INNOVATIVE INTEGRATED AIRBORNE AND WIRELESS SYSTEMS FOR LANDSLIDE MONITORING

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ABSTRACT:

Landslides are a widespread phenomenon over the Italian territory and economical losses due to this hazard are impressive (an average of 2 billion of euros per year in the last 50 years). In the framework of the WISELAND research project (Integrated Airborne and Wireless Sensor Network systems for Landslide Monitoring) funded by the Italian Government, we are testing new monitoring devices devoted to control large landslides at different degrees of activity. Integrated monitoring tools with a strong innovative character are being explored, in particular ground-based wireless sensor networks combined with airborne laser-scanning and hyperspectral surveys.

A wireless sensor network (WSN) consists of a set of low cost micro-computers capable to measure physical parameters and to communicate between them. Such a technique allows landslides remote monitoring, measuring spatially distributed parameters and recognizing deformation patterns. Ground-based sensor networks can be effectively integrated with grid-based data measured by the use of airborne techniques. The Light Detection and Ranging (Lidar) technology is used primarily to densely map wide areas, even in presence of a thick vegetation coverage, to retrieve high resolution Digital Terrain Models (DTMs); DTMs are fundamental in monitoring and describing landslide movements. Hyperspectral sensors are capable to measure parameters such as soil moisture content, vegetation coverage and surface roughness, that can be correlated with slope movements.

In the first year of the project we tested and validated these monitoring tools on two large earthflows, which are representative of the widespread slope instability in the Northern Apennine: the Silla landslide (Bologna Province, Italy) and the Valoria landslide (Modena Province, Italy). Although characterised by different geological settings and evolution stages, both landslides are associated to a high degree of risk because of the presence of vulnerable elements and their tendency to periodic and abrupt reactivations.

Periodic airborne surveys were performed in Valoria site in different periods, in order to monitor the surface displacement of the slopes. Multitemporal Lidar DTMs allowed the calculation of a differential surface, therefore highlighting absolute height variations and recognizing the main landslide components. Hyperspectral data helped in the landslide characterization; for instance the analysis of PCA components are also correlated with results coming from DTM analysis and this has been evidenced to be a proper system to identify depletion and accumulation zones.

A prototype wireless sensor network was installed at Silla landslide in July 2009. The network consists of four nodes (located in the upper part of the landslide) configured with static routing table which forward packets (one data every 15 minutes) to a master node connected to a laptop. Parallel to this test, a new node hardware platform, more shaped for low power – high range data transmission in outdoor conditions has been developed and it is now ready to be deployed in the field.

1. INTRODUCTION

Landslide occurrence is related to a variety of factors such as underlying geology, mechanical properties of soil and rocks degree of weathering, groundwater conditions, and the presence (or absence) of geologic structures such as joints, faults, and shear zones (Fell et al., 2000). Because of this complexity, landslide monitoring is commonly adopted both in the early detection of risk factors and as an effective tool for landslide hazard management and analysis (ex. Sassa & Canuti, 2008).

This paper's aim is to demonstrate the possibility to successful apply high resolution Lidar and hyperspectral airborne remote sensing techniques to landslide monitoring in the special case of an active, large earthflow characterised by rapid to moderate rate of movement (the Valoria landslide, Northern Apennines, Italy). In addition we intend to develop and test low-cost innovative monitoring system, based on wireless sensor network technology, to improve our understanding of a typical slow-moving landslide in the same area (the Silla Landslide).

The activities described in this paper are part of the research project WISELAND (Integrated Airborne and Wireless Sensor

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2. REMOTE SENSING

2.1 Laser scanning and Hyperspectral Imagery

The possibility to directly acquire a high density and accurate 3D point cloud has made Lidar the preferred technology for topographic data collection; high-resolution DSMs and DTMs, in forestry areas are some example of the potentiality of this methodology (Wehr et al., 1999; Holmgren, 2004; Coren et al., 2006).

