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Procedia Computer Science 138 (2018) 338–345

Procedia Computer Science

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CENTERIS - International Conference on ENTERprise Information Systems / ProjMAN - International Conference on Project MANagement / HCist - International Conference on Health and Social Care Information Systems and Technologies, CENTERIS/ProjMAN/HCist 2018

Analysis of InSAR displacements for the slopes around Odelouca reservoir

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Abstract

Odelouca is the second largest earth dam in Portugal and holds an important water reservoir. A displacement map for the slopes around the reservoir during the initial phase of the first filling was built using a multitemporal interferometric synthetic aperture radar (MTI) technique. A method based on cluster and time series analysis is proposed in order to find patterns on the obtained scatterers. The points are aggregated through a measure of the similarity between their displacement time series and form clusters, whose properties can then be evaluated. The analysis can be complemented by additional information for a better understanding of the influence on the ground of the storage of such a large amount of water. Three different patterns were identified on the data: stable scatterers, scatterers moving away from the sensor and scatterers moving towards it. A set of outliers was also detected. One of the clusters may contain points susceptible to landslide occurrence.

Keywords: Radar interpretation; slope instability; cluster analysis; time series analysis; Odelouca dam

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Selection and peer-review under responsibility of the scientific committee of the CENTERIS - International Conference on ENTERprise Information Systems / ProjMAN - International Conference on Project MANagement / HCist - International Conference on Health and Social Care Information Systems and Technologies.
10.1016/j.procs.2018.10.048

1. Introduction

The first filling of a water reservoir is a critical phase of the life cycle of a dam. The storage of a large quantity of water has an impact not only on the structure, but also on the slopes, which may become unstable and prone to landslide occurrence. The case of the Vajont dam, in Italy, where a rockslide into the water reservoir caused the overtopping of the dam and victimized almost 2000 people is well known [1]. Although dams are usually monitored through geodetic methods or embedded equipment, little data exist about the slopes. Traditional geodetic methods for displacement measurement on the slopes have large costs associated, thus they are rarely performed. MTI techniques may be an interesting alternative, as they enable the remote measurement of displacements, for a large number of points and with a frequency that depends on the satellite revisit time.

The interpretation of MTI results is not an easy task, as a large amount of points is usually available and it is not practicable to manually check the displacement time series of each of them. In the last years, methods for radar interpretation have been proposed. Some authors developed a tool that performs a series of statistical tests on the displacement time series to identify typical behaviors [2]. Another study uses multiple hypotheses testing to obtain kinematic parameters for each scatterer [3]. Cluster analysis has been applied to MTI results for different purposes: radar interpretation [4] and outlier detection [5].

In this study, a method to help the interpretation of MTI data is presented. Displacement time series of scatterers are compared to each other, enabling the aggregation of scatterers with similar behavior into clusters and the analysis of spatial patterns in the data. Standard displacement time series are obtained for each cluster in order to aid the assessment of the scatterers' behavior changes through time. This procedure is performed automatically and does not require *a priori* knowledge on the study area. Here, it is being applied to the slopes around a water reservoir before and during the initial phase of its first filling.

The paper is organized in the following sections: the second section presents the study area and the used dataset, the third one shows the methods. Sections four and five contain the results and their discussion, respectively. The sixth section presents the main conclusions of the work.

