applications, and main open PSI problems [6]. Furthermore, [7] proposed the PSI chain of the Geomatics (PSIG) Division of CTTC. It has been applied in various studies [3,8–11].

TS contains the surface deformation occurring among time-ordered SAR images from a reference image. It includes the accumulated displacement at every satellite acquisition along the satellite Line of Sight (LoS) direction. To detect and classify TSs with useful information on land dynamics, statistical methods are needed. In the following, a brief review of various studies is discussed, which have proposed post-processing methods to classify PSI time series. [12] labelled each displacement time series to "Affected targets" and "Unaffected targets". Deformation rates of TS sub-samples were calculated using a simple linear regression to evaluate the magnitude of the deformation velocity changes and accelerated or decelerated patterns. Later in 2012, [13] developed the method to calculate two indexes to depict the deviation using a predefined deformation model. Then, [14] proposed an automatic method of PSI time series based on a conditional sequence of statistical tests. Time series were classified into distinctive predefined trends, which described various types of ground deformation. [15] considered the [12–14] methods to highlight the ability of automatic detection of motion trends in the interpretation of DInSAR data. This comprehensive study used ERS-1/2 SAR, RADARSAT-1, ENVISAT ASAR, ALOS PALSAR, TerraSAR-X, and COSMO-SkyMed data along with advanced DInSAR techniques to improve the TS quality and trend analysis considering the implementation of methodologies for automatic TS analysis. Furthermore, [16] proposed a principal component analysis methodology to analyse multi-sensors and multi-temporal DInSAR time series to interpret the geological areas affected by land subsidence/uplift and seasonal movements. [16] also identified localized intermittent periodicities using three wavelet tools to interpret TS information for a landslide. More recent studies [17,18] generated continuously updated ground deformation data and highlighted any anomalous trends and/or acceleration affecting the area of interest. [20] also investigated a procedure to compute the minimum required number of parameters to model a given time series reliably with polynomial functions. These studies have tried to recognize straightforward deformation trends (e.g., linear and uncorrelated); however, natural and human-made displacements include more complex trends, such as bilinear and quadratic. Likewise, almost all of publications have not yet taken into account time series affected by noises and errors.

Since the above methods have not fully categorized and detected various trends and TSs with errors, we present an automatic approach to classify TS in seven classes (PS TS classifier) and to find TS affected by phase unwrapping errors from PSIG products based on Sentinel-1 SAR images. We also propose verification steps to distinguish stable targets (non-moving areas), which are incorrectly categorized as unstable points. The organization of the paper is as follows. Section 2 first provides information on study area; then, it describes the dataset. An overview of the method is explained in Section 3. The classified map and a graph of number of each class are shown in Section 4. Finally, Section 5 presents a conclusion of the study.

2. Study area and Dataset

2.1. Study Area

The case study lies on the infrastructure of a railway in Barcelona metropolitan areas, where expands to the Mediterranean coast in South of Barcelona and from North to Igualada. The railway connects various cities, including

Martorell, Iguadala, Cornella, and Barcelona. The length of railways is approximately 73 km. Around 60 km^2 of Catalunya has been analysed for potential deformations. Continuous and discontinuous urban fabrics are the dominant land uses of the region, followed by industrial or commercial units, non-irrigated arable land, and forests. Considering the length of railways from mountainous regions on North to coastal regions on South, the elevation varies around 400 m.

2.2. Dataset

Sentinel-1 globally provides continuity of C-band SAR freely-access images. Sentinel-1 consists of a constellation of two satellites, Sentinel-1A and Sentinel-1B, which covers Europe with a revisit time of six days. In this study, 230 of Sentinel-1 images were exploited over the study area. Using the PSIG approach, time-series deformation of each study area has been extracted. Large number of interferograms were also generated from 230 SAR images over the region from March 10, 2015, to November 22, 2020. The PSIG method extracted 78359 PS.

3. Method

This study's main goal is to provide an advanced procedure using DInSAR time series data to classify land deformation trends and investigate PS with phase unwrapping errors (PUE) based on the approach proposed by [14]. To this end, various statistical analyses have been applied over PS TS to investigate an efficient approach in C++ language. Ground displacements were categorized by [14] in six trends; then, a methodology was proposed to separate them. In this study, PUE class has been added to those six to finally seven statuses have been selected as patterns of land movements identified TS classes:

- Stable: no deformation occurs. There is no trend (e.g., linear, quadratic, and bilinear) in these points.
- Linear: the TS is characterized by a constant slope.
- Quadratic: the displacement rate varies continuously in time.
- Bilinear: there is the presence of a breakpoint. TS is divided into two periods, where each period can have a different linear rate.
- Discontinuous with constant velocity (DCV): a breakpoint divides TS into two segments, which have approximately equal constant slope.
- Discontinuous with different velocity (DDV): a breakpoint divides TS into two segments, which have different slopes.
- Phase Unwrapping Errors: There could be one or more jumps due to phase unwrapping inside the TS (We illustrate this class as *Jump* in figures).

