

Self-organizing-Map Analysis of InSAR Time Series for the Early Warning of Structural Safety in Urban Areas

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Abstract. Among the many causes of collapse of civil structures, those related to the downfall of foundations are crucial for their likely catastrophic consequences. Interferometric synthetic aperture radar (InSAR) techniques may help monitoring the time evolution of ground displacements affecting engineered structures in large urban areas. Artificial neural networks can be exploited to analyze the huge amount of data that is collected over long periods of time on very dense grid of geographical points. The paper presents a neural network-based analysis tool, able to evidence similarities among time series acquired in different points and times. This tool could support an early-warning system, aiming to forecast critical events in urban areas. The implemented procedure is tested on a dataset of InSAR time series recorded over an area of the city of London.

Keywords: Remote sensing · Collapse prevention · Early warning in urban areas · InSAR time-series · Artificial neural network · Autoencoding · Ground settlements · Structural safety

1 Introduction

The health monitoring of civil structures generally entails performance assessment and structural damage detection, which are typically achieved through in-situ sensing campaigns [1–6]. When very big structures (dams, viaducts, aqueducts) or blocks of many buildings (in urban areas) need to be monitored, classical in-situ techniques may become expensive and even impractical. In these cases, remote sensing based on InSAR techniques can be very useful for reveling signs of distress characterizing a structure or an infrastructure during its life span [7–10].

Such techniques can help to monitor long-term ground displacements, the most critical of which can put the foundations' stability of structures and infrastructures at risk [11–14].

This study aims to provide a data analysis procedure, which can be used as a tool to forecast incoming phenomena of foundation downfalls and subsidence in large urban areas. For this purpose, an artificial neural network-based algorithm is implemented to process InSAR data in real-time to obtain an automatized alert system. A database of ground displacement time-series recorded over a long period of time (more than four years) at a high-density grid of geographical points within the city of London, is adopted to test the method.

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It can be noted that neural network-based methods have been already applied to the civil engineering field [15, 16], while early-warning systems have been developed to forecast different kinds of risk [17–21]. However, there is a lack of systematic automatized procedures to analyze InSAR-recorded time-series of ground displacements in urban areas, able to provide failure risk early-warning systems.

Based on clustering subsets of sequences through a neural network learning, the method presented in this paper leads to identify similarities among time series acquired in different points and times. The assumption is that critical events, such as downfalls and subsidence, are preceded by typical behaviors of the ground. Therefore, based on similarities with previous records, a monitoring system able to foresee incoming critical events can be developed. The paper aims to demonstrate the suitability of the approach to detect such similarities, while the detection of actual critical cases is beyond the scope of this work.

2 The Early-Warning Method

A Self Organizing Map (SOM [22]) is a kind of artificial neural network [23, 24] that is trained through Unsupervised Learning (UL) [25]. Unlike the more popular supervised learning (Multi-Layer Perceptrons, Support vector machines, Radial basis functions), where the neural network is adapted in order to associate training input patterns to corresponding desired outputs, the UL is based on finding unknown features of the input data distribution, such as principal directions [26] or presence of clusters [27]. Thus, unlike in the supervised learning, in the UL it is not possible to define an error since no target is defined. An internal updating rule is defined instead, which tends to "imitate" the inputs of the training set. It is worth to note that some operations are mandatory in both supervised and unsupervised learning as, for instance, splitting the dataset into Training, Validation and Test sets. In this work, the SOMs are used to cluster the time sequences of displacements, in order to highlight similarities between on-line recorded data and pre-selected sequences exhibiting critical behaviors.

A flowchart of the method is provided in Fig. 1. In some phases of the process the intervention of the Operator is foreseen. Anyway, it is limited only to the selection of the set of examples, without prejudicing the unsupervised learning paradigm.

The method follows three separated branches: Sequences selection, Training and Monitoring. In the Sequence-selection phase, a subset of time sequences is selected for the successive phase of Training. This selection aims to reduce the number of training examples, by increasing the relevance of critical behaviors. A ranking of the time sequences is preliminary obtained, based on a given feature that can be, for instance, the range of values or the instantaneous rate. Only the sequences that are above a fixed position in the ranking are kept for the Training phase (ranking-based selection). During the Sequence-selection phase, the Operator establishes the feature for the ranking and the threshold for the selection. The selected sequences are thus stored into the database. The obtained subset is furtherly reduced before the Training (cluster-based selection), by using a SOM which clusters the subset of sequences. The Operator selects some clusters of interest, and the sequences belonging to these clusters form the final Training set, which is stored into the Database.

The Training phase consists in clustering the time windows extracted from the sequences. Once the Operator has set the window duration, the training is processed automatically. Let N be the number of samples of each sequence and W the samples of a window, then $F = N - W + 1$ is the number of windows for each sequence. The number of sequences of the Training set multiplied by F gives the set of patterns that are clustered by a new SOM network, which will be used as alarm generator in the Monitoring phase. The clusters containing windows associated to critical events are labelled as "warning". Both the trained SOM and the list of warning clusters are stored into the Database.