2. Study area and dataset

2.1. Odelouca dam

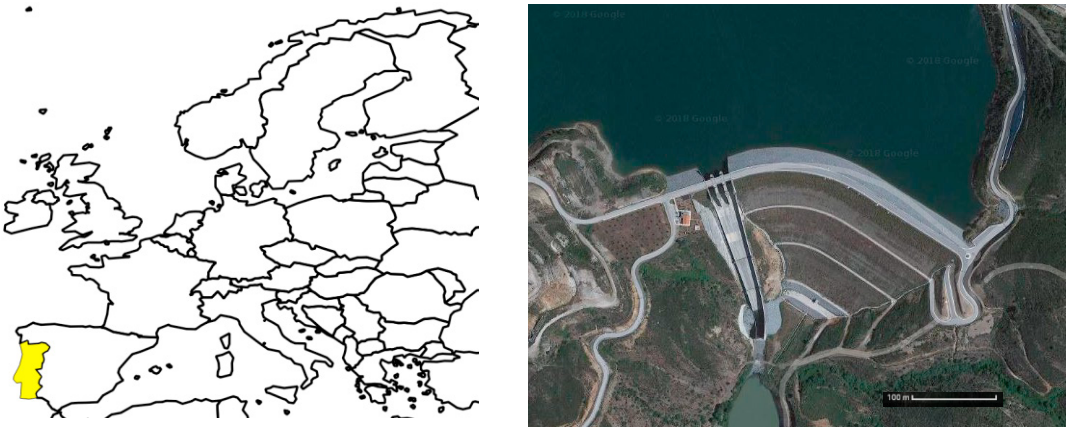
Odelouca is the second largest earth dam in Portugal. It is located in Monchique municipality, Algarve, the southernmost region of the country (Fig. 1) and it is the main source of water for public usage in the region. The dam is 76 m high and its crest is 418 m long. The reservoir spans an area of 7.8 km^2 and has the capacity for holding a maximum of 128 hm^3. The structure construction ended in March 2009 and the first filling of the reservoir started in December 2009 [6]. Several surveying operations have been performed for displacement measurement on the dam between 2010 and 2014, observing both vertical and horizontal displacements through levelling, tacheometry and global navigation satellite system (GNSS). The observed points are located on the dam crest, on the banquettes in the downstream wall and there are also some points on the emerged part of the upstream wall. The *in situ* measurements show settlements around 18 cm during that time interval for some of the points [7].

2.2. Dataset

The first filling of the reservoir is a critical phase of the structure and its surroundings safety. Therefore, this study was performed with images acquired before and during the first filling in order to check any behavior changes on the slopes around the reservoir. A dataset of 20 L-band SAR images from ALOS-1 PALSAR-1 sensor, acquired between December 2006 and April 2011 was used. These images have a revisit time of 46 days, however the time series shows some acquisition gaps, with the longest one lasting 230 days (Fig. 2). The images were acquired in Fine Beam Single (FBS) and Fine Beam Dual (FBD) modes. Polarization HH was used. L-band was used instead of C-band due to the presence of vegetation on the region of interest (ROI).

The digital elevation model (DEM) obtained from Shuttle Radar Topography Mission (SRTM) was used, with 90 m of spatial resolution. SRTM was obtained from data collected in 2000, when the dam was not built yet.

Water level values in the reservoir had been accessed through the National Information System for Hydric Resources. These values were acquired every 15 days for the Odelouca stream, between December 2009 (when the first filling started) and September 2014. Therefore, there is only a small time interval with both SAR images and water levels available.



(a) (b)

Fig. 1. (a) location of Portugal (in yellow); (b) Odelouca dam (©Google maps).

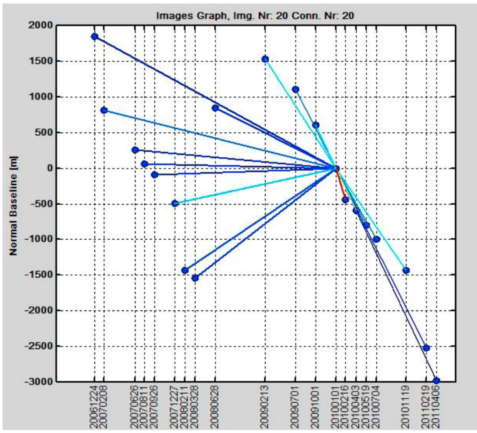


Fig. 2. Distribution of temporal (horizontal axis) and normal (vertical axis) baselines.