The basic idea was proposed by [14] to automatically classify PSI TS based on a conditional sequence of statistical tests. The result was finally categorized in three classes (i.e., uncorrelated, linear, non-linear trends) instead of the six preliminary classes. In this research, the following improvements are proposed to classify all seven classes: detecting PUE in four stages using various statistical tests, including an average estimator, the coefficient of determination (adjusted R-squared), Explained Sum of Squares (ESS), Residual Sum of Squares (RSS), and Mean Squared Error (MSE); utilizing new robust statistical tests to classify correctly stable points, which are classified wrongly as *Linear*, *Quadratic*, and *Bilinear*; and using more conditions and another statistical test after linearity checking (e.g., adjusted R-squared). The input is the TS and output are the labelled PS. The proposed procedure is explained step by step as follows:

a) First, we search PSs with phase unwrapping errors using the average of every 7-images interval.
b) A linear regression is fitted over the remaining PS to identify *Stable* points.

c) Unstable points are tested by a segmented regression (i.e., the Bayesian Information Criterion (BIC) of a two-line unconstrained model) to check for abrupt changes in TS.

d) If there is no breakpoint inside a TS, a quadratic regression is fitted to classify it as a *Linear* or *Quadratic*. This primary classification is then tested against the second and third stages of PU errors, along with uncorrelation checking to distinguish *PUE* and *Stable* PSs.

e) A discontinuity test is calculated to separate *Bilinear* points. The uncorrelation and PU errors tests are also applied at this level.

f) Finally, a test for the equality of slopes is computed to split TS with different or constant velocity.

4. Results and Discussion

The automatic PS TS classification procedure was applied over 60 km^2 with 78359 PS. The aim is to classify accurately all TS to seven classes using rigorous thresholds. Fig. 1 illustrates the final TS maps of the region using automatic PS TS classifier extracted from PSIG time series product of Sentinel-1 SAR images considering seven classes of land deformation. It also includes two zoomed images of the classified maps. PS TS classified maps provide the spatial distribution of target trends, as well as an important input for GMS systems. They can also highlight anomalies of targets movements over each period using monthly, seasonal, and yearly maps. Regarding the fact that PS are mostly over reflectivity areas, urban areas of the maps are appeared dense.

