

Accepted Manuscript

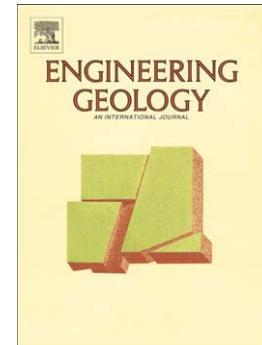
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PII: S0013-7952(15)30117-4
DOI: doi: [10.1016/j.enggeo.2015.12.022](https://doi.org/10.1016/j.enggeo.2015.12.022)
Reference: ENGEO 4204

To appear in: *Engineering Geology*

Received date: 11 May 2015
Revised date: 21 December 2015
Accepted date: 25 December 2015



Please cite this article as: Massimi, Vincenzo, Asadi-Zeydabady, Masoud, Buscema, Massimo, Dominici, Donatella, Lodwick, Weldon, Simeoni, Lucia, The contribution of artificial adaptive system to limit the influence of systematic errors in the definition of the kinematic behavior of an extremely-slow landslide, *Engineering Geology* (2015), doi: [10.1016/j.enggeo.2015.12.022](https://doi.org/10.1016/j.enggeo.2015.12.022)

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The contribution of Artificial Adaptive System to limit the influence of systematic errors in the definition of the kinematic behavior of an extremely-slow landslide

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Abstract

This paper describes the application of some new mathematical algorithms, developed at Semeion Research Center and based on Artificial Adaptive System (AAS), to the redundant measurements of displacement of an extremely-slow landslide that may be affected by some systematic errors. The main aim is to understand if AAS may overcome their influence in the definition of the landslide kinematic behavior thus being able to use the measurements even though they differ by systematic errors. This would be a particularly good result for the monitoring of extremely-slow landslides that move at displacement rates less than 16 mm/year and can be recognized only with instrumentation, usually of geodetic type for the ground surface and inclinometers for the subsurface. In the short time, displacements are so small that they may include systematic errors of the same order of magnitude that can neither be identified nor reduced. For the monitoring of extremely-slow landslides it is therefore recommended to use redundant measurement systems and check the reliability of data by comparing the displacements. This paper shows how the use of the Artificial Adaptive System may get the information on the landslide kinematic even when there is no agreement between displacements measured with the different techniques. The validation of these results was made by comparing them with the well-known data field and a good agreement was found.

Keywords: extremely-slow landslide, small displacements, Artificial Adaptive Systems, systematic errors

1. Introduction

The measurement of surface and subsurface displacements is requested for the geotechnical characterization of slope movements represented as a 3-D matrix (Leroueil S., 2001), the three axis being the type of movement, the movement stage and the type of material. The spatial distribution of displacements helps to describe the type of movement, while the history of the rate of displacements may suggest the movement stage by relating the velocity to the triggering or aggravating factors. Spatial and temporal distributions of displacements define the kinematical behavior of a landslide. When dealing with extremely slow landslides that, accordingly to the velocity scale given by the International Geotechnical Society's UNESCO Working Party on World Landslide Inventory (WP/WLI) (1995) and by Cruden and Varnes (1996), move with rates less than 16 mm/year the displacements are detectable only with instrumentation because the revealing factors that would provide evidence of movement are not easily recognizable. Some examples of displacement monitoring of extremely-slow to slow landslides are given in Simeoni and Mongiovi (2007), Macfarlane (2009), Di Maio et al. (2010), Puzrin and Schmid (2012), Bovenga et al. (2013), Massey et al. (2013), Cohen-Waeber and Sitar (2013), Miao et al. (2014).

The difficulties in monitoring extremely-slow landslides reside in the fact that the accuracy of measurements is not good enough to reduce the effects of the systematic errors (Simeoni and Ferro, 2015). It is reasonable and easy to understand that the systematic errors, which may affect the measures, might cause a different interpretation of the landslide kinematical behavior with respect to the real situation. Therefore, to reduce this risk, it is necessary to evaluate the reliability of the measurements using redundant monitoring systems (Dominici et al. 2014).

The different and redundant measurement techniques of geodetic type widely used for the ground surface movements of extremely-slow landslides are Total Station, GNSS and Levelling (Radicioni et al. 2012). Recently, remote sensing techniques such as ground-based or *space borne* (Corominas J., 2014; Cohen-Waeber and Sitar, 2013; Cascini et al. 2010) InSAR have also been used. Subsoil movements are generally measured by means of inclinometers. It is well known that the inclinometer can (and do) introduce systematic errors (Mikkelsen P.E., 2003).

Due to the complexity of the soil behavior, especially in problems involving great volumes and heterogeneous soils, since the early 1990s Artificial Intelligence has revealed to be a tool complementary to conventional computing methods to support decisions and assist in solving engineering problems (Toll, D.G. 1996). Artificial Neural Networks are Learning System models within the field of the Artificial Adaptive Systems and represent the most used applications in geotechnical engineering especially when the prediction of the soil behavior is requested (Shahin et al. 2009; Vijith H. et al. 2014; Sousa R.L. et al. 2014; Park H.J. et al. 2013).

This work investigates the contribution of the Artificial Adaptive System to a better understanding of the kinematic of extremely-slow landslides including displacement measurements that are affected by systematic errors. In order to verify this, one case study of extremely-slow landslide, named T64 and located in the alpine Isarco Valley in Northern Italy (Simeoni et al., 2014), was analyzed. This case had redundant information from total station and inclinometers with total station and inclinometer displacements similar in direction but greatly different in magnitude (Dominici et al. 2014).

These differences have a high probability of being correct due to different systematic errors which affect the measurements and which, at the same time, are really difficult to identify or reduce through classical measurement analysis. In the T64 case study, in fact, both inclinometer and Total Station measurements may achieve sub-millimeter precisions (Simeoni and Mongiovi', 2007) (Simeoni and Benciolini, 2007). Nevertheless as discussed in a previous research (Dominici et al. 2014), systematic errors due to the precarious stability of the geodetic reference system were identified to be of the order of millimeters. With

some measurement analysis, a more reliable reference system was identified for T64, with the origin on vertex B3 and X axis oriented toward the point B1 (see Figure 5) but it should still conserve some movements that introduce systematic errors in the vector of displacements. Also for inclinometers some problems with the installation or the measurement accuracy may occur (Mikkelsen, 2003; Simeoni, 2006) introducing systematic errors that cannot be easily reduced (Simeoni and Ferro, 2015).

In the following paragraphs, some recent theories developed at Semeion Research Center are presented and applied to our case study focusing our attention on the added information which is obtainable using these algorithms on measurement analysis with respect to the classical approach. The results obtained are compared and validated with the geological model of the landslide and the characteristics of the sliding surfaces and boundaries.

2. Introduction to the Artificial Adaptive System

The Artificial Adaptive System (AAS) forms part of the vast world of Artificial Intelligence (AI), nowadays called more properly Artificial Sciences (AS). Artificial Sciences mean those sciences for which an understanding of natural and/or cultural process is achieved by the re-creation of those processes through automatic models. In particular, Natural Computation would construct automatic models of complex processes and it represents an alternative to Classic Computation (CC). CC, in fact, has great difficulty in modeling natural processes, especially since it often has to impose external rules to understand and reproduce them, when formalizing these processes in a mathematical model. Artificial Adaptive Systems are theories able to create artificial models simulating natural phenomenon. Artificial Adaptive Systems include Evolutive Systems and Learning Systems. Artificial Neural Networks are the most well-known Learning System models within AAS (Buscema and Grossi, 2009). We direct the reader to the bibliography for an exhaustive treatment of these systems. Some good examples of the application of Artificial Neural Network for the slope stability evaluation and the landslide displacements prediction are described in Wang et. Al. (2005) and Lian et. Al. (2015) respectively. Here attention will be focused only on the algorithms that were applied to the active and extremely-slow landslide, seen as a natural phenomenon of diffusion. Diffusion may be synthetically described as the phenomenon of spatiotemporal propagation of a certain variable across a medium, where the modes of propagation crucially depend on the characteristic of the medium and the entities of interest (Buscema et al., 2013). Applying this concept to the physical phenomena of active and extremely-slow landslide, the variables are represented by the displacements over time of a certain number of monitored points while the medium is represented by the landslide body itself. As we mentioned in the introduction, the variable represented by the redundant measurement of displacements may be affected by different systematic error, and our approach uses some recently theories and algorithms developed at Semeion Research Center called respectively, Twisting Theory (TWT) and Crowd Clustering Algorithm (CCA) to get information on the landslide kinematic without rejecting any measurements.

2.1 Twisting Theory and Twisting Algorithm (TWT)

Twisting Theory (TWT) and Twisting Algorithm (TWA) were developed by M. Buscema in 2010 at Semeion Research Center of Sciences of Communication in Rome (Buscema et al., 2013). TWT and TWA¹ are protected by a USA patent.

The main concept based on of Twisting Theory is to consider M entities located in the two-dimensional space, identified by their Cartesian Coordinates (X,Y) or geographical coordinates (Φ, ω) observed at a sequence of times $n=1, \dots, N$ (see Table 1) which tend to move because of the action of some inherent forces. Each entity thus describes one pattern of movement, for simplicity is assumed to be linear, in the space and suppose moreover that the space is covered by a grid, and that the force that acts on the entities also acts on the grid, so that the change of position of the entities brings about accordingly a distortion of the original grid. We call all points belonging to the grid *geometrical points*.

The *Twisting Theory* (for short TWT) is a model able to infer how each geometrical point of the grid will modify its coordinates at each temporal step when any entity of the grid will move toward its new position (Buscema 2013). To illustrate the idea, consider the following 36x36 grid with five entities and a trajectory in two time steps (see Fig. 1). The approach of TWT is to divide trajectories into N given sub-steps of equal length (Fig. 2), so that each entity is dynamically identified by the coordinates of its place of origin, by the moving local target corresponding to the movement at each single sub-step, and by the trajectory of the deformation.