3. Methods

3.1. MTI processing

A version of the persistent scatterer interferometry (PSI) technique implemented at SARPROZ© software [8] that considers non-linear displacements was applied on the data. An area of 18 km x 18 km containing the reservoir of Odelouca dam was selected. An image acquired on January 2010 was selected as master and the slaves were coregistered into its geometry. Atmospheric Phase Screen (APS) was estimated for a set of scatterers with high amplitude stability index values and then interpolated for all pixels in the image. As the images were acquired before and during the initial phase of the first filling, linear displacements are not expected, as changes in the ground behavior might have occurred. Therefore, a non-linear displacement model was applied for cumulative displacement and residual height estimation. For further analysis, only scatterers (here called non-linear persistent scatterers – nlPS) with temporal coherence greater or equal than 0.95 were used.

3.2. Cluster analysis

A program was developed in R [9] to perform the clustering of nlPS with similar behavior. The construction of nlPS clusters enables the simultaneous analysis of properties of thousands of points, avoiding the need to manually check them individually.

The data required to perform the cluster analysis is obtained from the MTI processing: coordinates, altitude, cumulative displacement, temporal coherence and the displacement time series. The selection of nlPS for the analysis is performed based on the ROI of the study and on a threshold for temporal coherence. Additional information for nlPS characterization can be inputted, for example slope, distance to geological faults or distance to water lines. In this study, nlPS located around the reservoir inside a buffer of 1 km were considered. Three additional variables were used: slope, curvature and aspect; which may provide information about the susceptibility for landslide occurrence [10]. The additional variables were built from SRTM using ArcGIS® software.

The clustering of the nlPS is performed based on the displacement time series of each point. The similarity between the time series of each couple of nlPS is computed, building a similarity matrix. A hierarchical clustering method is then used to aggregate the nlPS with the most similar displacement time series, successively until all nlPS are together in a single cluster. Analyzing the distances between each cluster, an adequate number of clusters to describe the problem being studied can be identified.

In this study, the similarity between displacement time series was evaluated using a technique called dynamic time warping [11][12]. The distance between the displacement values corresponding to each pair of dates from the time series was computed and then the shortest path was chosen. Constraints may be imposed on that path. A constrain on its slope was applied to avoid the association of displacement values observed at very different epochs.

Hierarchical clustering methods consider each element being clustered (here the nlPS) as individual clusters and use an aggregation criterion to join the most similar clusters into new ones. In this study complete linkage was used as the aggregation criterion, which aggregates clusters with the smallest distance between them. The considered distance is that between the farthest elements composing each cluster [13]. The method was chosen due to its ability to form compact clusters but also for being sensitive to the presence of outliers.

After choosing the number of clusters to consider, aggregated measures for each cluster were computed, namely the centroids for all the variables, boxplots with their dispersion values and standard displacement time series for each cluster. The standard displacement time series are the average displacement time series of the nlPS that form each cluster. Displacement standard deviation for each cluster was also plotted.

4. Results

The MTI processing enabled the detection of 2682 nlPS. The cumulative displacement values for the time interval between December 2006 and April 2011 vary from 104.8 mm away from the sensor to 100 mm towards the sensor. However, such values are only observed for a small number of nlPS, probably corresponding to outliers. Most cumulative displacement values are between -40 mm and +40 mm. Fig. 3 shows the cumulative displacement map obtained for the ROI.

The similarity matrix built from the similarities between the displacement time series for each pair of nlPS enabled the construction of a dendrogram, which is a tree graph showing how each cluster is agglomerated to each other and the distance between each cluster. Whenever two clusters separated by a large distance are aggregated, it means that the nlPS forming those clusters are not very similar and thus, they might be considered as separated clusters. It was verified that solutions considering two or four clusters could be appropriate to evaluate this problem. The solution of two clusters was verified to separate the nlPS into a cluster with points scattered along the ROI showing extreme cumulative displacement values (probably outliers) and a cluster with all the remaining nlPS. As we are interested in identifying spatial heterogeneities among the non-outlier nlPS, the solution with four clusters was chosen instead.