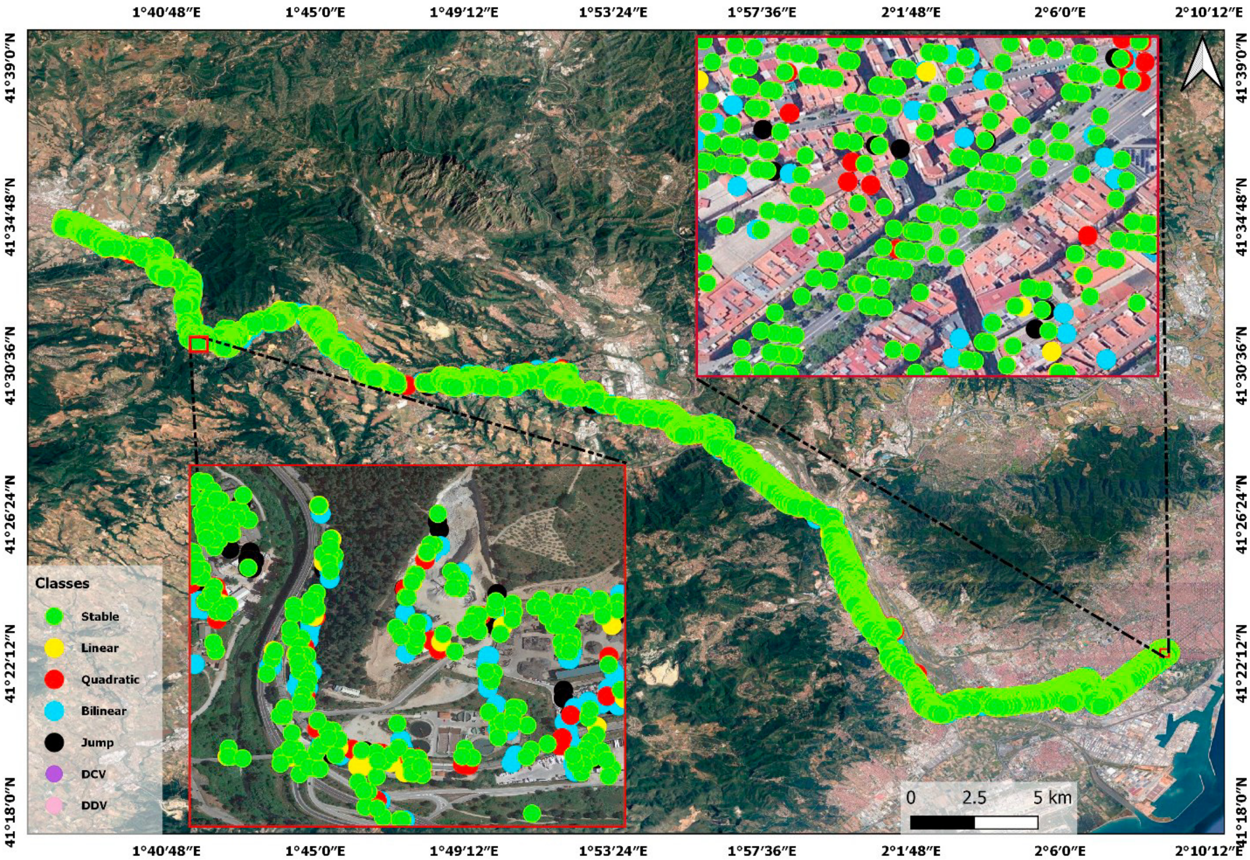

Fig. 1. Ground movement classified map of the Barcelona - Martorell - Igualada railway in 7 classes. The class of jump refers to TSs affected by PU error.

Fig. 2 show that majority of the PS were classified as *Stable*, which was anticipated since most PS do not have significant displacements over large areas. 25.1% of the study area was classified as unstable points indicating movements on those regions. In addition to the analysis of other trends, around 2399 points with PU errors were detected after four stages of PU error analysis. Additionally, *Bilinear* is the second class in number of points. Noises and residual atmospheric errors can add small jumps inside TS causing *Linear* PS to be classified as *Bilinear*. *Linear* and *Quadratic* classes were the following classes. 3565 points were *Linear* and 3340 *Quadratic*. These two groups draw more attention since their analysis are more straightforward and demonstrate crucial deformations. Indeed, regarding the orbit of satellite (i.e., ascending or descending), the displacement can be toward the satellite or vice versa. The constant rate indicates long timescales ground deformations, such as subsidence and landslides.

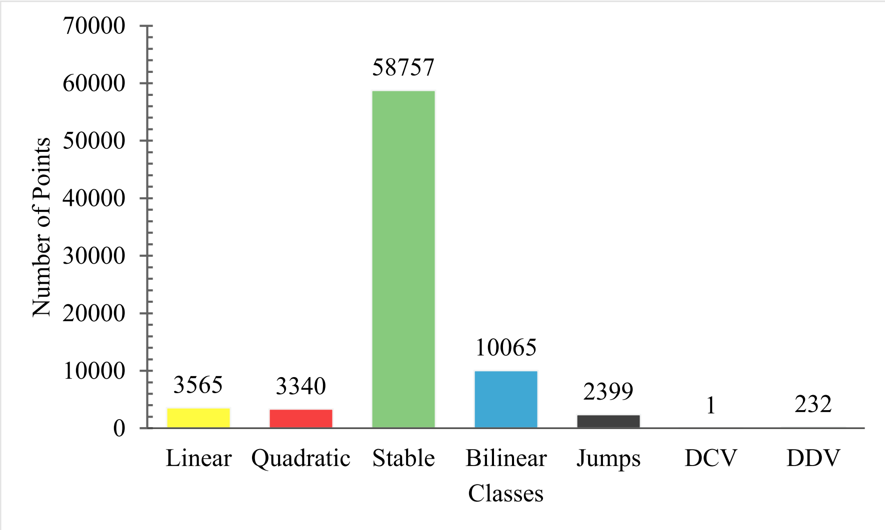

Fig. 2. Number of PS points in each class. The class of jump refers to TSs affected by PU error.

5. Conclusion

TS classification can supply additional products to detect vulnerable regions against ground deformations. Combination of the TS classified map and land cover/land use maps improves decision making for land cover/land use applications. Therefore, a PS TS classifier was prepared to evaluate the distribution of deformations trends and detect significant movements. 230 of Sentinel-1 SAR images were first procced by PSIG method to extract TS data. Then, various statistical analyses were applied to classify PS TS to seven stable and unstable trends. The method could accurately classify these trends. Finally, four stages of analyses detected points affected by PU error for the first time.

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