The Monitoring phase generates early warnings of potential critical events in the area under control. For each of the monitored points in the area, a window covering the last W samples of the recorded time-sequence, is extracted. All these patterns (last windows of the time series) are fed to the previously trained SOM, which assigns them to the different clusters. The Monitoring phase can follow two distinct paths. In the first one (Procedure 1), an alarm is generated for all the windows falling in "warning" clusters, and the corresponding points are highlighted in the city map. The criterion to label as "warning" a cluster is established by the Operator. In the alternative path (Procedure 2), a specific event represented by a noticeable window is chosen by the Operator, and the cluster which this window belongs to is labelled as "warning". Again, the windows of the monitoring set that fall in the "warning" cluster, make the corresponding geographical points be marked in the city map as "warning points".

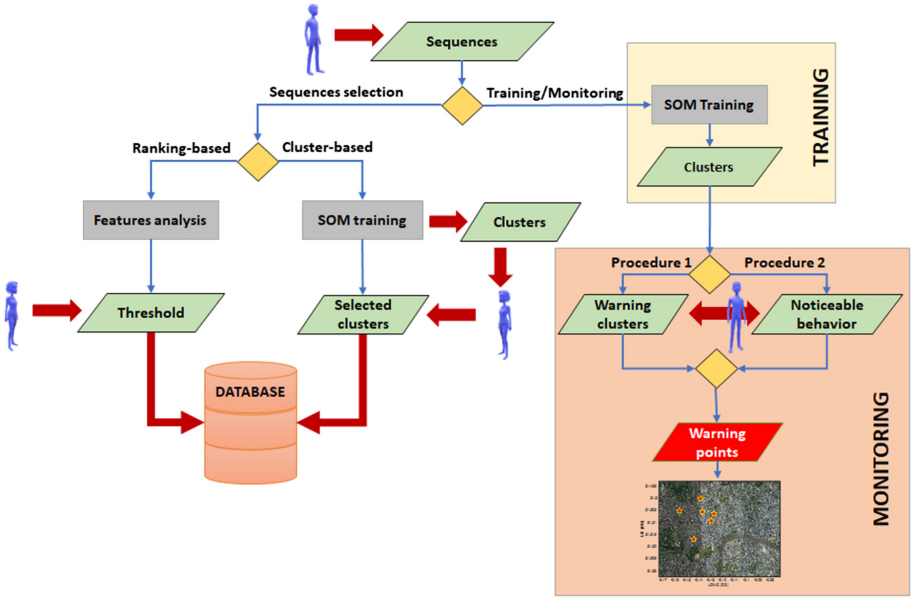


Fig. 1. Flowchart of the method

3 Applying the Method to a Database of Sequences (London)

A database of displacement time-histories recorded by means of InSAR remote sensing at 228701 geographical points of a large area of the city of London (see Fig. 2) and elaborated through the multitemporal technique MT-InSAR was considered to test the method described in Sect. 2. The same geographical area and InSAR time-histories have been used in [8, 9], to which the reader may refer for more details about the data. The displacements were recorded from April 2011 to December 2015 at irregular time-intervals. Four instances of time-histories taken from the database are plotted in Fig. 3. Three of them show a behavior that may require attention, while the last one is a normal trend of ground displacements.

By means of linear splines, the sequences were divided into regular time intervals and collected in a matrix of 228701 rows and 81 columns, these latter corresponding to the samples.

A subset of sequences was initially selected through the ranking-based criterion, assuming the range of values in the sequence as parameter for the ranking. A lower bound of the positions in this ranking was set and the sequences overcoming this bound were kept as the first skimmed subset. This subset was made up by 57176 sequences. The cluster-based criterion was then applied to this subset. A SOM network, with 10×10 outputs, was trained to obtain a clustering of the subset. The clusters of interest were finally selected based on their behavior, and the sequences belonging to them formed the training set of the early warning system. The final training set contained 5960 sequences.

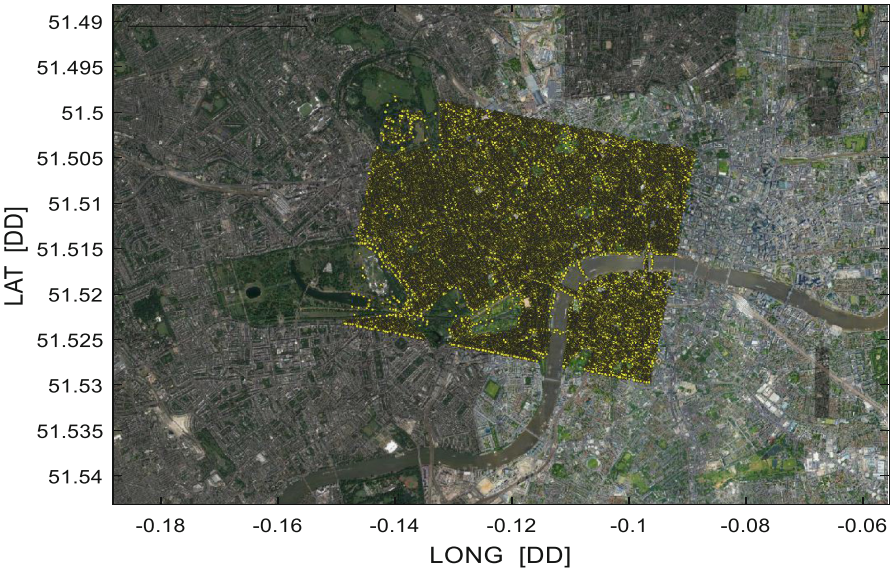


Fig. 2. The geographical points of the database of London, scale 1:50000 [8, 9].