A typical Lidar system consists of a laser ranging and scanning unit, together with a POS (Position and Orientation System), which encompasses an integrated Differential Global Positioning System (DGPS) and an Inertial Navigation System (INS) (Cramer, 1999). The laser ranging unit measures the distances from the sensor to the mapped surface, while the onboard GPS/INS component provides the position and orientation of the platform. Lidar data collection is carried out in a strip-wise fashion and the ground coordinates of the laser footprints are derived (Baltsavias, 1999).

The Lidar we used is an Optech ALTM3100; it is a small footprint Lidar system that is able to acquire data up to 100 kHz frequency. In spite of very dense and precise spatial data, these systems are rather poor in spectral sensitivity (Coren et al., 2006). In order to overcome this problem, a hyperspectral dataset has been acquired. The hyperspectral system we used is an AISA Eagle system (Hyvärinen, 2003). It is a hyperspectral sensor allowing the acquisition of a maximum of 255 bands, ranging from visible bands to near-infrared ones. This sensor is the most appropriate to precisely detect many different terrain features. AISA Eagle is a complete, pushbroom system, consisting of a hyperspectral sensor head, a miniature GPS/INS sensor, a data acquisition unit in a rugged PC with display unit and power supply.

2.2 Data acquisition and processing

In this study Lidar Optech ALTM 3100 was used in the Valoria Landslide (Modena Province, Italy). Lidar datasets have been acquired in 2006, 2007 and 2009. The study area was surveyed from an altitude of 1500m above ground level (agl), with a mean sampling density of about 4 points/m^2; the radiometric resolution of Lidar data, scan frequency and scan width were 12bits, 70Hz and ±25° respectively. The last Lidar survey was performed on 30th March 2009 with the same sensor and the same acquisition parameters.

All the datasets were processed using PosPac software for the trajectory computation. The final point cloud was obtained using Optech DashMap software, while TerraScan software (produced by Terrasolid Corporation) was used for data classification, in order to produce a good ground map of Valoria landslide (Axelsson, 1999). Typical vertical component errors are lower than 0.10 m while errors in the horizontal component are in the order of 0.5 m; this precision is impossible to obtain if using classical photogrammetry (Glenn, 2006).

Hyperspectral data were acquired on 16th June 2009, using the AISA Eagle system. The flight was performed at 3000 m of altitude (agl), acquiring 255 bands and setting a ground resolution of 2 m. The final geocoded hyperspectral dataset was obtained using a self-made software called HSP, developed by OGS.

All the remote sensing datasets are in the following projection: WGS84 ellipsoid, UTM32 North projection.

2.3 Lidar differential DEMs

The Valoria landslide is a large, active earthflow which mostly involves low-plasticity scaly clays (Manzi et al., 2004; Corsini et al., 2006). It has been completely reactivated in 2001, and since then it has been intermittently active with displacement that in one season could be in the order of hundreds of meters. This recent evolution has caused a significant modification of slope morphology, with quite distinct depletion and accumulation zones.

In the past some photogrammetric digital elevation models have been computed and analysed. For instance, the differential analysis of a DEM of 1973 and of a DEM of 2003 resulted in a clear enough identification of major depletion and accumulation zones occurred after the 2001 reactivation event (Corsini et al 2007). However, due to an inconstant bias between elevation values even in stable zones, it was impossible to compute volumes precisely.

In this study, Lidar data from 2006, 2007 and 2009 have allowed a rather precise quantification of depletion in the source area and of accumulation along the slope and at the landslide toe. Lidar data bracket in time a quite significant acceleration event occurred in winter 2008-2009. Therefore, a significant picture of slope modification in given by the differential analysis of 2007 and 2009 DEMs (Figure 1). More specifically, a depletion of about 460.000 m^3 has been estimated for the landslide's head zone. At the same time, the landslide toe has shown a marked bulging, associated to downslope sliding. This has been the result of movements that, on the basis of topographic total station monitoring data, have exceeded 200 m in some slope sectors.

