OBJECT-BASED CLASSIFICATION OF TERRESTRIAL LASER SCANNING POINT CLOUDS FOR LANDSLIDE MONITORING

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Abstract

Terrestrial laser scanning (TLS) is often used to monitor landslides and other gravitational mass movements with high levels of geometric detail and accuracy. However, the unstructured TLS point clouds lack semantic information, which is required to geomorphologically interpret the measured changes. Extracting meaningful objects in a complex and dynamic environment is challenging due to the objects’ fuzziness in reality as well as the variability and ambiguity of their patterns in a morphometric feature space. We present a point cloud based approach for classifying multi-temporal scenes of a hillslope affected by shallow landslides. The 3D point clouds are segmented into morphologically homogeneous and spatially connected parts. These segments are classified into seven target classes (scarp, eroded area, deposit, rock outcrop and different classes of vegetation) in a two-step procedure: a supervised classification step with a machine learning classifier using morphometric features, followed by a correction step based on topological rules. This improves the final object extraction considerably.

KEYWORDS: 3D scene analysis, object-based point cloud analysis, machine learning, topology, geomorphology, erosion
INTRODUCTION AND RELATED WORK

MAPPING OF LANDSLIDES by close-range and remote sensing (Tofani et al., 2013; Scaioni et al., 2014), i.e. collecting topographic information of locations where landslides occur (Rogers and Chung, 2016), as well as the quantification of extent and volumetric dimension are essential for building up landslide databases (Zieher et al., 2016). Such databases provide input for process models and landslide risk analysis (Corominas et al., 2014). High-resolution topographic data can be acquired from ground-based or airborne platforms, typically using either laser scanning (Höfle and Rutzinger, 2011) or structure-from-motion and multi-view-stereo image matching techniques (Westoby et al., 2012).

Terrestrial laser scanning (TLS) is a well-established technique for monitoring landslides and gravitational mass movements in general (Jaboyedoff et al., 2012; Scaioni et al., 2014). TLS produces three-dimensional point clouds with high levels of detail and accuracy, making it particularly suitable for detailed investigations and monitoring tasks at hillslope scale (cf. Ghuffar et al., 2013; Guarnieri et al., 2015; Barbarella et al., 2015). Multi-temporal scans are often used to quantify surface changes. However, the unstructured TLS point clouds lack semantic information, which is required to interpret the measured changes from a geomorphological point of view.

Landslides produce distinct morphological signatures in the surface (Pike, 1988), which are represented in airborne laser scanning digital terrain models (ALS DTMs). Thus, morphometric parameters, such as roughness or curvature, are calculated from ALS DTMs and used for the characterisation or detection of entire landslides or morphological objects within a landslide (Glenn et al., 2006; McKeen and Roering, 2004; Booth et al., 2009; Kasai et al., 2009; Tarolli et al., 2010). Van den Eeckhaut et al. (2012) conceptualise a landslide considering the morphological characteristics of its parts. This conceptualisation is adopted in a rule-set and used together with morphometric features and a supervised classification to map landslides in ALS DTMs.

Object-based image analysis (OBIA) workflows have shown advantages in detection and mapping landslides in optical satellite and airborne imagery (Martha et al. 2010; Stumpf and Kerle, 2011; Kurtz et al., 2014). Such approaches i) suppress a noisy (“salt-and-pepper”) appearance in classifications of high resolution data and ii) integrate spatial context. For supervised classifications of close-range and remote sensing data non-parametric classifiers, such as random forests and support vector machines have proven successful (Mountrakis et al., 2011; Weinmann et al., 2015; Belgiu and Dragut, 2016; Li et al., 2015).