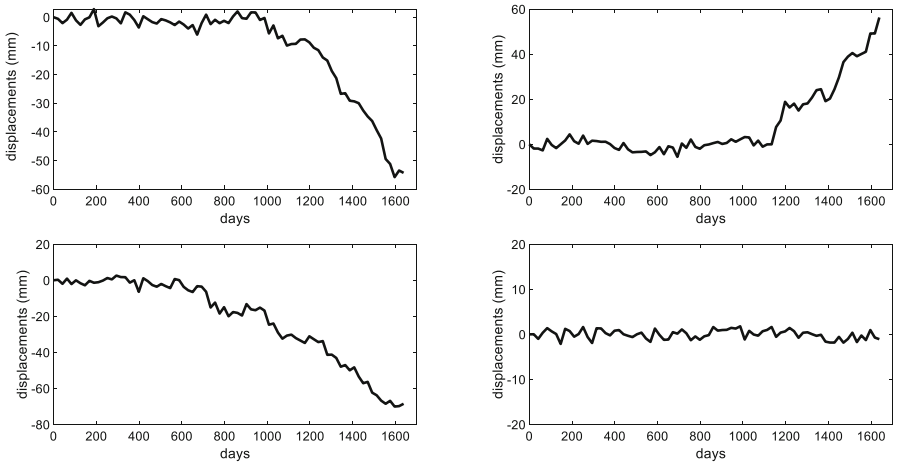


Fig. 3. Some sequences of displacements taken from the database of London

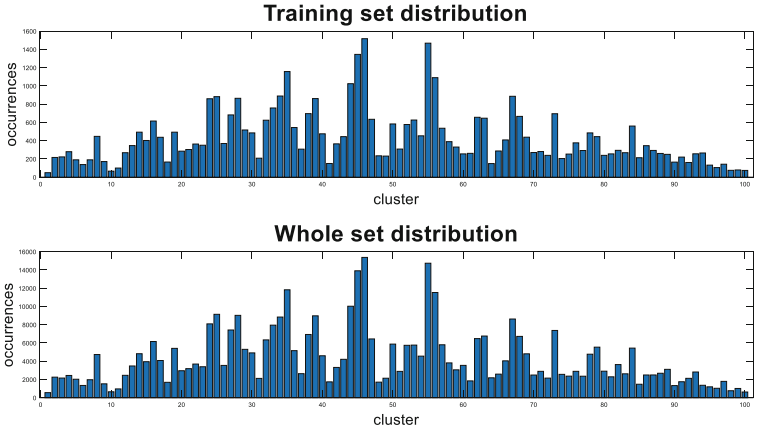


Fig. 4. Histogram of the clusters' incidence in the training subset and in the entire set.

A new SOM network, with 100 outputs, was trained on sequences' windows of 10 samples. It is worth to note that each sequence gave rise to $81 - 10 + 1 = 72$ windows, so that the dataset for the training consisted of $5960 \times 72 = 429120$ windows. A 10% of this dataset was considered as training set, while the remaining part was adopted as validation set. Figure 4 shows how the windows are distributed among the clusters in the training and validation sets, respectively. A comparison between the two histograms highlights the capability of the SOM network, trained over the training set, to represent the whole distribution.

The trained SOM was ready to generate warnings over the last (most recent) windows of all the sequences of the monitored area. This could be done by applying Procedure 1 (warning clusters) or Procedure 2 (noticeable behavior).

3.1 Monitoring Through Procedure 1

According to Procedure 1, an analysis of the clusters obtained by applying the SOM network to the patterns of the Training set, was preliminarily made. The analysis was based on a density-contour-plot of points related to each cluster. Based on this analysis criterion, most of the clusters have been found to be of very little interest to the goal of the procedure, due to the homogeneous distribution of the involved points in the area (an instance of a non-significant cluster is provided in Fig. 5).