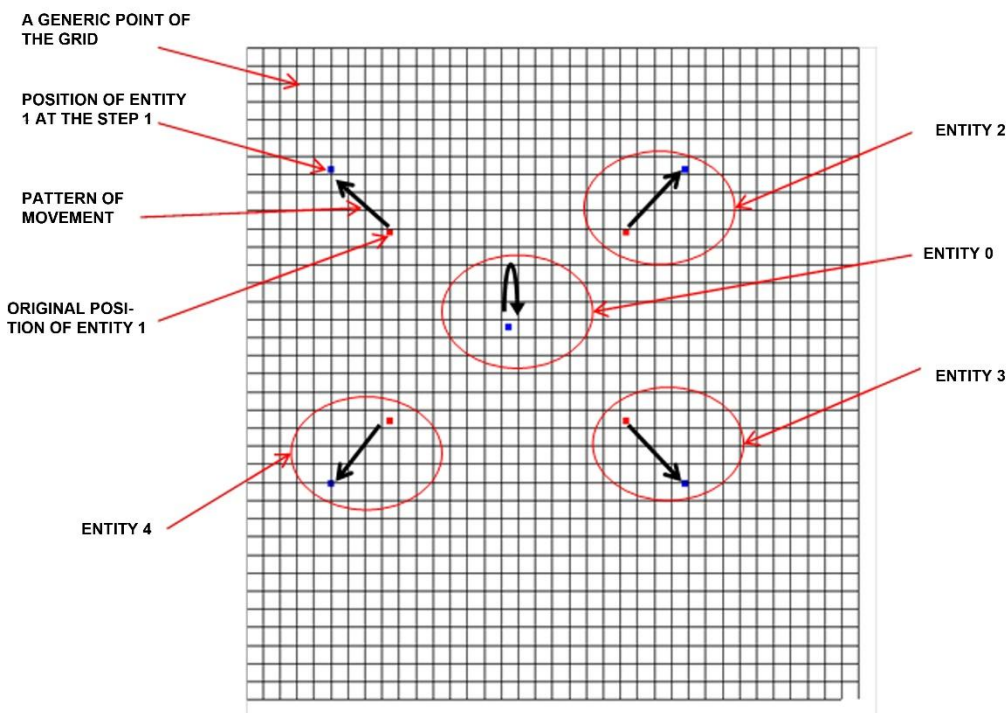


Figure 1. An example of entity trajectories across the grid

¹ M Buscema, Twisting Theory (TWT): a new theory and a new class of Algorithms able to model the global deformations of the space, considering the trajectories of only a little sample of points along the time flow. Applicant : Semeion Research Center & CSI. Inventor: M Buscema.. USA Patent : 12/969,887 . Deposited 16-Dec-2010. Publication date: Mar 4, 2014. Number: US8666707 B2.

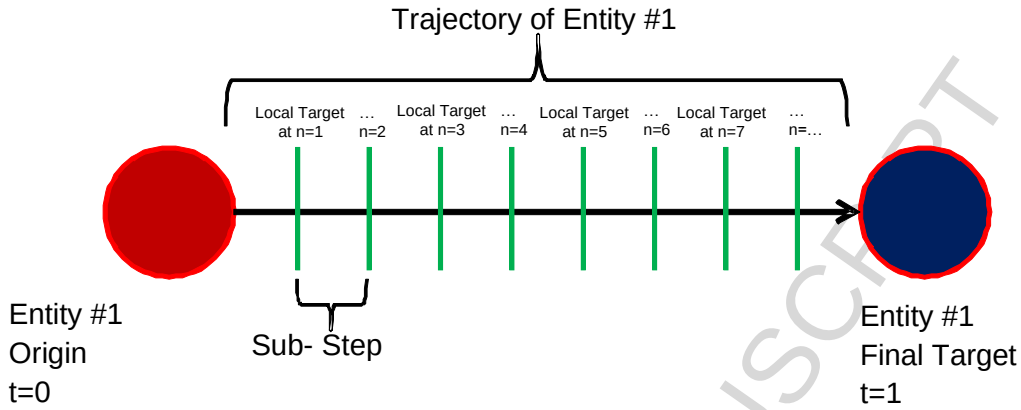


Figure 2. Splitting of the entity trajectory into sub-steps

TWT focuses upon the distances between a given geometrical point and the position of each given entity as it moves along its trajectory, measuring how distances vary at each sub-step of the trajectory, and is expressed in equations (1) and (2).

$$d_{ij}^S(n) = \sqrt{(x_i^P(n) - x_j^S)^2 + (y_i^P(n) - y_j^S)^2} \quad (1)$$

$$d_{ij}^T(n) = \sqrt{(x_i^P(n) - x_j^T(n))^2 + (y_i^P(n) - y_j^T(n))^2} \quad (2)$$

Legend:

$x_i^P(n), y_i^P(n)$ = Coordinates of a generic point (i) of the grid at substep (n);

when $n=0$, geometrical points fall upon the regular grid.

$x_j^S(n), y_j^S(n)$ = Origin Coordinates of each entity (j). $j \in [1, 2, \dots, C]$

$x_j^T(n), y_j^T(n)$ = Local target of the coordinates of each entity (j) at any substep (n);

when $n=0$, the entity lies at its origin, whereas when $n=N$ the entity has completed its trajectory.

$d_{ij}^S(n)$ = Distance of a generic point (i) from the origin of any entity at substep (n);

$d_{ij}^T(n)$ = Distance of a generic point (i) from the local target (n) of any entity at substep (n).

This variation in the distance may be interpreted as the accumulation of potential energy that is consequently free to act upon the grid (Fig. 3), i.e. upon the position of the geometrical points themselves. The more the varying position of the entity along its trajectory tends to change its distance from the given geometrical point from step to step, the more the grid is consequently 'stretched' or 'shrunk' accordingly.

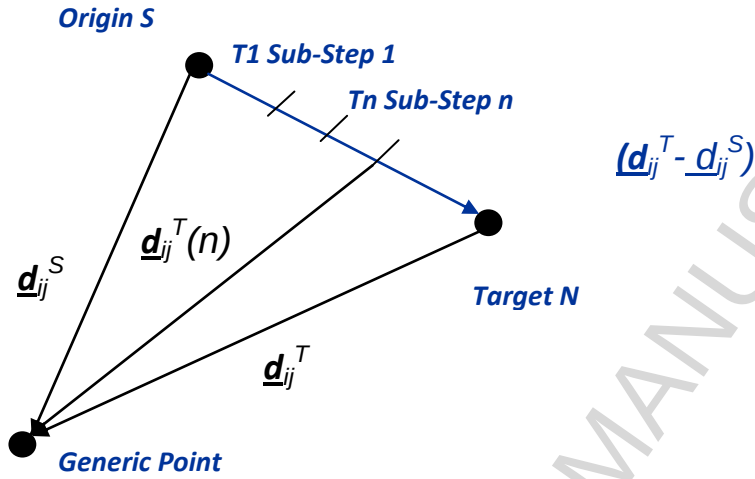


Figure 3. The sub-trajectory of the entity and the accumulation of potential energy

In mathematical terms, the variation of potential energy Δ across the whole trajectory may be expressed by equations (3),(4) and (5):

$$d_{i,j(n)}^S = \sqrt{(x_{i(n)}^P - x_j^S)^2 + (y_{i(n)}^P - y_j^S)^2} \quad (3)$$

$$d_{i,j(n)}^T = \sqrt{(x_{i(n)}^P - x_{j(n)}^T)^2 + (y_{i(n)}^P - y_{j(n)}^T)^2} \quad (4)$$

$$\Delta_{i(n)} = \sum_{j=1}^N \exp\left(-\frac{(d_{i,j(n)}^S + d_{i,j(n)}^T)}{\alpha}\right) \cdot |d_{i,j(n)}^S - d_{i,j(n)}^T| \quad (5)$$

Consider that

- a. $d_{i,j(n)}^S$ is the distance between a generic point P_i and the original position of one of the monitored vertices, $S_j(x_j^S, y_j^S)$;

- b. And $d_{i,j(n)}^T$ is the distance between the same generic point P_i and the new position of the monitored vertex at sub-step (n) , $T_j(x_{j(n)}^S, y_{j(n)}^S)$;
- c. And $|d_{i,j(n)}^S - d_{i,j(n)}^T|$ is the magnitude of vertex displacement (when $|d_{i,j(n)}^S - d_{i,j(n)}^T| = 0$, there is no displacement);
- d. Assume that α is a number representing the mechanical elasticity of the material ($0 = \text{Maximum of elasticity}$);

So the summation $d_{i,j(n)}^S + d_{i,j(n)}^T$ is the total work in the space (energy) that the generic point P_i has to do to make null its distance from original and from the new location of the same vertex.

At this point the negative exponential ($\exp(-x)$) is a generic decay function of the influence of the vertex displacement on the generic point P_i .

Equation (5) calculates the deformation (potential energy) that all the monitored vertices act on each generic point of the plane, P_i .

where α is the deformation factor. The potential energy is then transformed into kinetic energy, i.e. it produces a deformation of the grid as determined by the movement of the entity and expressed by equations (6),(7),(8) and (9).

$$\delta x_{i(n)}^{[p]} = \sum_j^N \exp\left(-\frac{d_{i,j(n)}^{[s]} + d_{i,j(n)}^{[t]}}{\alpha}\right) \cdot (x_j^{[s]} - x_{j(n)}^{[t]}) \quad (6)$$

$$\delta y_{i(n)}^{[p]} = \sum_j^N \exp\left(-\frac{d_{i,j(n)}^{[s]} + d_{i,j(n)}^{[t]}}{\alpha}\right) \cdot (y_j^{[s]} - y_{j(n)}^{[t]}) \quad (7)$$

$$\begin{cases} x_{i(n+1)}^{[p]} = x_{i(n)}^{[p]} + \Delta_{i(n)} & \delta x_{i(n)}^{[p]} < 0 \\ x_{i(n+1)}^{[p]} = x_{i(n)}^{[p]} - \Delta_{i(n)} & \delta x_{i(n)}^{[p]} \geq 0 \end{cases} \quad (8)$$

$$\begin{cases} y_{i(n+1)}^{[p]} = y_{i(n)}^{[p]} + \Delta_{i(n)} & \delta y_{i(n)}^{[p]} < 0 \\ y_{i(n+1)}^{[p]} = y_{i(n)}^{[p]} - \Delta_{i(n)} & \delta y_{i(n)}^{[p]} \geq 0 \end{cases} \quad (9)$$

Equation (6) and (7) calculate the same deformation as equation (5) for the x and y coordinates of a generic point P_i .