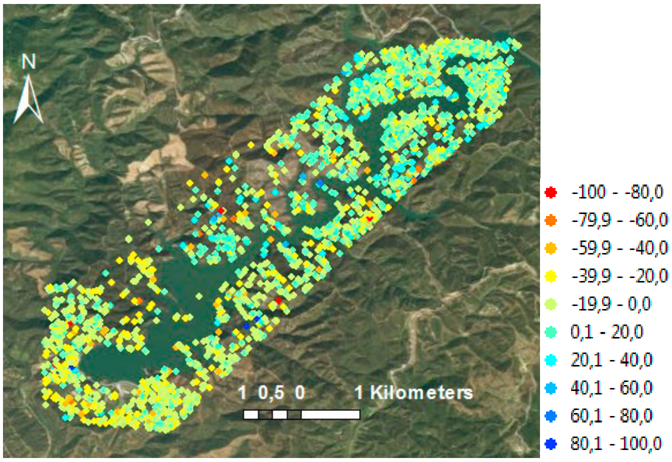


Fig. 3. Map of cumulative displacement (mm) between December 2006 and April 2011.

Fig. 4 shows the location of the nlPS forming each cluster. Cluster 1 is mainly located nearby the dam, while cluster 2 has a larger number of points farther from it. Cluster 3 corresponds to a few isolated nlPS scattered along the ROI, while cluster 4 is formed only by three nlPS far from each other.

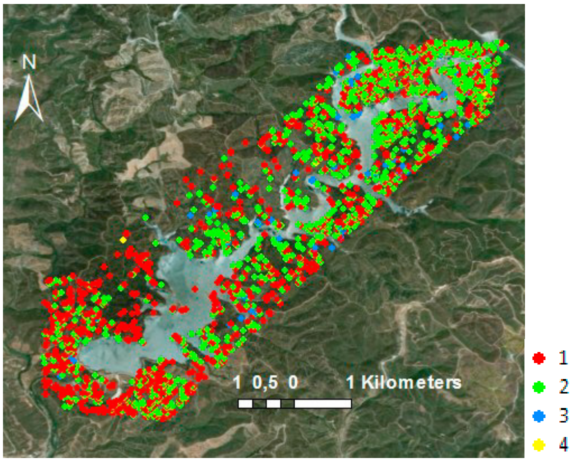


Fig. 4. Location of the nlPS forming each cluster.

Table 1 presents the properties of each cluster. Most nlPS are included in clusters 1 and 2. Cluster 1 is the only one that presents average movement away from the sensor, while the remaining three show movement towards the sensor with different magnitudes. Clusters 1, 2 and 3 show similar average slope values, with only cluster 4 presenting a larger one (17.5º). Clusters 1 and 2 are mainly located on convex regions (positive curvature), while clusters 3 and 4 can be found in concave areas (negative curvature). Aspect values increase clockwise with origin from North, so in average, nlPS are located in slopes facing southwest for all clusters.

Table 1. Cluster properties.

Cluster	Number of nlPS	Relative number of nlPS (%)	Average cumulative displacement (mm)	Average slope (º)	Average curvature (m^{-1})	Average aspect (º)
1	1169	43.6	-17.0	12.9	0.044	213
2	1435	53.5	3.1	13.2	0.021	209

3	75	2.8	38.6	12.3	-0.004	211
4	3	0.1	181.4	17.5	-0.266	227

Fig. 5 shows the standard displacement time series for each cluster. It is observed that nlPS from cluster 1 show a trend to move away from the sensor, while nlPS from cluster 2 are mainly stable, showing a few oscillations. The nlPS forming cluster 3 tend to move towards the sensor and nlPS in cluster 4 also shows movement towards the sensor but with larger magnitude. Displacement dispersion around the average value is not large, assuring that the nlPS forming each cluster have similar displacement time series.