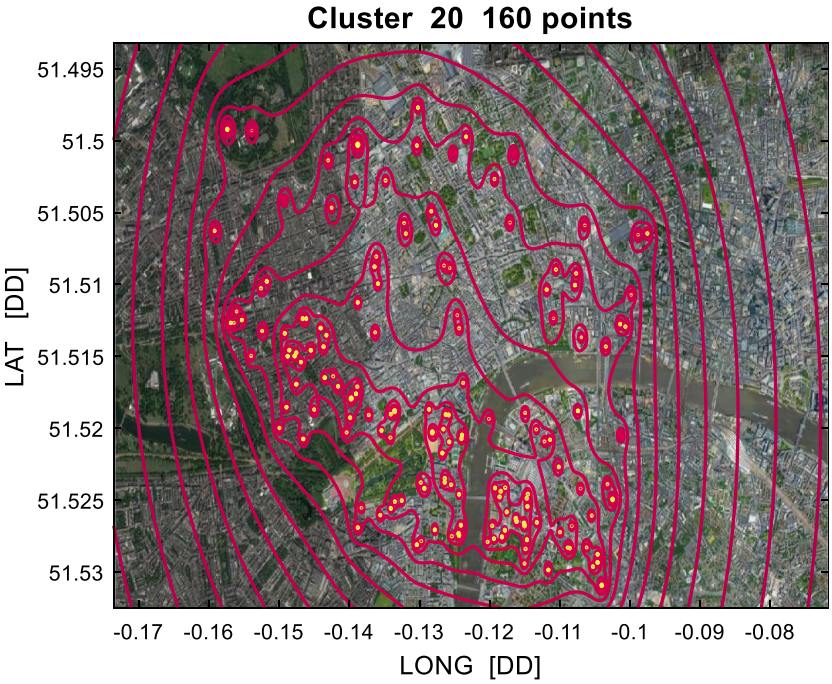


Fig. 5. An instance of the density distribution of the geographical points relevant to a non-significant cluster (Procedure 1).

Only two clusters were selected to the phase of monitoring, namely Cluster 46 and Cluster 10. The first one (see Fig. 6) was labelled as "warning" due to the high concentration of points on specific areas (yellow clouds of points). Such areas were found to lay along the path of the cross-rail twin tunnels that were under excavation during the period of acquisition of the data. The effects of these excavations on adjacent buildings were studied in [8, 9]. The second "warning" cluster was chosen due to the low number of involved points (see Fig. 7a), which is related to a rare and for this reason a possible anomalous behavior. Figure 7b shows the average trend and the upper and lower envelopes of the cluster.

It is to note that the criteria adopted herein to select the "warning" clusters in Procedure 1 are just some of the possible criteria that may be chosen by the Operator, who could also, for instance, base his decision on the examination of the average trend and the range of the displacements in the cluster. An examination of all the possible criteria that could be adopted is beyond the scope of this work, the aim of which is to demonstrate the attitude of the approach to reveal similarities between recorded and current time series. In this example, therefore, the choice of the critical clusters was made for the sole purpose of showing the functionality of the proposed method.

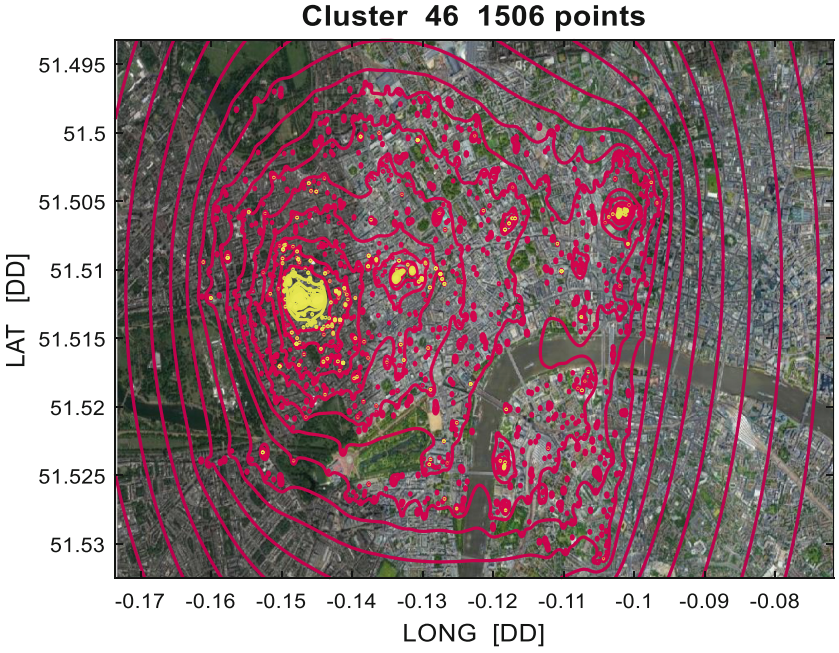


Fig. 6. Density-contour-plot of points related to cluster 46, selected to apply Procedure 1.

The trained SOM was then recalled on the windows to be monitored. Those that fell within the selected clusters made the points to which they belong be labelled as "warning". In Fig. 8 are displayed the geographical points associated to Cluster 46. The monitoring procedure evidenced that the swarm of points with analogous behavior is propagating over a larger area. The nature of this behavior is to be investigated after the training phase, when the cluster is defined. Since large clusters are characterized by dispersed behaviors, the kind and the likely severity of the phenomenon should be evaluated through in-situ inspections. Once this phenomenon has been classified as "critical", Procedure 1 is able to provide information about its ongoing spatial evolution.