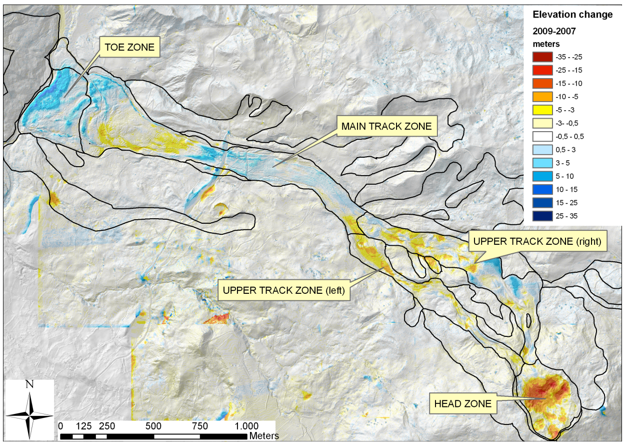

Figure 1. Deformation map obtained subtracting two Lidar DEMs (differential 2007 - 2009). Top left corner coordinates: 44° 20' 09.37'', 10° 30' 57.19''. Bottom right coordinates: 44° 18' 16.63'', 10° 34' 24.51''.

2.4 Principal Component Analysis (PCA)

When dealing with hyperspectral images, with a large number of useful bands, a fundamental task is to perform the so-called Principal Components Analysis (PCA) (Jolliffe, 2002; Coren et al., 2005) to reduce the amount of data to a smaller but significant dataset. In fact, in such images it is very likely that subsets of spectral bands are highly correlated one to each other. If this is the case, you will discover that the accuracy and reliability of a final classification image will suffer if you include highly correlated variables. As a general principle, PCA is a mathematical procedure, often applied in geodesy, transforming a number of (possibly) correlated variables into a

(smaller) number of uncorrelated variables, called "principal components". Referring to hyperspectral image processing, the objective of PCA is to reduce the number of bands of the dataset but contemporary to retain most of the original variability in the hyperspectral data.
The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible. A PCA is concerned with explaining the variance covariance structure of a high dimensional random vector through a few linear combinations of the original component variables. Considering a p-dimensional random vector:

$$\mathbf{X} = [X1\ X2\ ...\ Xp] \tag{1}$$

The k principal components of X are the k (univariate) random variables.
Let's consider Y1,Y2 , ...,Yk, which are defined by the following relationship:

$$\begin{aligned} Y1 &= \lambda 1X = l11X1 + l12X2 + ... + l1pXp \\ Y2 &= \lambda\ 2X = l21X1 + l22X2 + ... + l2pXp \\ &\dots \\ Yk &= \lambda\ kX = lk1X1 + lk2X2 + ... + lkpXp \end{aligned} \tag{2}$$

where the coefficient vectors λ1, λ2 ,..., λk are chosen in order to satisfy the following conditions:
• 1-st principal component: the linear combination λ1X that maximizes Var(λ1X) and λ1 = 1;
• 2-nd principal component: the linear combination λ2X that maximizes Var(λ2X) and λ2 = 1;
• Cov(λ1X, λ2X) = 0;
• j-th principal component: the linear combination λjX that maximizes Var(λ jX) and λj = 1;
• Cov(λ kX, λ jX) = 0 ; for all k < j.
This means that the principal components are the linear combinations of the original variables which maximize the variance of the linear combination and which have zero covariance (and hence zero correlation) with the previous principal components.
The numerical computation involving a PCA analysis is quite complicated for hyperspectral data, and only some specific software can truly accomplish it; ENVI software is one of the most extensively used for this purpose. After completing the PCA, it produces a new image, totally unlinked to the original one from a spectral point of view; each pixel contains the radiance information of each band, so it is proportional to the original information. In this way, a better discrimination of different terrain surfaces properties can be done, due to the consequent possibility to remove noisy bands. On the other hand, after PCA procedure run, it is not always possible to associate specific colours to specific objects in a "one-to-one" way. This is due to the fact that an optimum result can mostly be reached by subsequently applying a De-correlation Stretch (DS) inverse procedure.