Equations (8) and (9) apply these deformations on each coordinate (x,y) of the grid.

Finally, by means equation (1)-(9), (TWT) is implemented as a Twisting Algorithm (TWA) able to infer how each geometrical point of the grid will modify its coordinates at each temporal step when any entity of the grid movestoward its new position. Equations (5), (6) and (7) introduce a modified weighted deformation. The weighing factor gets smaller as the sum of the displacements, $d_{i,j(n)}^S$ and $d_{i,j(n)}^T$ increases. By increasing the deformation factor, the weighting factor increases. We could consider the weighting factor as the dynamical response of the system to the deformation. Large α leads to larger weighting factor and can be considered as a less stiff system (less resistant to deformation). To quantitatively define the kinematic of the landslide, in classical computation, the measurement data are processed and a subsequently qualitative hypothesis regarding average yearly velocities are formulated, usually using a statistic-based approach [Uzielli et. al 2014]. Applying Twisting Algorithm to the extremely-slow landslides means we want to analyze the measures taking into account not only the value of displacements obtained with the measurements but also the density of the monitored vertices and the mutual relations between each measured point and the interaction between each measured points and the geometrical space on which these measured points are located. This kind of approach allows us to obtain additional information with respect to the single analysis of displacements of various entities and enhances the quantity and quality of the description of landslide phenomena, because it's possible to build a continuous model using only a few discrete number of points.

2.2 Crowd Clustering Algorithm (CCA)

We also use a new algorithm to define the cause-effect relationship of a set of entities (that is, coordinates of the measured points) in a temporal discrete process in two dimensions. This algorithm is called the Crowd Clustering Algorithm. CCA was developed by M. Buscema at Semeion Research Center in 2013. The main aim of CCA is to build up a plausible Model that makes more explicit the causation process through which each entity at each time step influences which other entities at the next time step.

We assume that the dataset to be processed by CCA presents:

1. Space Position of each entity (Space – “S”),
2. Quantity of displacement of each entity (Quantity – “Q”)
3. The data for each entity at any time step (Time “T”)

The Causation Model (M) that CCA approximates has the general form:

$$M = \psi(S, T, Q). \quad (10)$$

A local Model (M[t,t+1]), describing all the more likely transitions of the all Entities (i , j) from the time(t) to the time(t+1) have the following representation:

$$M_{i,j}^{[t,t+1]} = \psi \left(dx_i^{[t,t+1]}, dy_i^{[t,t+1]}, dx_j^{[t,t+1]}, dy_j^{[t,t+1]}, \sigma m_i^{[t,t+1]}, \sigma m_j^{[t,t+1]}, \Delta \phi_i^{[t,t+1]}, \Delta \phi_j^{[t,t+1]} \right) \quad (11)$$

where:

$dx_i^{[t,t+1]}, dx_j^{[t,t+1]}$ = are the x displacements of the i-th and the j-th points from time t to t+1;

$dy_i^{[t,t+1]}, dy_j^{[t,t+1]}$ = are the y displacements of the i-th and the j-th points from time t to t+1;

$\sigma m_i^{[t,t+1]}, \sigma m_j^{[t,t+1]}$ = are the summation metric displacements of the i-th and the j-th points in time t and t+1;

$\Delta \phi_i^{[t,t+1]}, \Delta \phi_j^{[t,t+1]}$ = are the difference in phase displacements of the i-th and the j-th points from time t to t+1.

CCA needs data coming from a set of points placed in two-dimensional space (like GPS sensors or local coordinates), whose positions are dynamically sampled in different temporal steps, (see Table 1).

Table 1. Example of Dataset to be processed by TWT and CCA

PROCESS	SENSOR 1		SENSOR 2		SENSOR 3		SENSOR ...		SENSOR M	
	Lat.	Long.	Lat.	Long.	Lat.	Long.	Lat.	Long.	Lat.	Long.
t(1)	x1(1)	y1(1)	x2(1)	y2(1)	x3(1)	y3(1)	...	...	xM(1)	yM(1)
t(2)	x1(2)	y1(2)	x2(2)	y2(2)	x3(2)	y3(2)	...	...	xM(2)	yM(2)
t(...)	x1...	y1...	x2...	y2...	x3...	y3...	...	...	xM...	yM...
t(N)	x1(N)	y1(N)	x2(N)	y2(N)	x3(N)	y3(N)	...	...	xM(N)	yM(N)

The outputs of CCA algorithm applied to any dataset of this type are multiple:

- A table of the more likely and prevalent **cause-effect** relationships among the assigned sensors (points) during and at the end of the temporal flow;
- A sparse and a directed graph of the more effective **excitatory** relationships among the sensors during the whole process;

CCA algorithm consist of the following steps:

- The displacement of each sensor at each time step is calculated by means of equations (12) and (13):

Let

Legend : $n = [t, t-1]$;

$$(12) \quad dx_i^{[n]} = x_i^{[t]} - x_i^{[t-1]};$$

$$(13) \quad dy_i^{[n]} = y_i^{[t]} - y_i^{[t-1]};$$

These equations calculate the change in x and y at the step (n, n-1).

- b. The calculation of the phase and of the momentum between any couple of sequential displacements of all the sensors is represented by equations (14) and (15):

$$(14) \quad \varphi_i^{[n]} = \begin{cases} 0 & (dx_i^{[n]} > 0) \wedge (dy_i^{[n]} > 0) \\ \pi & (dx_i^{[n]} < 0) \wedge (dy_i^{[n]} < 0) \\ 2\pi & (dx_i^{[n]} > 0) \wedge (dy_i^{[n]} < 0) \\ \pi & (dx_i^{[n]} < 0) \wedge (dy_i^{[n]} > 0) \end{cases};$$

$$(15) \quad q_i^{[n]} = \arctg\left(\frac{dy_i^{[n]}}{dx_i^{[n]}}\right) + \varphi_i^{[n]}; \quad q_i^{[n]} \in [0, 2\pi];$$

Equations (14-15) calculate the Phase of each displacement at the step (n).

- c. Then calculation of the strength of each displacement of any sensor is calculated through the equation (16):

$$(16) \quad m_i^{[n]} = \frac{1}{m^*} \sqrt{(dx_i^{[n]})^2 + (dy_i^{[n]})^2}; \quad m^* = \text{Max}_{i,n}\{m_i^{[n]}\}; \quad m_i^{[n]} \in [0,1].$$

Equation (16) calculates the Magnitude of each displacement at the step (n). Each Magnitude is also linearly scaled in the interval [0-1] to preserve the same bounded metric.

- d. The calculation of the resonance of the phase, the momentum, and the strength of any couple of sensors are given by equations (17), (18) and (19):

Let $q \in [0, 2\pi]$; Phase; $m \in [0,1]$;

$$(17) \quad \alpha_{i,j}^{[n,n+1]} = \begin{cases} 2\pi - |q_i^{[n]} - q_j^{[n+1]}| & |q_i^{[n]} - q_j^{[n+1]}| > \pi \\ |q_j^{[n]} - q_j^{[n+1]}| & |q_j^{[n]} - q_j^{[n+1]}| \leq \pi \end{cases};$$

$$(18) \quad Q_{i,j}^{[n,n+1]} = 1 - \frac{2 \cdot \alpha_{i,j}^{[n,n+1]}}{\pi};$$

$$(19) \quad M_{i,j}^{[n,n+1]} = m_i^{[n]} \cdot m_j^{[n+1]};$$

Equation (17) calculates the phase difference of each point displacement and equation (18) scales them linearly in the interval [0,1], considering the phase opposition (1-x).

Equation (19) calculates the moment of the magnitudes of each point in two steps (n,n+1).

- e. And, finally, the global strength with which the displacement of each sensor acts on the displacement of any other, also considering their reciprocal geographical distance as weighting factor, is calculated by equation (20):

$$(20) \quad S_{i,j} = \sum_{n=1}^{N-1} Q_{i,j}^{[n,n+1]} \cdot M_{i,j}^{[n,n+1]} \cdot e^{-\frac{d_{i,j}^{[n]}}{\sigma}};$$

Equation (20) calculates how much strength, $S_{i,j}$, the phases and the moments of magnitudes of each point can influence any other point at each step (from $n=0$ to $n=N$), considering also their distance ($e^{-\frac{d_{i,j}^{[n]}}{\sigma}}$) at the time n . In other words how much each point at the time n can be consider to be the cause of the direction and magnitude of the displacement of any other point at the time $n+1$ for each time steps n to $n+1$.

The last step of the algorithm is as follows.

- f. The calculation, for each sensor, of the sensor acting with maximum excitatory strength along time is obtained by means of equations (21) and (22): This step allows us to choose which sensor is the most likely cause of any other sensor motion during the temporal flow:

$$(21) \quad E_{Win^+,j} = \underset{i}{ArgMax} \{S_{i,j}\};$$

$$(22) \quad \begin{cases} C_{i,j}^+ = 1 & i = Win^+ \\ C_{i,j}^+ = 0 & i \neq Win^+ \end{cases};$$

Equations (21-22) compute which point is the most likely cause of the displacement of any other point (considering magnitude and direction) during all the process. We can represent these probabilistic cause effect relations using a square matrix where the rows represent the points as possible causes and the columns represent the points as possible effects, and where the summation of each columns of this square matrix has to be 1. Each point may have only one cause, but each point may be the cause of different points – from 0 to all. This matrix is a simplification of the original matrix $S(i,j)$ where the influence of each point on any other is expressed by a specific value.

At the end of this process, we have one square matrix representing the cause-effect relation among sensors in temporal flow. It is a matrix of the excitatory relations, $C^+(i,j)$, among the sensors indicating which sensor imposes the direction of its displacement on which other.