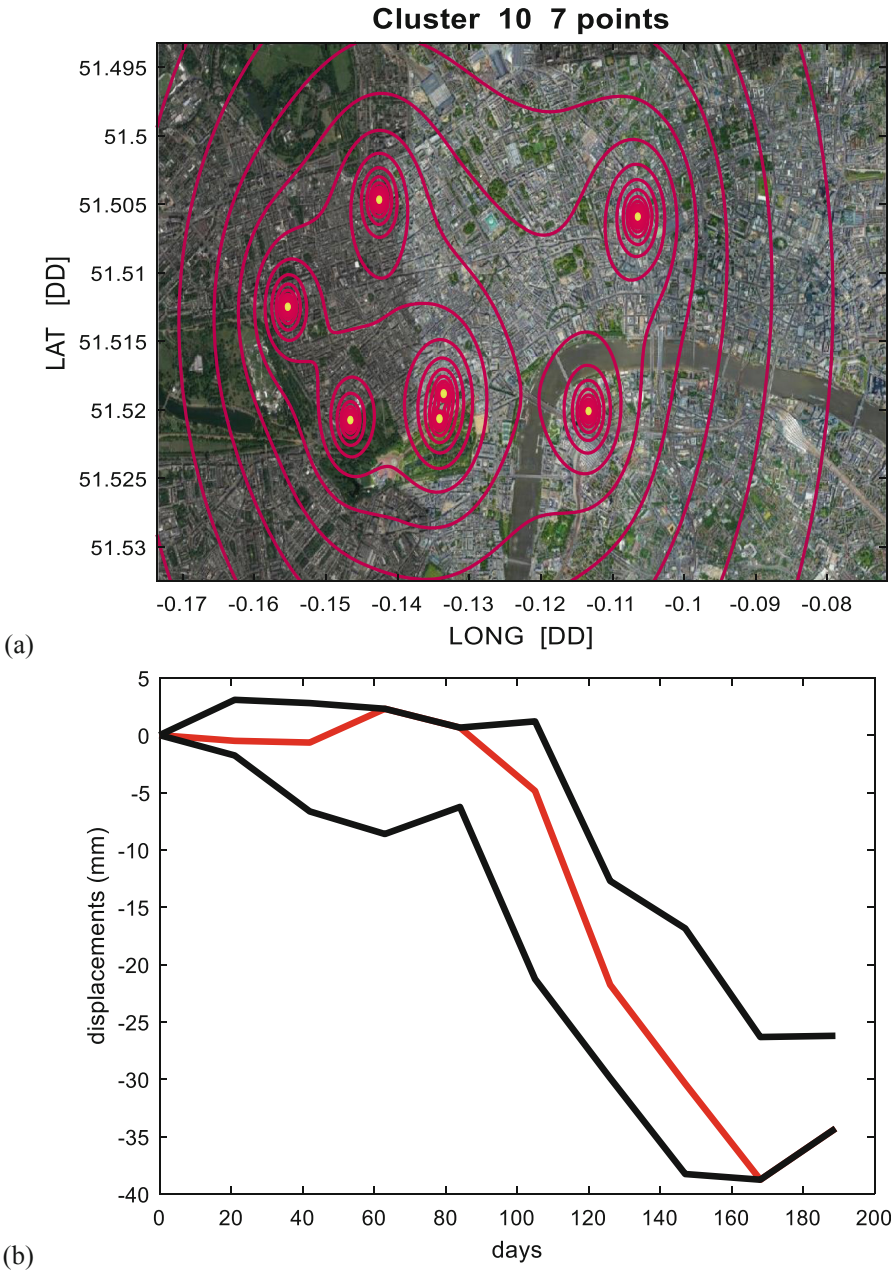


Fig. 7. (a) Density-contour-plot of points related to Cluster 10, selected to apply Procedure 1; (b) prototype (in red), upper and lower envelopes (in black) of the cluster (Color figure online).

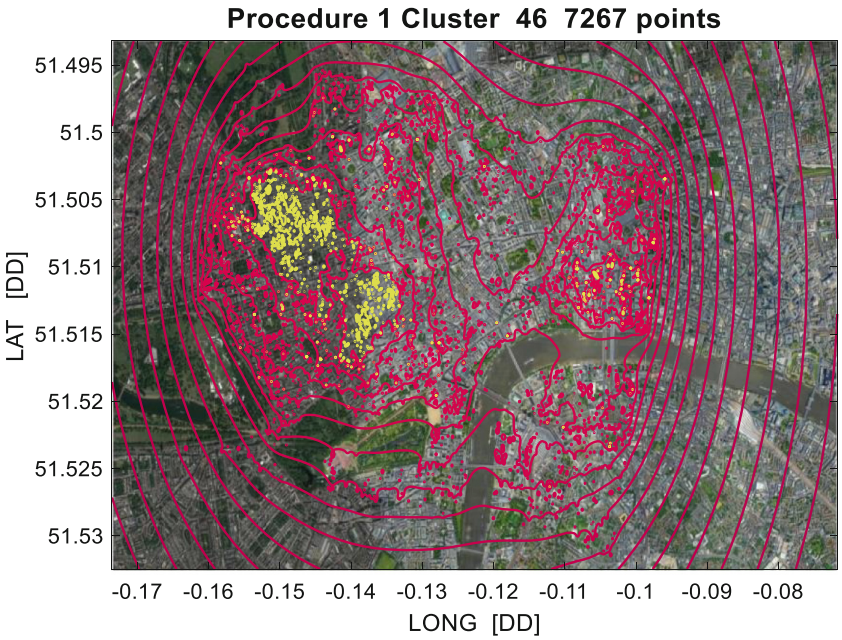


Fig. 8. Density-contour-plot of points obtained by applying Procedure 1.