2.5 Geomorphometric analysis

Morphometric analysis of Lidar derived Digital terrain Model (DTM) has been performed using MicroDEM software (Guth, 2008). In this paragraph we focus on some theoretical concepts about morphometric parameters and their computation.
Slope and aspect are calculated in correspondence of every DTM grid point; the vector normal to ground is so defined by applying the steepest neighbor algorithm (Chapman, 1952). The direction cosines of this normal vector are then calculated. A 3mx3m matrix is computed, containing the sum of cross products values. Eigenvalues and eigenvectors are extracted from this matrix, normalizing the eigenvectors. Eigenvalues are indicated as S1, S2 e S3; usually S1> S2> S3.
The morphometric terrain analysis is usually performed considering these indexes (Guth, 2003):
1) Flatness: defined as:

$$f = \ln\left(\frac{S1}{S2}\right) \tag{3}$$

Large values indicate flat terrain, low values rugged terrain. It correlates strongly and negatively with slope or relief.
2) Terrain organization: defined as:

$$t = \ln\left(\frac{S2}{S3}\right) \tag{4}$$

Large values indicate a dominant linear fabric to the terrain, low values isotropic topography.
3) Terrain organization: orientation trend of S3. It indicates the dominant trend to the terrain fabric; its direction is between 0 and 180°. It is used in eigenvector analysis of SSO diagrams.
4) Strength: defined as:

$$c = \ln\left(\frac{S1}{S3}\right) \tag{5}$$

Large values indicate flat terrain, low values rugged terrain. It looks very similar to the flatness parameter. It correlates strongly and negatively with slope or relief.
5) Shape: defined as:

$$k = \frac{f}{t} \tag{6}$$

Large values indicate a dominant linear fabric to the terrain, low values isotropic topography. It correlates moderately with terrain organization.
In this study we principally considered Flatness and Terrain organization; the other parameters are supposed to be analyzed in future further investigations.
Flatness and Terrain organization of DTM were calculated by applying the formulas previously mentioned; this was done after classifying Lidar data and generating the ground class by applying the Axelsson algorithm (Axelsson, 1999) embedded in Terrascan software. DTM data have been gridded and interpolated on a regular 2mx2m grid; this operation is necessary because the Fabric Organization algorithm can't be applied on point cloud and needs gridded data. An error have certainly been introduced, but it has been considered of no importance in this study.

2.6 Data interpretation

The application of morphometric algorithms appeared as a powerful methodology to monitor the Valoria landslide.

Figure 2 and 3 represent Flatness and Terrain Organization respectively. Top left corner coordinates of these images are: 44° 19’ 30.10’’, 10° 32’ 39.03’’. Bottom right coordinates are: 44° 18’ 31.29’’, 10° 33’ 35.19’’. In Figure 2 we can observe low Flatness values (from 1 to 2) corresponding to zones with higher differential displacement (see highlighted zones 1 to 5); low Flatness values are associated to rough terrains, and roughness appears to be proportional to stress on landslide surface. Zones highlighted in this figure correspond to high displacement zones in Figure 1.
In Figure 3 we can observe that Terrain Organization values are, instead, quite high in four zones (1 to 4). It’s an interesting phenomenon, associated to the presence of a dominant linear fabric; topography generates very clear lineaments on landslide flux directions.
Zones highlighted in Figure 3 are not characterized by high slope values (see Figure 4); high slope values don’t correspond therefore to high Terrain Organization values. It means that in Valoria the zones where slope is relatively high are not moving very fast.