This matrix can be represented by means of a direct and weighted graph. This graph naturally has clustered all the sensors and their asymmetric relationship.

The outputs of CCA algorithm represents the dynamic of the process. This a hypothesis and it needs to be verified experimentally. In case of extremely-slow landslides, this approach allows us to analyse, using the displacements of a discrete number of monitored points, the mutual relations in terms of excitatory forces between each monitored point and all the others. With this approach it is possible to analyse if the landslide presents a unique system of relations which means that the system of excitatory forces are all connected or if there are different groups of forces acting separately.

In addition, using these new algorithms, it is also possible to put in relation and analyse together vertices monitored with different and redundant monitoring systems. This is important to evaluate and see how some possible systematic errors affect the interpreted landslide kinematic behavior.

In the next sections, the application of these theories and the main results of the T64 case study of extremely slow landslide are presented.

3. T64 landslide case study

The T64 extremely slow landslide, also known as Castelrotto landslide (Simeoni & Mongiovì, 2007), is located in the Isarco Valley that is one of the most important alpine valleys in Northern Italy because it contains major transport infrastructures connecting Italy to central Europe through the Brenner pass. A summary of the main characteristics of the landslide is given in Table 2, and a preliminary geomorphological map is shown in Figure 4.

At site T64, the geomorphological study is still in progress and so far it is possible to identify a triangular-shaped landslide area bordered by a main scarp and divided in two units: the northern unit involves debris and moves faster than the southern unit, where disaggregated rock prevails on debris.

Table 2. Main characteristics of T64 extremely slow landslides

<i>Slide name</i>	T64
<i>Maximum thickness (m)</i>	Northern part: 30 Southern part: 60
<i>Width (m)</i>	600
<i>Length (m)</i>	500
<i>Sliding area (m²)</i>	150.000
<i>Volume (m³ x 10⁶)</i>	2.5
<i>Geology and slide mass characteristics</i>	Bedrock: ignimbrite and tuff Sliding mass: debris and disaggregated rock; the sliding mass can be separated in two units, northern unit and southern unit Sliding surface: between bedrock and debris
<i>Average slope inclination (°)</i>	30
<i>Sliding surface residual shear strength- laboratory (°)</i>	10-30
<i>Sliding surface shear strength- back analysis (c'=0) (°)</i>	26-27
<i>Water table</i>	Occasionally 4 m above the sliding surface
<i>Structure interaction</i>	Motorway tunnel and road
<i>Displacement monitoring</i>	Structure: Total Station and 12 concrete monument + 3 target, since 2004 Subsurface: 7 inclinometers, since 1997 Subsurface: 7 IPIs (real time 2000)
<i>Pore water pressure monitoring</i>	10 piezometers, since 1997
<i>Rainfall monitoring</i>	2 Raingages
<i>Displacement rate (mm/y)</i>	Northern part: 5-10 Southern part: 2-5
<i>Movement stage</i>	Active

In order to identify the depth of the landslide units and which of them interact with the transport infrastructures, extensive field measurements of displacements were carried out using inclinometers and Total Station. Some piezometers were also installed to study the pore-water pressure distribution (Simeoni et. al, 2014).

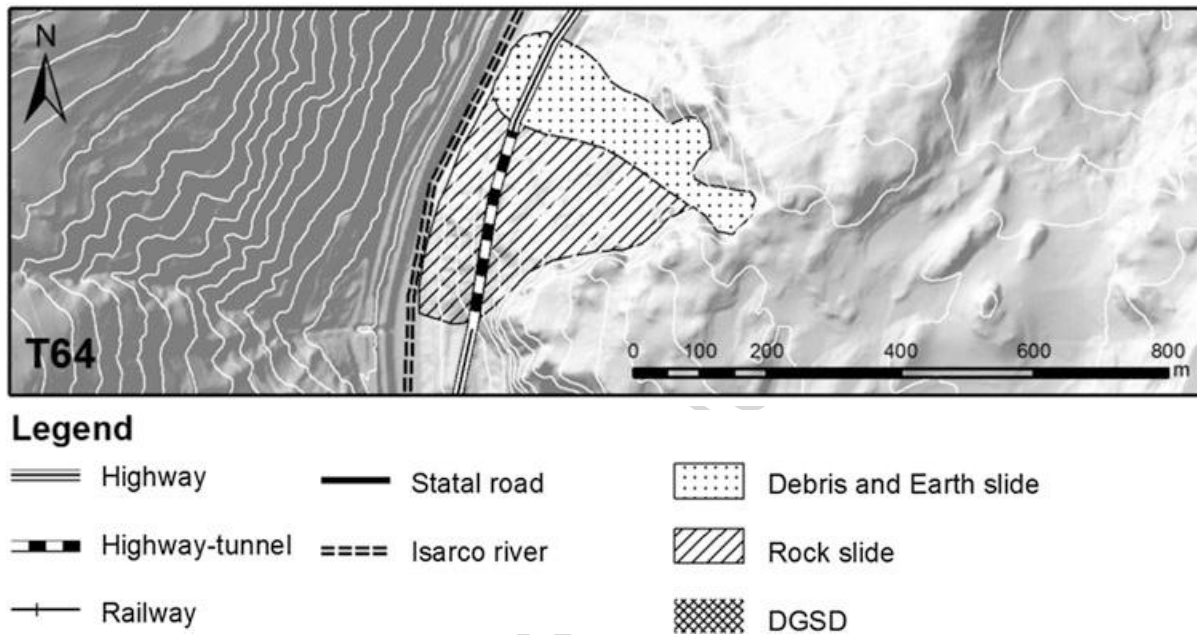


Figure 4. Landslide units of T64 case study

The location of inclinometers and vertices measured with Total Station are shown in Figure 5.

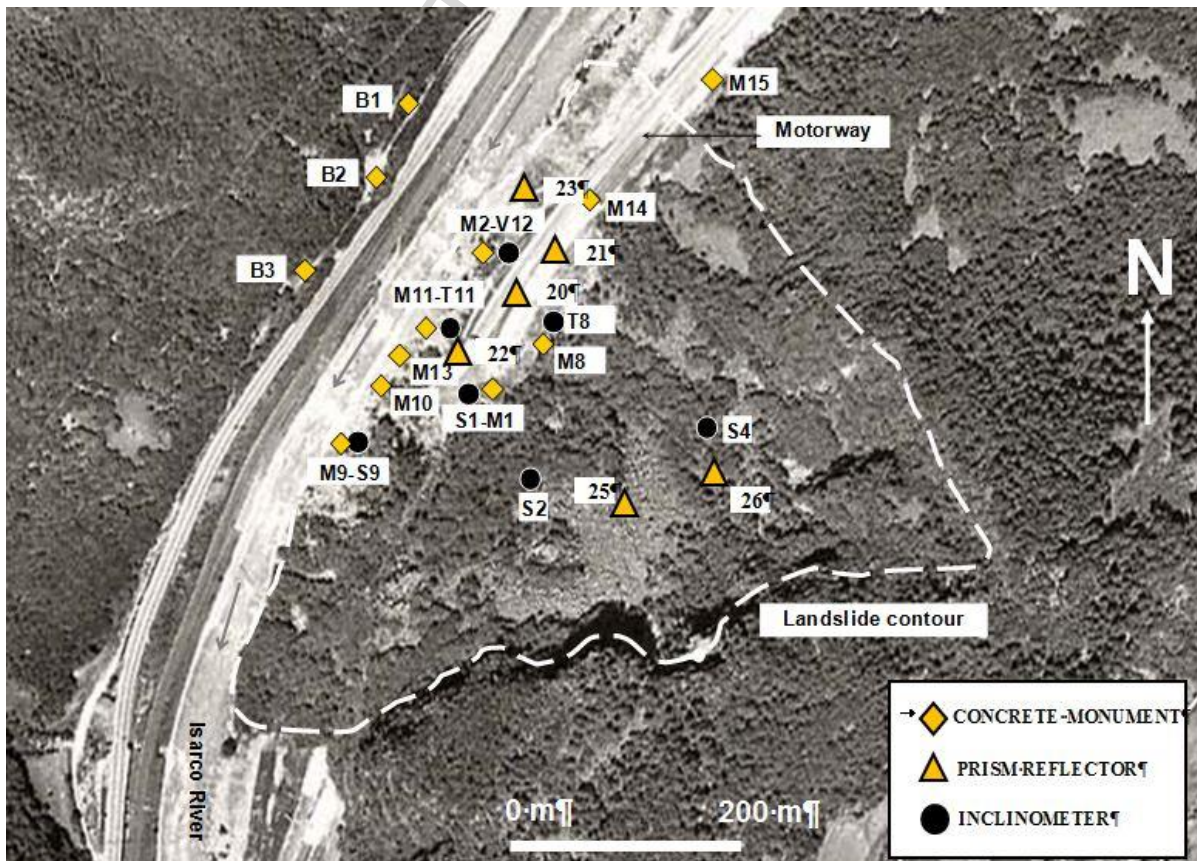


Figure 5. Monitoring Network

The geodetic monitoring network of T64 (Figure 5) is composed of 12 concrete monuments, 9 on the landslide and 3 on the opposite slope plus 4 prisms located on the road structures at the toe of the landslide and 2 prisms installed on two large boulders close to the South-Eastern scarp. The reference system has been imposed on the opposite slope.

The measurements were carried out from 2005 to 2012 using a total station Leica TCA2003 characterized by the precisions equal to 1" (0.3 mgon) for the horizontal and vertical angles and 1 mm + 1 (mm/km) for the distance measurements. The structure of the concrete pillar guaranteed the perfect forced centering on planimetry. The precision obtained with the least square adjustment of the measurements is normally less than one millimeter to few millimeters for the furthest points (Dominici et al. 2014).

Subsurface displacements were measured from 1997 to 2010 with 7 inclinometers with tubes as deep as 100 m (Simeoni and Mongiovi, 2007). Measurements were always carried out by using two of the four grooves and therefore it was not possible to be completely confident of the presence and magnitude of systematic errors. Simeoni (2006) found that at least the fifty percent of measurements included systematic error due to the instrument bias.