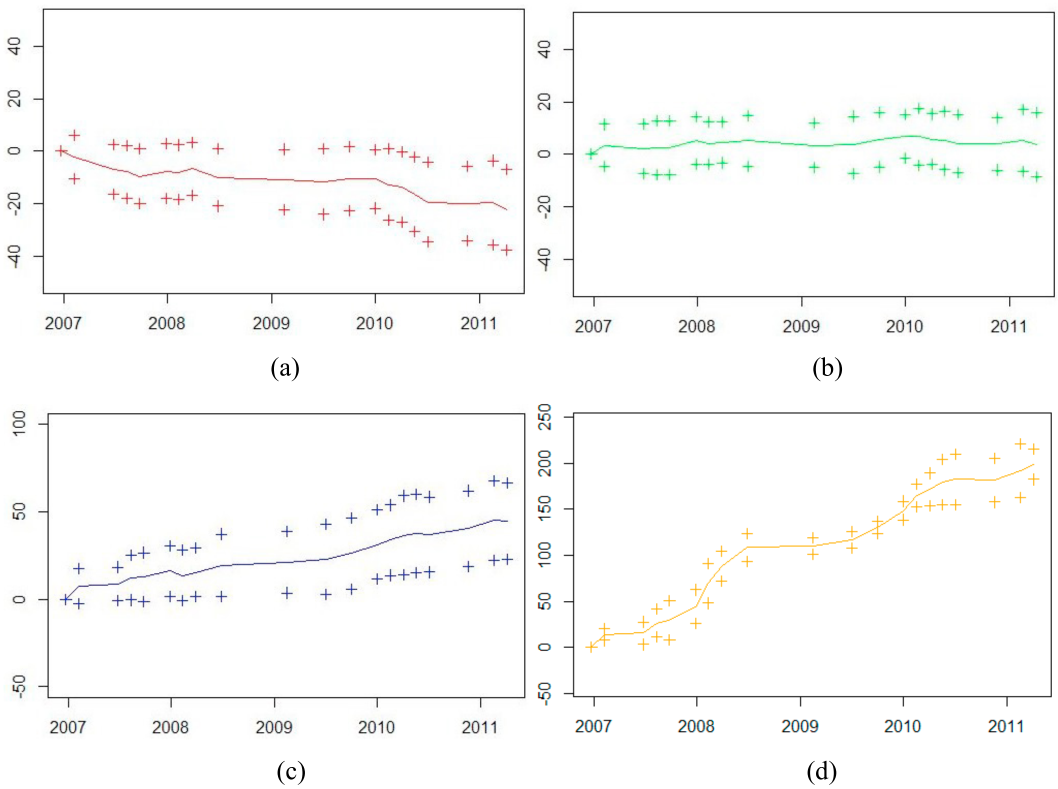


Fig. 5. Standard displacement time series: (a) cluster 1; (b) cluster 2; (c) cluster 3; (d) cluster 4; vertical axis is displacement in mm; crosses are average displacement plus and minus one standard deviation.

5. Discussion

The usage of L-band images enabled the detection of a large number of nlPS even on a vegetated area. Cluster 4 is formed only by three isolated nlPS, which show displacements with large magnitude. These nlPS were considered as outliers and are not used for further analysis.

The nlPS from the other three clusters are spread through the ROI. Those belonging to cluster 1 are located mainly downstream and nearby the dam. In average they show movement away from the sensor (17 mm in approximately four years) and their standard displacement time series shows larger movements away from it between December 2006 – September 2007, March 2008 – June 2008, January 2010 – July 2010 and February 2011 – April 2011. The last two intervals are already during the first filling of the reservoir, thus it is possible that the observed displacements away from the sensor may be caused by the ground settlement due to the weight of the water that was being accumulated there. This result is coherent with the region close to the dam being the most affected. The reason for the movement away from the sensor for the first two time intervals is still being researched.

The nlPS from cluster 2 are mainly located on the regions far away from the dam. They present an average cumulative displacement of 3.1 mm in four years and the standard displacement time series shows some oscillations, but not a clear trend away or towards the sensor. This result is coherent with the regions farther away from the dam being less affected during the initial phase of the first filling, as probably the water had not reached those areas during the time interval with available SAR images.

The nlPS from cluster 3 show an almost linear trend of movement towards the sensor, with an average cumulative displacement of 38.6 mm.