In contrast to raster-based approaches, only little attention has been given to 3D object-based analysis for mapping landslides in point clouds and for thorough analysis of its subparts. Most studies that use point clouds for landslide investigations focus on change detection or deformation analysis, without extracting semantic objects from the point cloud. For enhanced process understanding of mass movements and secondary erosion, Dorninger et al. (2011) characterise landslides by segmenting ALS and TLS point clouds into planar patches. Monserrat and Crosetto (2008) and Oppikofer et al. (2009) analyse the rotation and translation of individual parts of a point cloud. The automated discretisation of such parts, however, is difficult since the raw 3D point cloud only samples the exposed surface. It provides a detailed geometric representation (x, y, z coordinates) but lacks semantic information on discrete geomorphological objects or object classes (e.g. landslide scarp or deposit). Brodu and Lague (2012) developed a method to classify 3D
point clouds of natural scenes based on the dimensionality of point neighbourhoods at multiple scales. They use the knowledge that the geometry of different objects tends to behave unique at different scales, making it possible to distinguish between vegetation and rocks, and riparian vegetation from the ground. The surface morphology of landslides and their (vegetated) surroundings is complex and dynamic, particularly at the detailed scale of TLS surveys. In such complex natural scenes, extracting geomorphologically meaningful objects of several different target classes remains challenging. The challenges relate to the objects’ fuzziness in reality as well as the (intra-class) variability and ambiguity (overlap between classes) of their patterns in a morphometric feature space.

More research concerning 3D scene analysis and semantic object extraction from point clouds is dedicated to urban environments (Niemeyer et al., 2014; Guo et al., 2015; Weinmann et al., 2015; Pu et al., 2011) and forestry applications (Bremer et al., 2013; Reitberger et al., 2009). In general, object-based point cloud approaches aim at assigning semantic labels to the 3D points by relating them to distinct object classes (e.g. traffic signs, buildings, facades, roofs, trees etc.). Typically, workflows combine a segmentation of the point cloud into spatially connected units (segments) with a subsequent classification of the resulting segments (Rutzinger, 2008). Some recent approaches for point cloud classification are based on an initial oversegmentation, for example using super-voxels (Lim and Suter, 2009; Ramiya et al., 2016). Often, they utilize spectral information, such as RGB colour values (Li et al., 2016; Ramiya et al., 2016). Spatial contextual reasoning is used in the computer vision and robotics community to classify or interpret 3D point clouds (Hu et al., 2013; Shapovalov et al., 2013).

In this paper, we present a point cloud based approach for automatically classifying multi-temporal scenes of a hillslope affected by shallow landslides. Our first objective is to extract discrete and geomorphologically meaningful objects from TLS point clouds and maximize the objects’ consistency throughout the time series. The objects are associated to one of seven target classes (scarp, eroded area, deposit, rock outcrop and different classes of vegetation). Our second objective is to maintain the spatially accurate, detailed and three-dimensional representation of the scene as a point cloud throughout the analysis. We pursue these objectives by integrating machine learning methods for supervised classification and a topological rule-set in an object-based analysis workflow. This approach is tested on a series of nine point clouds from a test site with two landslides. To briefly demonstrate the practicability and value of the object extraction, we also show an example for monitoring of secondary erosion processes on the level of point cloud objects.

**Test Site**

The test site is located in the Schmirn valley (Tyrol, Austria). Two shallow landslide scars (Fig. 1) have existed there for a few decades. The larger one of the two landslide scars is approximately 15-20 m wide, 30 m long (excluding the rather diffuse runout /depositional zone) and has a maximum depth of two metres. The landslides are still active, with retrogressive erosion at their scarps (i.e. clods of material slide or topple downward from the landslide scarp). Occasionally the sliding mass has been reactivated. Moreover, secondary erosion of already exposed areas by runoff, wind or snow movement can occur.

Geologically, the test site is characterized by Bündner Schist covered by regolith.
The hillslope is approximately 35° steep, facing southwest and located at about 1700 m elevation. The lower part of the landslides’ surroundings is used as a meadow and the upper part as an occasional pasture. Larch trees and shrubs are scattered in some sections of the test site. A few rock outcrops exist in the lower part.

Fig. 1. The two landslide scars at the test site (upper part).

METHODS

The automated classification of geomorphological objects is based on a segmentation of the 3D point cloud scene into morphologically homogeneous and spatially connected parts. These segments are classified into seven target classes (scarp, eroded area, deposit, rock outcrop and different classes of vegetation) in a two-step classification procedure. The first step is a supervised classification using morphometric features. In a second step, misclassified segments are corrected based on topological rules. In the following sections, we explain each processing step in detail.