Redundancy was available at site T64 with respect to the displacements computed at the ground surface by using either the Total Station and the inclinometer measurements. However, from 1997 to 2004, the displacements were monitored only with inclinometers and Figure 6 shows the displacement vectors obtained in approximately one year of observations, from September 1997 until October 1998. This computation was performed either by integrating the displacements occurring only at the sliding surfaces (sliding displacements) or integrating along the whole tube (ground surface displacements).

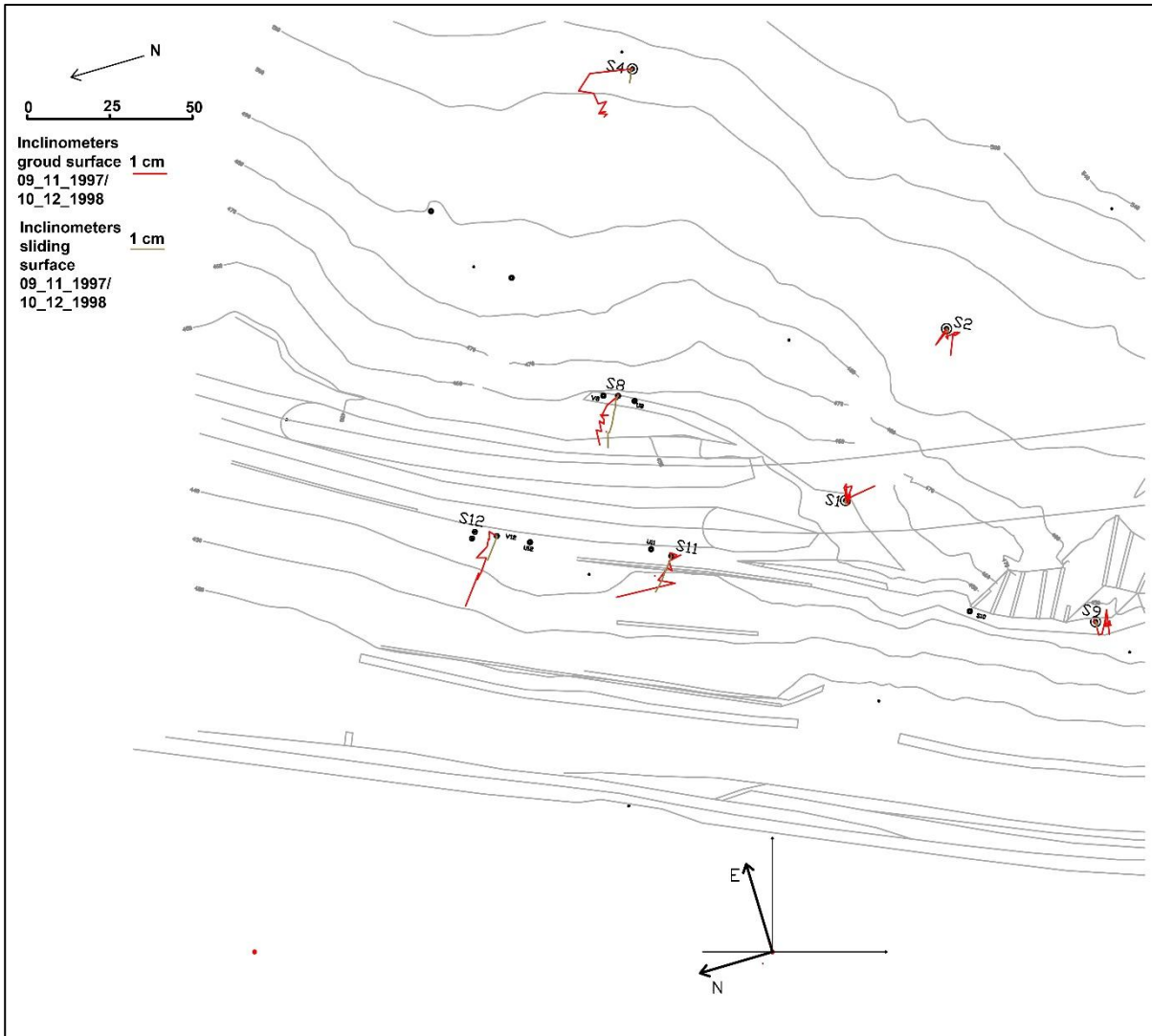


Figure 6. Inclinometer Displacements (9-1997/10-1998)

Since 2004, the T64 landslide was monitored with redundant systems and Figure 7 shows the planimetric displacement vectors corresponding to the multi-year monitoring of displacements performed from 2005 to 2010 with inclinometers and Total Station. Looking at the spatial distribution of displacements in Figure 7 and the time distribution in figure 8, it is evident that there is not a good agreement between Total Station and ground surface inclinometer displacements, making the measurement reliability doubtful and making it difficult to define a precise kinematic behavior of the landslide.

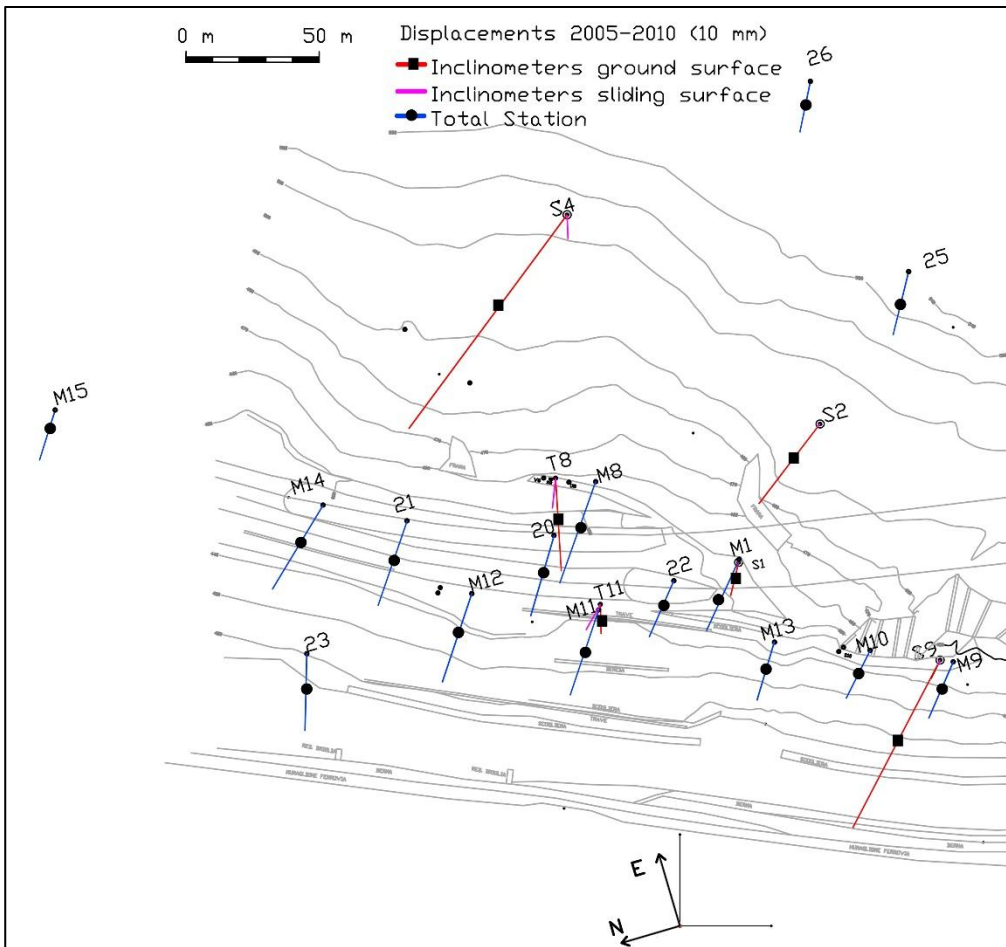


Figure 7. Redundant planimetric displacements (2005-2010)

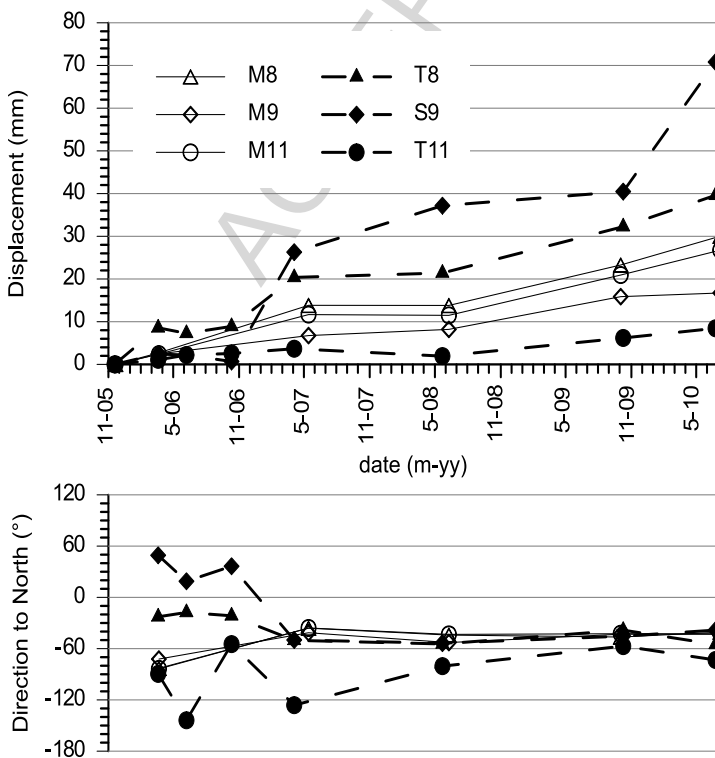


Figure 8. Time distribution of Inclinometer and Total Station displacements (2005-2010).

The differences, especially in magnitude of displacements, between inclinometers and Total Station measurements have a high probability due to some different systematic errors. The most important is related to some motion of the points that materialize the geodetic reference system (B1, B2 and B3 in Figure 5) as described in Dominici et al. 2014.