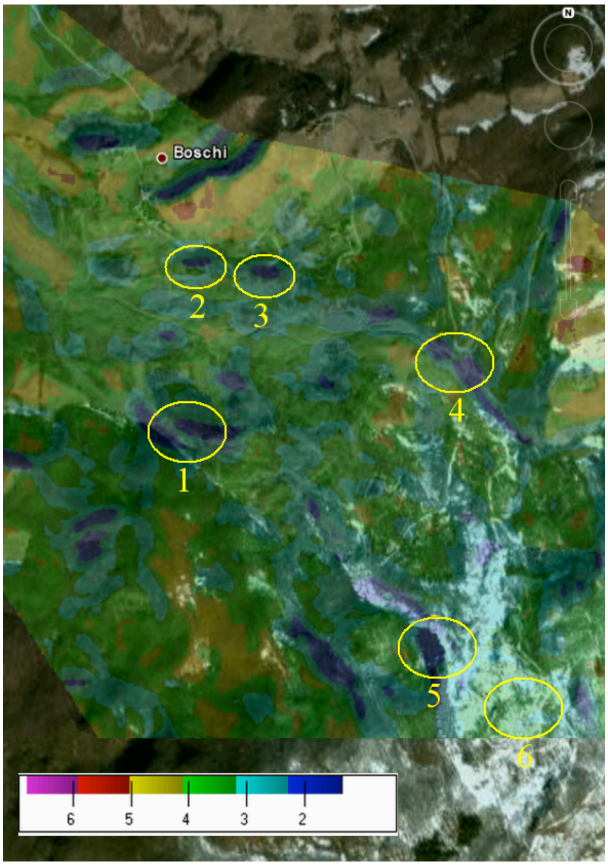

Figure 2. Flatness strength map superimposed on Google Earth image.

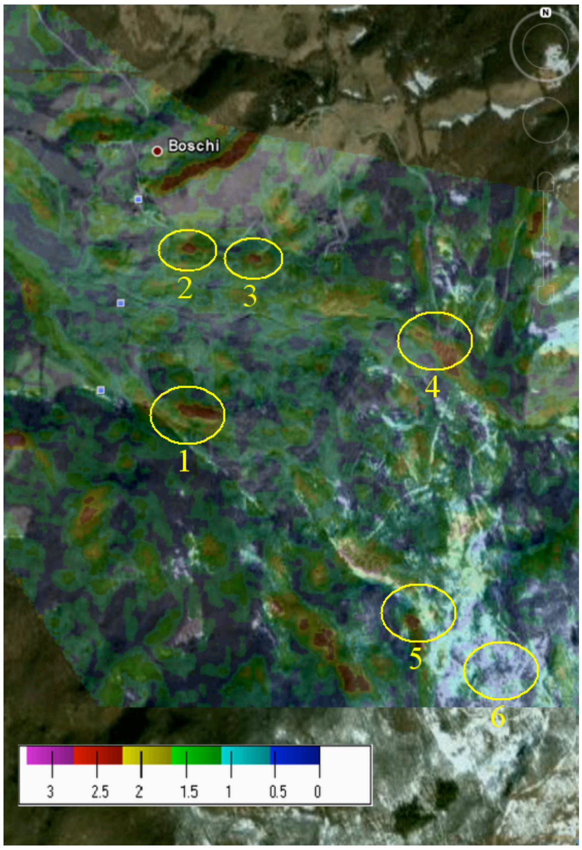

Figure 3. Organization strength map superimposed on Google Earth image.