Data Acquisition and Pre-processing

The site with the two landslides has been surveyed with a TLS twice a year since 2011. This results in a series of nine TLS point clouds (scenes PC_01 – PC_09) which are used for testing the proposed point cloud classification approach. Two different TLS instruments were used: an Optech Ilris-3D (PC_01 – PC_05) and a Riegl VZ-6000 (PC_06 – PC_09). Due to different scanner specifications (such as wavelength, beam divergence and capability to record multiple returns) sensor dependent differences within the point cloud time series must be assumed.

Scans from two different positions were acquired each time to reduce occlusions. The scans were registered via sphere targets and iterative closest point adjustment (ICP; Besl and McKay, 1992). To reduce the data volume of the point clouds and homogenize the point density to some extent, 3D block thinning (with 3 cm blocks) was applied, retaining only the point which is closest to each block centre. These steps as well as the
following analysis workflow are implemented with Python scripting combined with the FOSS GIS SAGA (System for Automated Geoscientific Analysis; Conrad et al., 2015) and the proprietary SAGA add-on Laserdata LIS (Wichmann, 2015).

**Point Cloud Features and Segmentation**

*Local Neighbourhood Features*. The point clouds are characterised by computing point cloud features (2D z-range, 3D/2D density ratio, slope, standard deviation from plane, omnivariance and geometric curvature). These features describe the local morphology around each individual point using neighbourhoods of 0.2, 0.4 and 1.0 m radius. For the defined radii a 3D and a 2D neighbourhood definition is used. The 2D neighbourhood is defined as a vertically oriented cylinder of infinite height, centred at the search point. The 3D neighbourhood is defined as a sphere centred at the search point.

The 2D z-range is the difference between the highest and the lowest z value found in the 2D neighbourhood. The 2D/3D-ratio is defined as the number of points found in the 3D neighbourhood, divided by the number of points found in the 2D neighbourhood.

The set of neighbouring points found by the 3D radius search is used for a principle component analysis (PCA). The point set is encoded into a 3x3 covariance matrix ($A^TA$) given by

$$ A = \begin{bmatrix} x_1 - \bar{x} & y_1 - \bar{y} & z_1 - \bar{z} \\ \vdots & \ddots & \vdots \\ x_k - \bar{x} & y_k - \bar{y} & z_k - \bar{z} \end{bmatrix}, $$

and

$$ A^TA = \begin{bmatrix} \sum_{i=1}^{m} (x_i - \bar{x})^2 & \sum_{i=1}^{m} (x_i - \bar{x})(y_i - \bar{y}) & \sum_{i=1}^{m} (x_i - \bar{x})(z_i - \bar{z}) \\ \sum_{i=1}^{m} (x_i - \bar{x})(y_i - \bar{y}) & \sum_{i=1}^{m} (y_i - \bar{y})^2 & \sum_{i=1}^{m} (y_i - \bar{y})(z_i - \bar{z}) \\ \sum_{i=1}^{m} (x_i - \bar{x})(z_i - \bar{z}) & \sum_{i=1}^{m} (y_i - \bar{y})(z_i - \bar{z}) & \sum_{i=1}^{m} (z_i - \bar{z})^2 \end{bmatrix}. $$

From this covariance matrix, eigenvectors and eigenvalues are derived. The eigenvector corresponding to the shortest eigenvalue defines the plane fit normal of an orthogonal regression plane and the centroid of the point set defines a point on this plane.

Slope is defined by the angle between the plane normal and a vertically oriented direction vector. The standard deviation from plane feature describes the standard deviation of the orthogonal point distance to the local fit plane (defined by the plane normal and the point centroid). The omnivariance ($\lambda_0$) is a measure for the volume of the neighbourhood. It is defined by equation (3) and the three eigenvalues ($e_1, e_2, e_3$) found by PCA with

$$ \lambda_0 = \frac{3}{\sqrt{e_1e_2e_3}}. $$

After the normal vectors are defined for each point by PCA, the 3D point neighbourhoods are evaluated in a second program run, allowing the comparison of the fitted normal vector of the search point ($n_p$) with the normal vectors of all neighbouring points ($n_{np}(j)$) of the set of point neighbours. The geometric curvature ($gc$) is defined by