Given the large amount of measurement data, this case study may be considered a good case study to test the possible contribution of the proposed new theories and algorithms in understanding the kinematic behavior of the extremely-slow landslide also when there is no agreement between displacements measured with redundant techniques due to the presence of different systematic errors. In the next section the input data for data mining analysis using Twisting Algorithm and Crowd Clustering Algorithm are presented.

4. Data Analysis Artificial Adaptive System (AAS)

This section presents the different dataset used in this study. In fact, considering the large number of measurements at our disposal, different sets of coordinates and combinations, as shown in Table 3, were considered as input data for our analysis using these new algorithms. In particular in T64, with respect to the inclinometer measurements, either the displacements on sliding surface or the integrated displacements refer to the ground surface were analyzed. In addition, considering the fact that from November 2005 until June 2010, the inclinometer and geodetic measurements were made almost simultaneously, it was also possible to analyze them together as a unique dataset where, for inclinometer displacements, we considered the displacements integrated up to the ground surface. It is important to mention that inclinometer S8 and S11 were replaced by Inclinometers T8 and T11 after October 1998.

Table 3. T64: Scheme of input data for Twisting analysis (see figure 5)

TECHNIQUE OF MEASUREMENT	PERIOD	NUMBER OF MEASUREMENT SET	NUMBER OF MEASURED POINTS
Inclinometers	09/1997	11	7
	10/1998		S1, S2, S4, S8, S9, S11, S12
Inclinometers	04/2005	10	6
	06/2010		S1, S2, S4, T8, S9, T11
Total station	11/2005	6	15
	11/2012		M1, M8, M9, M10, M11, M12 M13, M14, M15, 20, 21, 22 23, 25, 26
Total station + Inclinometers	11/2005 06/2010	5	21 M1, M8, M9, M10, M11, M12 M13, M14, M15, 20, 21, 22, 23 25, 26, S1, S2, S4, T8, S9, T11

4.1 Data analysis with Twisting Theory (TWT)

The structure of the input data used by the Twisting Algorithm is represented by the (X,Y) components of local coordinates over the time referred to by the geodetic reference system of each monitored point. Also the initial position of the inclinometer was located with respect to the geodetic reference system. In this way we have a unique reference system but the displacements are computed using two different techniques of measurement. The number of measurements represents the number of time step ($t_0, \dots, t_N$) while the number of points represent the number of input coordinates for each time step. About the parameters, each time step has been divided into ten sub-step to better analyze the transition between each step and the subsequent one. The behavior of the sliding mass is taken into account by the factor $\alpha=40$, which simulates the soil stiffness, and a value of lattix factor $L=2$, which represents the density of a grid, as high as possible.

The factor of deformation α may be considered as an empirical weighting factor that allows us to define the displacement of the geometrical points of the grid with respect to the displacements of the measured entities (see Equations 6 and 7). Using different values of the factor α yields different results and therefore we are still studying how to obtain the optimal values of this coefficient with respect to the geological and geotechnical characteristics of the site. However, in this study, the value of $\alpha=40$ was chosen among others because the TWT models resulted in more coherent results compared to the known geological and geotechnical information and the attention here is mainly on the description of the information that is possible to obtain using this algorithm for the extremely-slow landslide kinematic analysis.

4.2 Data Analysis with Crowd Clustering Algorithm (CCA)

The CCA, as discussed in section 2.2, is an algorithm designed to determine a plausible model that makes explicit the more likely causation process through which each entity at each time step influences each other entity at the next time step. The input data has the same structure as the input of the Twisting Algorithm but the output is completely different. CCA is able to infer the cause-effect relationship among the monitored points over time, at every temporal step in a way that each calculation has a memory of the previous one. The results of this computation are expressed both in numerical and graphical terms. In this study we used the CCA algorithm to analyze the cause-effect relationship between the various monitored points with redundant techniques. We investigated if the cause-effect relations found between the various points measured with their respective techniques separately (e.g. inclinometer and Total Station measurements analyzed independently), when analyzed together, as single set of measures, they conserve the same structure of cause-effect relations. This may represents another important test to verify if TWT and CCA can help in the analysis of the extremely-slow landslides also in case that some systematic errors affect the measurements causing different values of displacement as for T64 landslide.

5. Results

This section presents the main results obtained with Twisting Algorithm and Crowd Clustering Algorithm, validating them with the geological and geotechnical information. The results are summarized in Table 4.

Table 4. Summary of results

ALGORITHM	CASE STUDY	TECHNIQUE OF MEASUREMENT	PERIOD	RESULT	VALIDATION
TWT	T64	Inclinometers	09/1997 10/1998	Twt Model on Sliding Surface	Good agreement with the well-known geological differences

					<i>between the two units</i>
TWT	T64	Inclinometers	11/2005 06/2010	Twt Model on Ground Surface	Good overlap of the common area
TWT	T64	Total Station	11/2005 06/2010	Twt Model on Ground Surface	between the two different models
TWT	T64	Inclinometers + Total Station	11/2005 06/2010	Twt Model on Ground Surface	Same result with respect to the separated models
CCA	T64	Total Station	11/2005 06/2010	Excitatory relations Clusters analysis	The clusters subdivision is congruent with respect to the characteristics of the landslide
CCA	T64	Inclinometers	11/2005 06/2010	Excitatory relations Clusters analysis	Inclinometer S1, located close to the boundary between the fastest and the slowest landslide units, has a congruent role of connector between the two units
CCA	T64	Inclinometers + Total Station	11/2005 06/2010	Excitatory relations Clusters analysis	Congruence with the result obtained considering the total station and inclinometer measurements separately

Starting from the coordinates of each vertex of the monitoring network, the result of the application of the Twisting Theory is an estimation of the process of landslide propagation using the coordinate values at each time step as input value. To process these data, the software Twisting v. 4.1[®] developed by Semeion Research Center was used. The software updates the results as the analysis of sub-steps goes on saving each result. From these results, some characteristics of the landslide body were highlighted. In fact, in Figure 9 it is possible to see the final TWT model on the sliding surface of T64 obtained with the analysis of 11 sets of inclinometer displacements on the sliding surface over a period of approximately one year (09-1997/10-1998). The most evident result is the clear separation between the left and the right side of the landslide body in agreement with the well-known geological difference between the two units (see Figure 4). In order to validate this agreement, the TWT model was superimposed on the geological map as shown on the right side of the Figure 9. This separation in two units may be governed by the presence of a fault/fracture. In this case what is important to highlight with this result is that it was obtained with only 1 year of observations which means considering only few millimeters of displacement (Figure 6). If we consider that in the case of extremely-slow landslides, we sometimes need to wait many years in order to obtain enough information to understand the landslide's kinematic behavior, this result seems to demonstrate the possibility of obtaining important evidence which may help in the interpretation of

landslide phenomena from just one year of data by the monitoring network. This may be useful also during the planning phase of the extensive investigation required in order to fully define a phenomenon. Moreover, at the time of these measurements there was not a redundant monitoring system to evaluate the reliability of the measurements which in the case of extremely-slow landslides is highly recommended. This level of agreement with the geological map seems to suggest that the magnitude of systematic error within these measurements does not interfere with determining the landslide characteristics. One further observation. The different shapes obtained by the twisting model between the left and the right side of the landslide, seems to reflect the geotechnical differences of the landslide body, characterized mainly by debris on the left and mainly by disaggregated rock on the right. The last observation we make is related to the boundary between the geological map and the twisting model. The highest level of agreement was achieved on the north side.



Given the redundancy of the monitoring systems, from 2005 until 2010, it was possible to analyze the differences between the final twisting models on ground surface obtained with displacements measured through Total Station (Figure 10, left) with respect to that obtained with inclinometers displacements integrated along the entire length of the tube (Figure 10, right).

Figure 9. TWT final model 97-98 (sliding surface). Overlapping with the geological map.

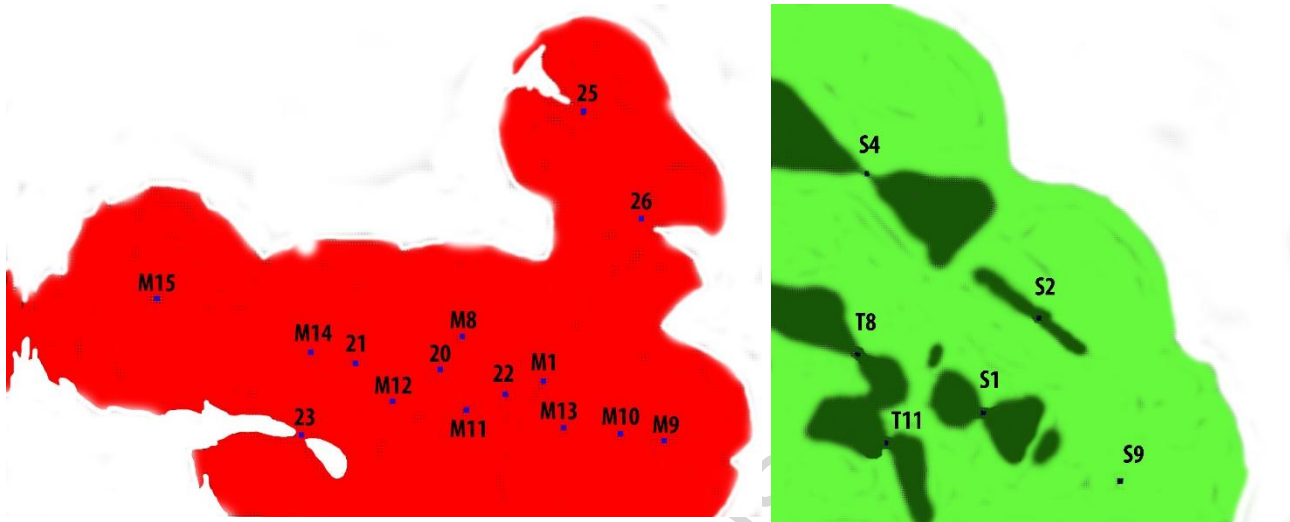


Figure 10. Left: TWT final model (Total Station)

Right: TWT final model (Inclinometers)

To facilitate the comparison between the two models they were superimposed in Figure 11 where the green area represents the twisting model obtained with inclinometers measurement, the red area represents the model obtained with Total Station measurements while the grey area represent the model obtained using both the inclinometer and total station measurements. It's important to remember that in this case the inclinometer S8 and S11 were replaced by inclinometer T8 and T11 and that inclinometer data of S12 can't be considered reliable over this period of time, and therefore S12 has not been used.