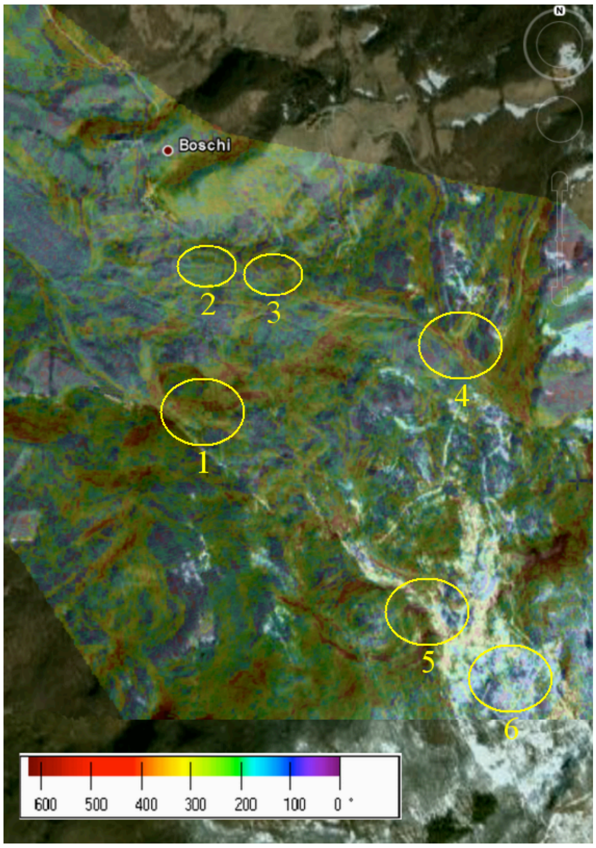

Figure 4. Slope map superimposed on Google Earth image.

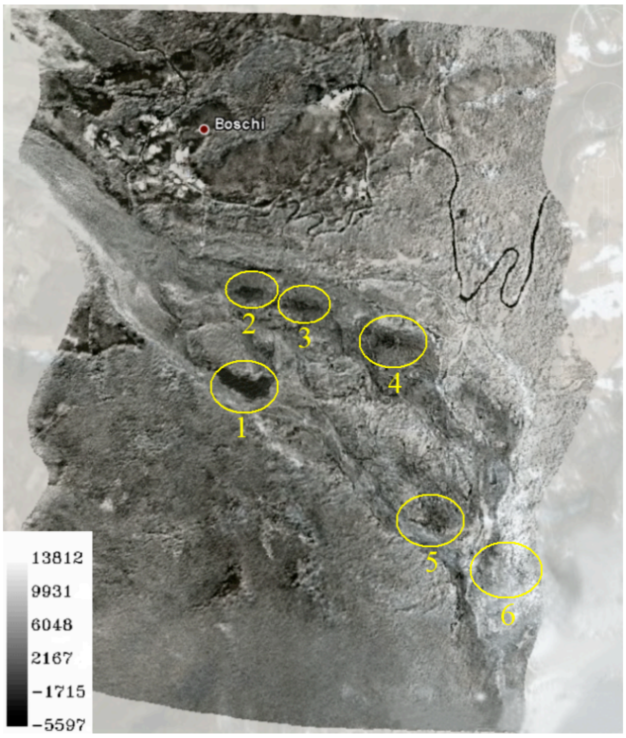

Figure 5. PCA image obtained from hyperspectral data.

Interesting results come from the analysis of the hyperspectral image after applying the PCA algorithm (see Figure 5). In the four zones previous mentioned (1 to 4), PCA values are very low; it means that terrain roughness strongly affects hyperspectral bands decorrelation. PCA was performed considering 210 bands: 44 bands were not taken into account because strongly affected by noise, especially in the Near Infrared field. This is a very interesting result and demonstrates that hyperspectral images can find a direct application to landslides monitoring, even if this is to be improved in further studies.
Also between Figure 2 and 5 we see a correspondence among zones 1, 2, 3 and 4. Zones characterized by a Flatness value equal to 2 or less than 2 correspond to zones affected by a higher bands decorrelation in PCA image (low PCA values). The same zones are characterized by a high Terrain organization value; it means that the predominant Fabric alignment is clearly marked.
Extending the analysis to Figure 4, we can observe that zones 1, 4 and 5 are also affected by a relevant slope; zones 2, 3 and 6 are instead characterized by a low slope value, even if Flatness and Terrain organization are sensibly relevant. Zone 4 is an accumulation zone and a high slope value is expected; zone 2 and 3 are instead depletion zones, so this result needs to be further investigated.
Zone 6 can be differently interpreted depending on the dataset analyzed; a correlation between results coming up from all the datasets (especially from PCA and DEM analysis) doesn't seem to exist.
As overall conclusion we can state that morphometric analysis performed jointly with the use PCA algorithms seems a promising methodology for landslides monitoring. Analysis described in this paper open the access to new research fields. Especially hyperspectral methods are worthwhile to be applied to landslide monitoring. PCA algorithms help identify some key structure in landslide dynamic. Further hyperspectral analysis may try to refine existing geologic maps and to identify the spatial distribution of previously unmapped or unknown faults and shear zones through the detection of minerals alteration. Although existing spectral-map libraries can be used to identify minerals; the spectra of a particular mineral can vary depending on the specific host rock; collection of field spectral data will be necessary to ground-truth the remotely sensed data. This analysis hasn't been included in this paper because the work is still in progress and some field measurements are still to be completed; soon we'll have some preliminary results.