Fig. 6 shows the comparison between the standard displacement time series and the water level on the reservoir for the time interval where both types of data are available. A large increase in the water level occurred on December 2010 (approximately 10 m), but its effect on the slopes is not clear on the standard displacement time series. For the three clusters, displacement away from the sensor is detected slightly after that large raise in the water level (the two last images), but there are not enough images to verify if that trend continues. That movement away from the sensor has the largest magnitude for cluster 1 and the smallest for cluster 3. By the time the first filling of the reservoir started, changes are found in the standard displacement time series. On the first six months of the first filling, nlPS from cluster 1 moved 8.8 mm away from the sensor, nlPS from cluster 2 also moved away from the sensor 2.8 mm and nlPS from cluster 3 moved 5.6 mm towards the sensor. Once again, the effect of the first filling on the reservoir banks is stronger for cluster 1, i.e., for the regions closer to the dam, as expected.

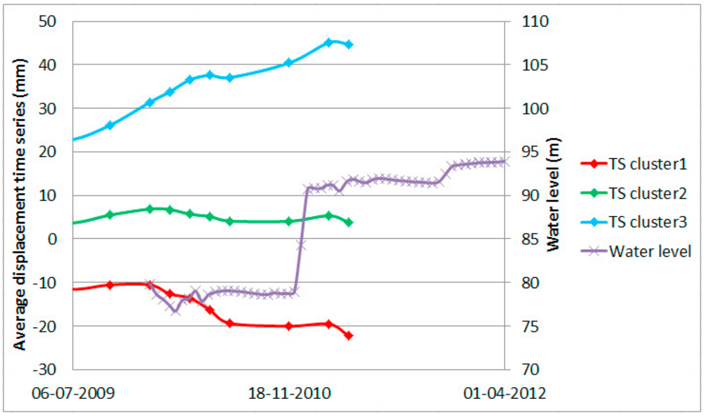


Fig. 6. Standard displacement time series (TS) for each cluster and time series of water levels.

Average slope and curvature can be used to compare the susceptibility to landslide occurrence between clusters. According to reference [10], landslides usually occur for slopes with values between 10º and 15º. The average slopes of the three clusters being studied are within this range, meaning that following this criterion, landslides may occur on any of them. According to the same reference, landslides are more likely to occur on surfaces slightly concave. Therefore, cluster 3 shows larger susceptibility to landslide occurrence than clusters 1 and 2, as it has average curvature below zero. Fig. 4 shows several nlPS from cluster 3 close to the water, which should be given some attention in future field works to check for ground instability. To the authors' knowledge, landslides have not occurred there until the present days, showing that the situation may have stabilized.

The main limitation of the presented approach is the processing time of the time series analysis. In this case, it took five hours in a computer with 3 GHz CPU and 4 GB of RAM.

6. Conclusion

This study presents the analysis of slope stability on the banks around the reservoir of one of the largest earth dams in Portugal, Odelouca dam. The paper proposes a method for analyzing the large amount of information obtained from MTI processing. It uses time series clustering techniques to form nlPS clusters and no *a priori* knowledge about the phenomenon under study is required. All mandatory data for the analysis is directly obtained from MTI processing, however the user can improve the analysis by adding supplementary data. The method enables the user to identify spatial patterns and to easily assess properties that would be difficult to get if nlPS were to be individually checked. The main limitation is the processing time.

Four clusters were identified on the ROI. The first one, mainly located near the dam, shows signs of behavior changes, possibly caused by the first filling of the reservoir. The second one, with nlPS farther away from the dam, seems to have a stable behavior. The third one presents properties which indicate some susceptibility to landslide occurrence. The fourth one contains outliers and was discarded from the analysis.

In conclusion, the proposed method enabled the identification and analysis of the behavior patterns present in the study area, which may be useful for geotechnicians to perform risk analysis.

Acknowledgements

The authors would like to thank JAXA for providing the ALOS-1/PALSAR-1 images in the scope of the 6th Research Announcement. D. Roque would like to thank the Portuguese Foundation for Science and Technology for a PhD scholarship (SFRH/BD/115882/2016).

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