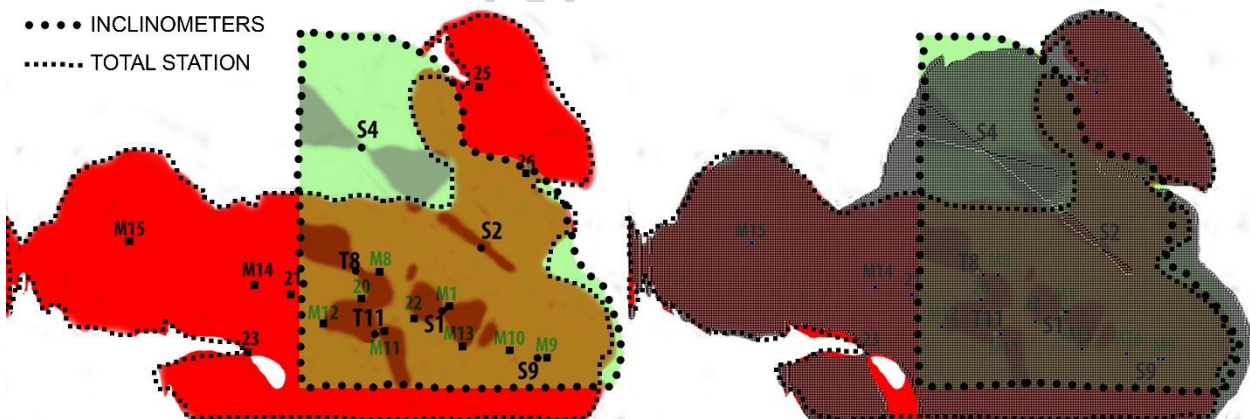


Figure 11.

Left: Inclinometer (green) Vs Total Station (red) TWT models

Right: Overlay (Inclinometer Vs Total Station) with (Inclinometer + Total Station (grey)) TWT models

It is worth noting in this result the high level of agreement obtained in the right side of the landslide boundary between these two models, despite of the significant difference between inclinometer and Total Station displacements at points S9 and M9 (see Figures 7 and 8). It is important because we have to consider that these two results were obtained considering redundant techniques of measurement, both as different dataset as shown on the left side of the Figure 11 and as unique dataset considering together inclinometer and Total Station measurements as shown in grey on the right side of the Figure 11.

Furthermore, it is important to mention that the level of agreement was obtained with measurements that differ in magnitude of displacements as those of systematic errors (see Figures 7 and 8). In fact, in order to clearly state the effectiveness of the TWT algorithm, it is important to remark that the result of the TWT model obtained by considering together inclinometer and Total Station measurements (grey model on the right side of Figure 11) that are affected by systematic errors with different magnitude (see Figures 7 and 8), does not differ from the result of the TWT models obtained by considering the datasets separately (TWT

models on the left side of Figure 11). This result holds both for the area where monitored vertices are redundant (e.g. S9 and M9 that are really close each other) and for the area where they are not (as inclinometer S4 and Total Station vertexes M14, M15, 21, and 23). This result demonstrates the potential capacity of these algorithms to compensate for the possible presence of some systematic errors of measurements that in case of extremely-slow landslides are very common. In fact, if the systematic errors within our measurements would have affected our problem, we should get different results because the measurements differ by just a quantity equal to the systematic error. Moreover, this evidence allows us to trust the results obtained in areas without redundancy measures, such as those including points M15, 25, 26 and S4.

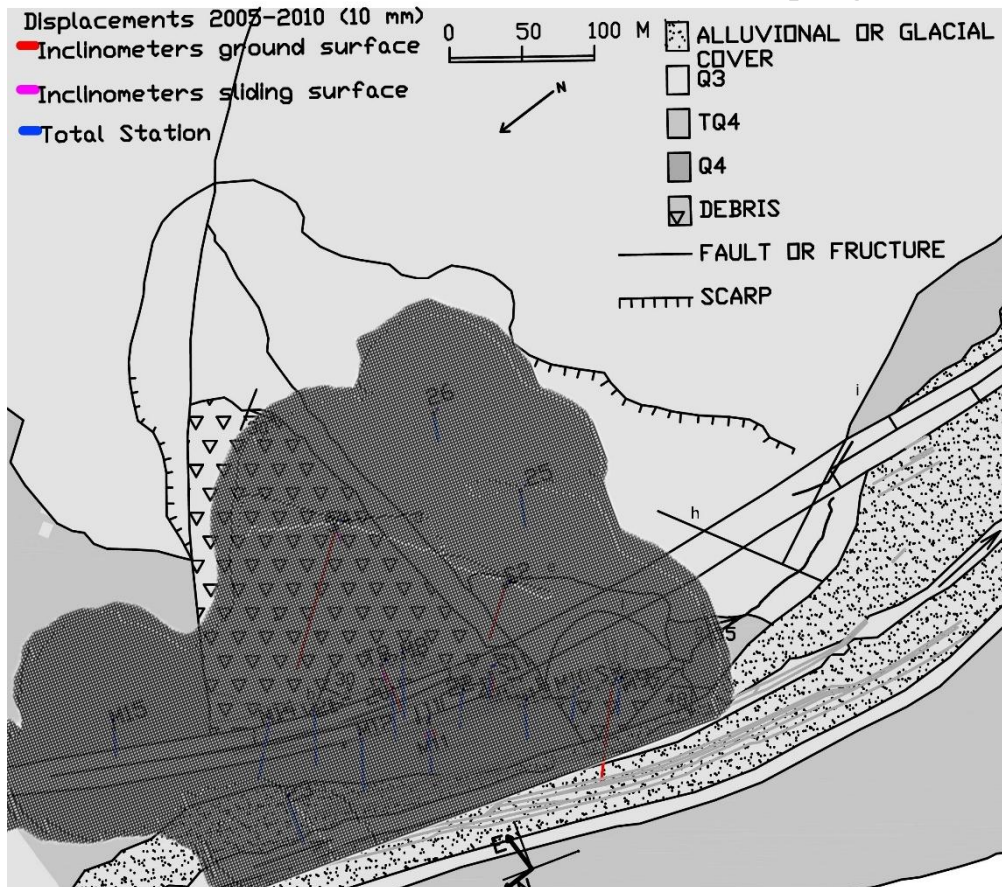


Figure 12. TWT model (Inclinometers and Total Station). Overlapping with geological map.

The result of the twisting model were superimposed onto the geological map as shown on the right side of Figure 12. It is evident that if we consider together, the inclinometer and Total Station measurements, the area affected by slope movements, as determined by twisting software, is wider with respect to the model obtained using only inclinometer displacements at the sliding surface (see Figure 9). As a consequence other shallow landslide units should be investigated, and in particular the cause of movement of the point M15.

The Crowd Clustering Algorithm (CCA) was used to analyze the relations on displacements between any monitored point and each other as previously discussed. The use of CCA in fact, allows us to examine the relations between the various entities initially considered as belonging to a single cluster, and subsequently, according to the causation model described in section 2.2, automatically subdivided in sub-clusters. At this point, the cause-effect relationship between the points belonging to each clusters and between the different clusters are defined and a sparse and a directed graphs is created. Looking at the

distribution of the excitatory relations between the entities, it's possible to visualize graphically the dynamic of the landslide and to highlight the excitatory leader.

Therefore using the same input data previously described, the cause-effect relations of T64 landslide were analyzed either for Total Station or inclinometers and the table 5 summarizes the results. In Figure 13, on the left side is shown the final excitatory graph relations between all points monitored with Total Station while the graph on the right contains the excitatory graph relations between the entities measured with inclinometers.

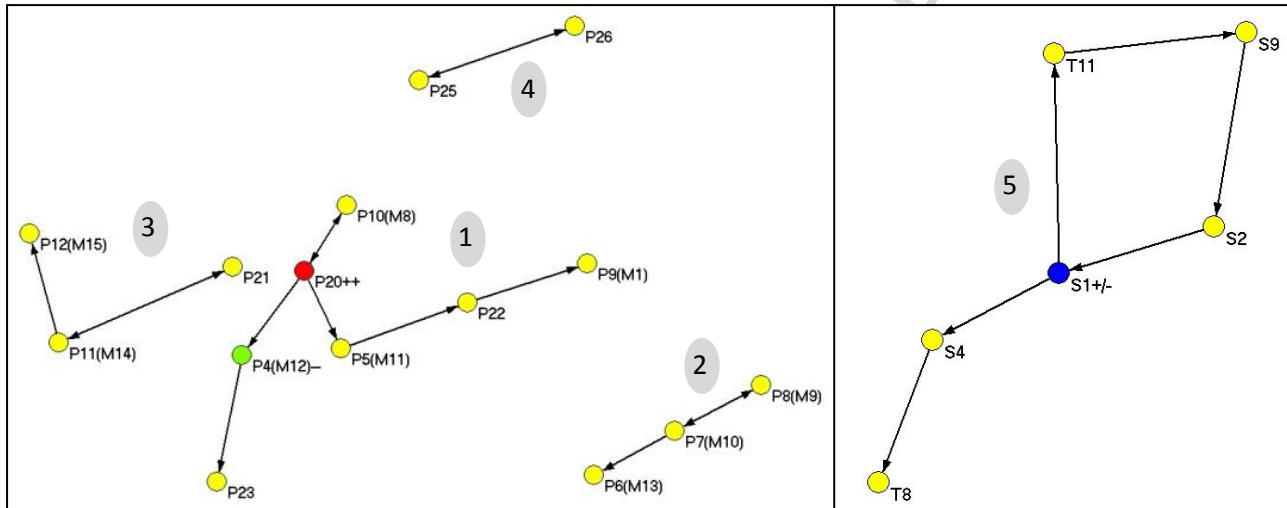


Figure 8. T64 Left: CCA Excit. Map (Total Station 05-10)

Right: CCA Excit. Map (Inclinometers 05-10)

Looking at the result obtained analyzing the Total Station measurements, it is interesting to note that in terms of excitatory relations four different clusters were created with the bigger one corresponding to the center of the landslide body while the other groups are located close to the boundaries and seem not to be correlated with the center of it. In particular, looking at the different points that forms the various clusters and their characteristics summarized in Table 5, the structure of the various clusters seems reliable.