When applied to Cluster 10, Procedure 1 did not provide any point. In this case, very few points belong to the cluster (see Fig. 7a) and a rather anomalous behavior characterizes the cluster (Fig. 7b). Therefore, it is reasonable that a similar behavior is not detected in the monitoring period.

3.2 Monitoring Through Procedure 2

By following Procedure 2, a window was selected due to its noticeable behavior, namely the one plotted in red in Fig. 9a. In Fig. 9b is evidenced the relevant geographical point. In this case, the cluster which this noticeable window belongs to was considered as a "warning cluster" in the monitoring phase. The monitoring was then carried out by following the same steps followed in Procedure 1. The geographical points labelled as "warning" according to Procedure 2 are plotted in Fig. 10a. It can be noted that only 6 points were found, which confirms the anomaly of the considered behavior. The windows belonging to these points are plotted in Fig. 10b (in blue) together with the selected noticeable window (in red). The comparison between the reference window and the windows detected though Procedure 2 shows the good ability of the method to find similarities of behavior.

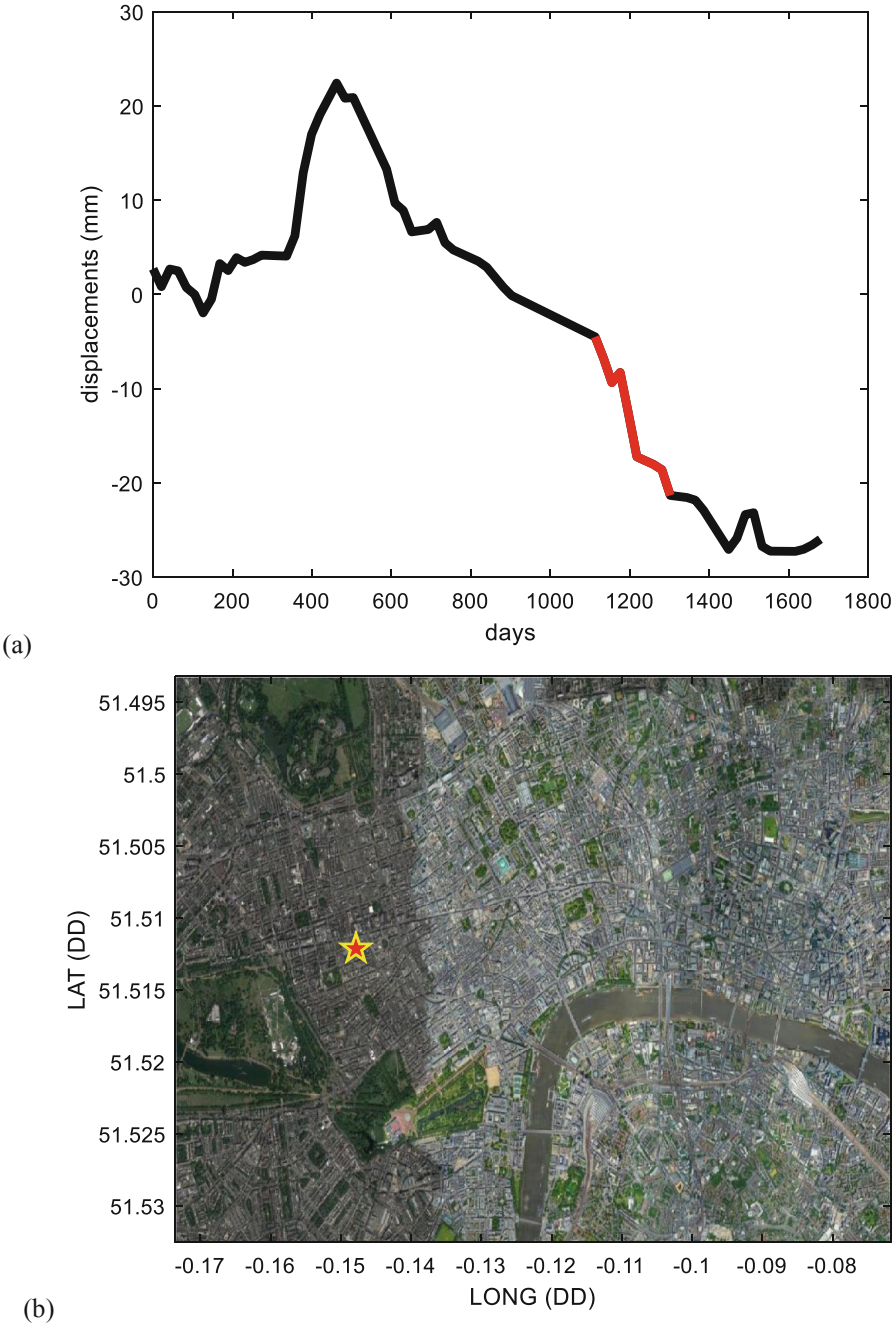
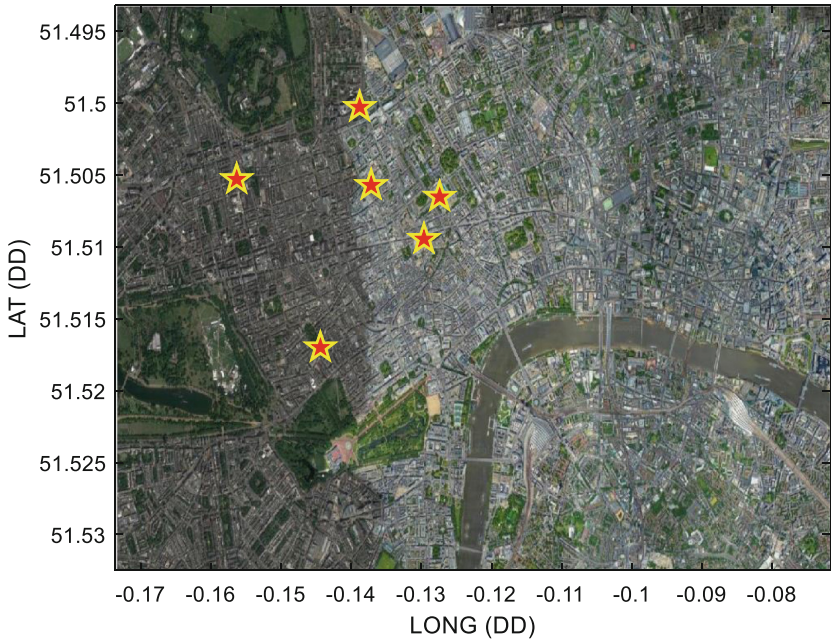
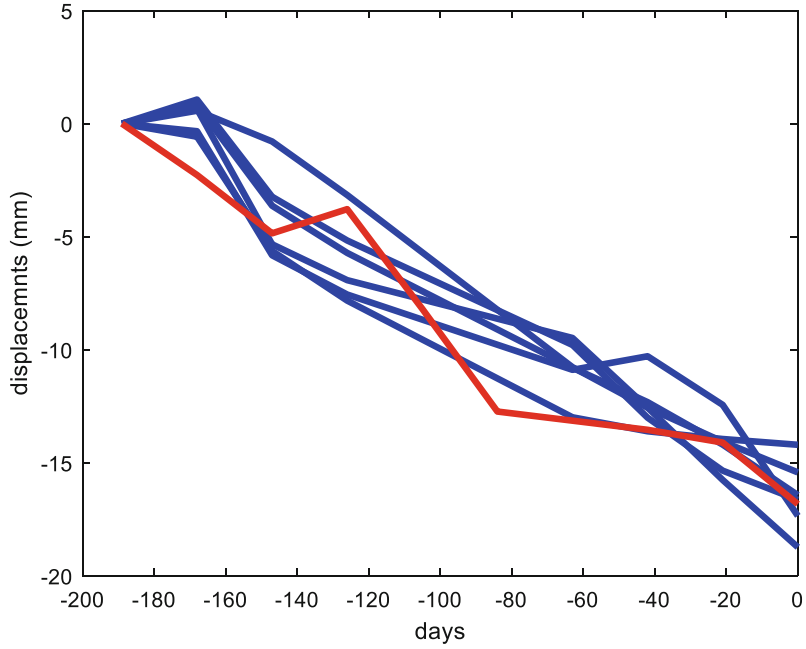