3. WIRELESS SENSOR NETWORK

Wireless sensor networks (WSN) are potentially very useful to monitor hostile natural environments such as landslides (Werner-Allen et al., 2006). The theoretical advantages include the connectivity to any possible sensor, the reasonable cost of components, the set up simplicity and the possibility of an easy web integration (Chong, 2003). Pioneer applications on landslide areas are encouraging (Sheth et al., 2006) and the research project aims to develop and deploy a prototype WSN system to collect spatially distributed data relevant for landslides (pore water pressure in the landslide body, surface displacements, soil moisture conditions).
In July 2009, a simple sensor network infrastructure was deployed in the upper part of the Silla landslide (Bologna Province, Italy), a slow-moving earthflow which last reactivated in 1994. The network consists of four nodes (Crossbow Micaz motes with TinyOS software) that, following a predetermined static routing table, forward data packets (one data every 15 minutes) to a master node connected to a laptop. The main effort, however, was devoted to improve the performance of the hardware available at the beginning of the WISELAND project (early 2007). In particular, new data compression algorithms were developed in order to reduce power consumption and to enhance the range of data transmission in outdoor conditions.
Although the WSN works correctly, the main problems related to the maximum distance among nodes (less than 50 m) and to the battery life (in the order of two months) were not completely solved. A new node hardware platform has been then developed. Six of the available nodes have been configured as "Data" nodes and three as "Bridges". The main task of data nodes is of sampling vibrations (via an on board 2 axis accelerometer) from slope movements originated by an active landslide; vibrations are sent to bridge nodes which, following a predetermined static routing table, have the goal of forwarding packets to a laptop, acting as a base station and collecting sensor readings. Accelerometers in the active zone sample acceleration values at 10 Hz. Bridges are placed at an average distance of 30 m, giving the network about 90 m of total extent. Every bridge is in charge of collecting packets coming from the associated accelerometer motes (two motes for bridge) and eventually of forwarding packets coming from more peripheral bridges. Close to the base station, and out of the active slope zone, we settled three more sensors to measure atmospheric pressure, humidity, light depth, temperature and acceleration. The latter has the aim of providing an external neutral reference for the accelerometers in the active zones. The new infrastructure is ready and will be deployed in the field in March 2010.

4. CONCLUSIONS

The study demonstrates the capabilities of remote sensing techniques to recognise the essential features of an active, rapid earthflow. Using a differential high resolution DTM approach a displacement can be easily detect and the zones with major displacement identified. Lidar acquisitions in different periods need so to be performed and considered.

Areas subjected to a strong landslide activity have been identified by direct DTM analysis. Zones subjected to high relative differential displacements are associated low Flatness values in the DTM analysis; these indicate rough terrains. The same zones are associated a dominant linear fabric; it doesn't seem to be correlated to the local slope obtained by DTM analysis.
Hyperspectral data revealed themselves to be very useful in roughness estimate and in vegetation zones detection and separation. PCA analysis is a very useful and powerful methodology to characterize the surface landslide features because of its sensitivity to surface roughness. Future studies will focus on terrain classification by supervised algorithms applications, in order to better identify the landslide lithology.
The field deployment of a prototype wireless sensor network raised important information regarding the maximum distance between nodes and the related power consumption that has to be minimized. A new node hardware infrastructure has been then developed and it will be installed in March 2010 in the upper part of a large, slow-moving earthflow.

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