Table 5. T64, CCA excitatory clusters and relations of total station and inclinometer measurements

TECHNIQUE OF MEASURE	CLUSTER	POINTS OF CLUSTER	RELIABILITY OF CLUSTER	RELIABILITY OF RELATIONS
TOTAL STATION	1	M1, M8, M11, M12 20, 22, 23	High reliability, in fact all the points belonging the cluster are located in the fastest unit of the landslide and many fractures on the tunnel are evident in this area.	The excitatory role of point P20 is not easily to justify but it is interesting to note that it is not linked to point P22, located on a different tunnel, and it is with point M1, located at and influenced by the border of the slowest unit. M8, M11, M12 and P23 on the other hand are undoubtedly known to belong to the fastest unit.

	2	M9, M10, M13	<i>High reliability because in this case all the points are located in the slowest unit of the landslide</i>	<i>The double relation between M9 and M10 seems reliable because in this unit the landslide mass is of disaggregated rock and consequently we may aspect a rigid movement. M13 miss the double relation probably because it is close the other landslide unit and may be affected by the fastest movements.</i>
	3	M14, M15, 21	<i>Seems reliable due to the singular position of the vertexes, in the Northern part of the landslide</i>	<i>The double relation between the point 21 and M14 is highly reliable due to the fact that both point are physically connected by the motorway tunnel while point M15 is located far away the tunnel</i>
	4	25, 26	<i>Reliable because these points are located on large boulders that are not fixed with the landslide body</i>	<i>The double interactions between these 2 points is quite surprising because the boulders move with the landslide but are also free to move on the ground surface independently to each other</i>
INCLINOMETERS	5	S1, S2, S4, T8, S9, T11	<i>The reliability of this cluster seems guaranteed by the structure of the relations</i>	<i>The structure of relations seems reliable considering the position and role of inclinometer S1 that is really close to the boundary between the slowest and the fastest landslide units and consequently, within the cluster S1 seems to have a role of</i>

					connector in terms of excitatory forces between the two different side of the landslide
TOTAL STATION + INCLINOMETERS	6	M1, M8, M11, M12, 20 22, 23, 25, 26, S1, S2 S4, T8, T11	The reliability of these clusters seems confirmed by the fact that their structures, obtained using together inclinometers and total station measurements, it's coherent with respect to the structure of clusters obtained considering separately the inclinometer and total station measurements	T8 has an important role (4 connections) confirming the importance in terms of excitatory role of the vertexes 20 and M8 tied together precisely by T8. The double interactions between T8 and M8 may represent the mutual interaction between these two point that were installed very close to each other to verify the redundancy. But the same was expected to occur between S1 and M1.	
	7	M9, M10, M13, S9		Considering the position and characteristic of the landslide, the role of Inclinometer S9 has been coherently identified by CCA.	
	8	M14, M15, 21		Not affected by the presence of inclinometers measurements as input data (different systematic errors)	

The same analysis as shown on the right side of Figure 13 was performed on inclinometer measurements, in particular, with the measurements performed in the same period of Total Station (2005-2010) and with the inclinometer displacements integrated till the ground surface in a way that the obtained graphs are directly comparable.

With respect to the excitatory relations, in this case, it is possible to see that inclinometer S1 plays an important role both in terms of excitatory and inhibitory. This result may appear to be unreasonable. However if we consider that the inclinometer S1 is located really close to the border line between the faster left side and the slower right side of the landslide, this result becomes more reasonable. The last test with CCA involved the analysis of both dataset until now individually analyzed as a single dataset. The result is shown in Figure 14.

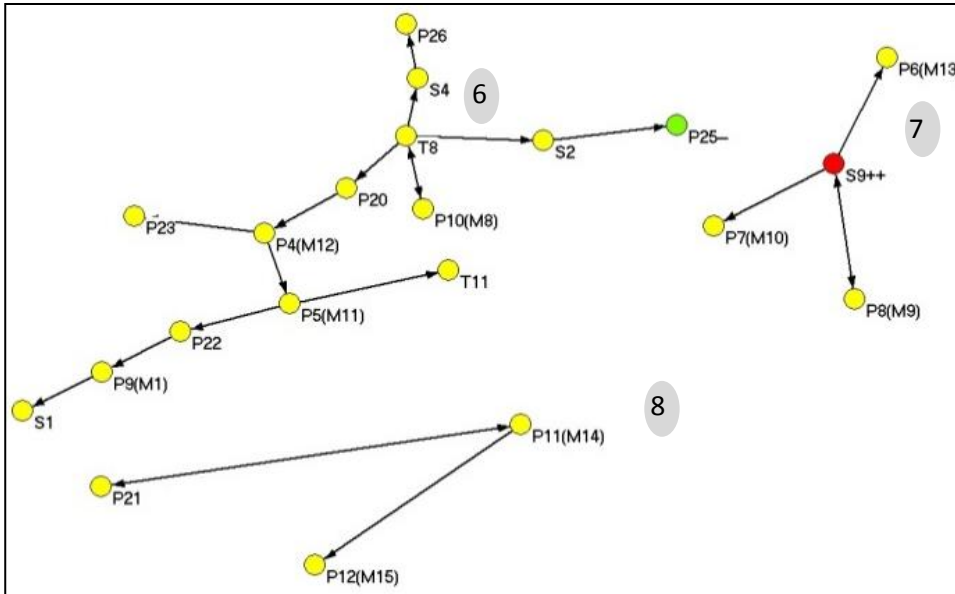


Figure 14. T64 Excit. Map (Incl.+T.S. 05-10)

What is interesting to recall in this result is that we analyzed together the inclinometer and Total Station measurements characterized by different magnitude due to systematical errors. The main structure of these graphs reflect the structure of the graphs obtained with separated analysis. In particular inclinometer T8, the only one with 4 connections, confirms the connections between the vertices 20 and M8 as previously described highlighting an important role of the area located close to the center of the landslide with respect to the kinematic of the landslide. Full validation will be possible when the geomorphological study, still in progress, is completed. A further particularity that demonstrates the validity of CCA is represented by the fact that a double connection between the points P11 and P21 was found by CCA in each excitatory graphs and effectively they are physically linked by the tunnel of the highway. This information, naturally, was unknown to the software. We would like to consider these results as a results which allow us to think that both the Twisting Algorithm (TWT) and the Crowd Clustering Algorithm (CCA) represent important tools able to uncover important characteristics of a landslide body and help us to understand the kinematic behavior even when some systematical errors affect our measurements.

6. Conclusions

Despite the fact that precision of the actual techniques of measure may achieve a submillimeter level, frequently, on monitoring systems, some systematic errors that cannot be identified nor reduced may affect the measurements with a magnitude of the same order of the displacements. In case of extremely-slow landslides these errors may cause a misunderstanding of the kinematic behavior of the landslide itself. To limit this problem it is necessary to evaluate the reliability of the measurements using a redundant monitoring system. With this work, we analyzed the T64 case of extremely-slow landslide located in the Isarco Valley (Northern Italy) where the value of the movements over time with the inclinometer or Total Station measurements were different just because of systematic errors. For this case study of extremely-slow landslide we presented and applied two new algorithms recently developed at the Semeion Research Center: the Twisting Algorithm and the Crowd Clustering Algorithm. With respect to the main results, that present an high level of agreement with the geological and geotechnical data, it seems possible to conclude that these algorithms help in the interpretation of the landslide kinematic behavior using the data from the monitoring activity based on a discrete number of points even when some systematic errors affect the measurements. For example, in the specific case of landslide T64, the TWT model confirmed the reliability of the movement in the area surrounding vertex M15, that was measured only by Total Station and whose displacement was initially supposed due to the systematic error. The capacity of the CCA algorithm to

interpret the cause-effect relations between each control points and the others was also tested. The results obtained seems to confirm our idea about the capabilities of the software to overcome the presence of possible systematic errors between different techniques of measurement. In addition, this study demonstrated that it is possible to obtain reliable information with only one year of observations with displacements of only few millimeters which may also include possible systematic errors. This may be considered an important result because, traditionally, in case of extremely-slow landslide it is necessary to wait for many years to fully understand the kinematic behavior.

This study may also be seen as an innovative approach in the analysis of diffusion phenomena of an active extremely-slow landslide because these algorithms have a bottom-up approach to estimate the global behavior of phenomena in space and time, avoiding any a priori assumption or ideal hypothesis. In fact, if we consider the classical forward approach or inverse analysis, several hypothesis with respect to the constitutive models and their parameters as well as the reliable boundary conditions are necessary (Puzrin A. M. and Sterba I., 2006). Naturally, further investigation needs to be carried out to define the optimal values of the algorithm variables as a function of the number of entities and the characteristic of the soil to define quantitatively the level of accuracy obtainable with these algorithms. Achieving this ambitious aim could help to create a physically based model for active landslides starting from the mathematical analysis implemented with TWT and CCA knowing only the displacements of few points of the landslide for a relatively short time. In addition, in case of monitoring networks that contain measured points both inside of the landslide body area and outside of it, we think that these algorithms may help to identify the perimeter of the landslide and, at the same time, may give useful information about the stability of the reference systems. We will continue to explore the usefulness of AAS in other datasets of extremely slow landslides.

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Highlights

- Two newest algorithms (TWT and CCA) of Artificial Adaptive Systems are presented
- The algorithms were applied to the T64 extremely-slow landslide
- The algorithms were applied to redundant measurements of displacements
- The use of TWT and CCA may limit the influence of systematic errors of measurements
- Despite the slow velocities, the kinematic was obtained with only 1 year of observations