Fig. 9. (a) Noticeable behavior and (b) relevant geographical point selected in Procedure 2.



(a)



(b)

Fig. 10. (a) Warning points obtained with Procedure 2; (b) reference window (red) and warning windows (blue) (Color figure online).

4 Conclusions

The paper presents a method to analyze big data relevant to time-series of displacements recorded through InSAR techniques in urban areas. The method highlights similitudes among displacement sequences by means of a self-organizing-map neural network. Based on the similitude between recent time-series and critical events occurred in the past, incoming critical behaviors can be forecasted.

A dataset of displacements time-series, recorded at a very dense grid of geographical points in a large area of London, is taken as a case-study to test the method. Rate and range of displacements are assumed as target features in the application. The method presented in the paper is a preliminary tool that can form the basis for the development of an automatized early-warning procedure to forecast critical events relevant to ground displacements that may affect the stability of engineered structures in large urban areas. The method is assumed to be used by expert operators, who can select the more appropriate time-window duration and decide which target features are more suitable to forecast specific alarm behaviors. The correct framing of the events labelled as "warning" should be directed to successive in situ inspections and expert analysis.

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References

1. Chen, C.H. (ed.): Ultrasonic and advanced methods for nondestructive testing and material characterization. World Scientific Publishing, Singapore (2007)
2. Porcu, M.C., Pieczonka, L., Frau, A., Staszewski, W.J., Aymerich, F.: Assessing the scaling subtraction method for impact damage detection in composite plates. J. Nondestruct. Eval. **36**(2), 1–16 (2017). https://doi.org/10.1007/s10921-017-0413-9
3. Porcu, M.C., Patteri, D.M., Melis, S., Aymerich, F.: Effectiveness of the FRF curvature technique for structural health monitoring. Constr. Build. Mat. **226**, 173–187 (2019)
4. Frau, A., Pieczonka, L., Porcu, M.C., Staszewski, W.J., Aymerich, F.: Analysis of elastic nonlinearity for impact damage detection in composite laminates. J. Phys: Conf. Ser. **628**(1), 012103 (2015)
5. Loi, G., Porcu, M.C., Pieczonka, L., Staszewski, W.J., Aymerich, F.: Scaling subtraction method for damage detection in composite beams. Procedia Structural Integrity **24**, 118–126 (2019)
6. Floris, I., Sales, S., Calderon, P.A., Adam, J.M.: Measurement uncertainty of multicore optical fiber sensors used to sense curvature and bending direction. Measurement **132**, 35–46 (2019)
7. Milillo, P., Porcu, M. C., Lundgren, P., Soccodato, F., Salzer, J., Fielding, E., Biondi, F.: The ongoing destabilization of the Mosul dam as observed by synthetic aperture radar interferometry. In: 2017 IEEE International Geoscience and Remote Sensing Symposium (IGARSS). pp. 6279–6282 (2017)

8. Milillo, P., Giardina, G., DeJong, M., Perissin, D., Milillo, G.: Multi-temporal InSAR structural damage assessment: the London crossrail case study. Remote Sens. **10**(2), 287 (2018)
9. Giardina, G., Milillo, P., DeJong, M.J., Perissin, D., Milillo, G.: Evaluation of InSAR monitoring data for post-tunnelling settlement damage assessment. Struct. Control Hlth. **26** (2), e2285 (2019)
10. Milillo, P., Giardina, G., Perissin, D., Milillo, G., Coletta, A., Terranova, C.: Pre-Collapse space geodetic observations of critical infrastructure: the Morandi bridge, Genoa, Italy. Remote Sens. **11**(12), 1403 (2019)
11. Raucoules, D., Colesanti, C., Carnec, C.: Use of SAR interferometry for detecting and assessing ground subsidence. Comptes Rendus Geosci. **339**(5), 289–302 (2007)
12. Kontogianni, V., Pytharouli, S., Stiros, S.: Ground subsidence, quaternary faults and vulnerability of utilities and transportation networks in Thessaly, Greece. Environ. Geol. **52** (6), 1085–1095 (2007)
13. Kong, T.B., Komoo, I.: Urban geology: case study of Kuala Lumpur. Eng. Geol. **28**(1–2), 71–94 (1990)
14. Cubrinovski, M., Robinson, K., Taylor, M., Hughes, M., Orense, R.: Lateral spreading and its impacts in urban areas in the 2010–2011 Christchurch earthquakes, New Zeland. J. Geol. Geophys. **55**(3), 255–269 (2012)
15. Monjezi, M., Hasanipanah, M., Khandelwal, M.: Evaluation and prediction of blast-induced ground vibration at Shur river dam, Iran, by artificial neural network. Neural Comput. Appl. **22**(7–8), 1637–1643 (2013)
16. Ghaboussi, J., Joghataie, A.: Active control of structures using neural networks. J. Eng. Mech. **121**(4), 555–567 (1995)
17. Rainieri, C., Fabbrocino, G., Cosenza, E.: Integrated seismic early warning and structural health monitoring of critical civil infrastructures in seismically prone areas. Struct. Hlth. Monitor. **10**(3), 291–308 (2011)
18. Carcangiu, S., Fanni, A., Pegoraro, P.A., Sias, G., Sulis, S.: Forecasting-aided monitoring for the distribution system state estimation. Complexity (2020)
19. Cannas, B., et al.: Towards an automatic filament detector with a Faster R-CNN on MAST-U. Fusion Eng. Des. **146**, 374–377 (2019)
20. Secci, R., Laura Foddis, M., Mazzella, A., Montisci, A., Uras, G.: Artificial neural networks and Kriging method for slope geomechanical characterization. In: Lollino, G., Giordan, D., Crosta, Giovanni B., Corominas, J., Azzam, R., Wasowski, J., Sciarra, N. (eds.) Engineering Geology for Society and Territory - Volume 2, pp. 1357–1361. Springer, Cham (2015). https://doi.org/10.1007/978-3-319-09057-3_239
21. Carcangiu, S., Montisci, A.: A Locally recurrent neural network-based approach for the early fault detection. In: IEEE 4th International Forum on Research & Technology for Society and Industry (RTSI), pp. 1–6. Palermo (2018)
22. Kohonen, T.: Self-organized formation of topologically correct feature maps. Biol. Cybern. **43**(1), 59–69 (1982)
23. Da Silva, I.N., Spatti, D.H., Flauzino, R.A., Liboni, L.H.B., dos Reis Alves, S.F.: Artificial neural networks. Springer International Publishing, Cham (2017)
24. Wang, J.: Artificial neural networks versus natural neural networks: a connectionist paradigm for preference assessment. Decis. Support Syst. **11**(5), 415–429 (1994)
25. Hebb, D.O.: The organization of behavior: a neuropsychological theory. Science Eds (1962)
26. Sanger, T.D.: Optimal unsupervised learning in a single-layer linear feedforward neural network. Neural Networks **2**(6), 459–473 (1989)
27. Maass, W.: On the computational power of winner-take-all. Neural Comput. **12**(11), 2519–2535 (2000)