$$ gc = \frac{1}{k} \sum_{j=1}^{k} \| n_p - n_{np}(j) \|. $$

5
**Point Cloud Segmentation.** For the subsequent object-based analysis the point clouds are partitioned into subsets of spatially connected points that represent morphologically homogeneous (sub-)objects, each belonging to one distinct object class of interest (Fig. 2). This segmentation procedure is a connected component analysis (implemented as seeded region growing with random seed points). At this step, three point cloud features are assumed to be particularly relevant for separating objects (3D/2D density ratio, omnivariance and geometric curvature for a neighbourhood with 0.2 m radius). An unsupervised preclassification in this morphometric feature space is performed with a cluster analysis. The feature spaces (attribute tables) of all point clouds are combined (merged) and clustered together to optimise the overall fit of this preclassification for the entire time series. Subsequently, the resulting feature space clusters are used to constrain the segmentation of each point cloud (separately) in the spatial domain. This aims at creating segments with unique object associations which are semantically consistent for all point clouds.

To keep the segments small and compact, the x- and y-coordinates additionally constrain the region growing, with a tolerance of maximum ± 0.6 m from the seed point allowed. This criterion follows the concept of an initial oversegmentation (Lim and Suter, 2009; Ramiya et al., 2016) as a basis for classification and prevents excessive generalisation of point cloud features.

Moreover, the cloud-to-cloud distances ($distance_{C2C}$) of each point cloud to its predecessor and to its successor point cloud in the time series are calculated. These distances are used to discriminate areas of change ($distance_{C2C} > 0.15$ m) and stable areas ($distance_{C2C} < 0.15$ m). This criterion prevents the region growing from including both areas of change and stable areas in the same segment.

![Diagram](image-url) **Fig. 2.** Point cloud segmentation method.
Segment Features. For the subsequent object-based analysis (classification of each segment) the local neighbourhood features are aggregated to their mean and standard deviation per segment. In addition to the local neighbourhood features, the same principles for feature calculation are applied on a segment basis, where the set of neighbouring points is defined by the set of segment points. As described for the local neighbourhood features, a PCA is performed for the segment points. The three eigenvalues \((e_1, e_2, e_3)\) directly derived by PCA are used as individual segment features. The slope and standard deviation from plane feature are computed as described above. The Sneed-Folk-form indices \((SFFI; \text{Sneed and Folk, 1958})\) are defined by

\[
SFFI_x = \frac{e_1 - e_2}{(e_1 - e_2)} \quad (5)
\]

and

\[
SFFI_y = \frac{e_3}{e_1}. \quad (6)
\]

Supervised Classification of Point Cloud Segments

The developed classification approach for point clouds integrates (i) a supervised machine learning classification and (ii) a classification with topological rules in an object-based analysis framework. The first classification step is a supervised classification using the 43 segment features as predictors (see previous section). Two different machine learning algorithms are tested, support vector machine (SVM) and random forest (RF). This step is implemented using scikit-learn, a machine learning package for Python (Pedregosa et al., 2011). The segments represent the samples for training a classifier to predict the class labels in all point clouds. The segment features are standardised by fitting a function to the training data, scaling each feature to zero mean and unit variance. The same function is used for feature scaling of all other scenes. To account for heterogeneous class sizes the class weights are balanced in the training phase by adjusting the weights inversely proportional to the class frequencies in the input data.

One point cloud scene (PC_07) is manually classified into the seven target classes \((\text{landslide scarp, eroded area, deposit, medium and high vegetation, low grass, high grass, rock outcrop})\). Some parts of the scene are difficult to classify with unique labels, both in the 3D point cloud and in the field or on photographs. This concerns for example the depositional zone but also parts of the scarp where no recent erosion occurred. Accordingly, potential inaccuracies/ambiguities and a certain degree of subjectivity in the reference data must be considered for interpretation of the accuracy analyses.

This reference data set is split (spatially) into training data (section containing the larger landslide) and validation data (containing the smaller landslide; Fig. 3). For both machine learning classifiers used, a few hyper-parameters (i.e. parameters not trained in the model) must be specified by the user or by a search procedure. The classifier and its hyper-parameters are optimized by cross-validation (Olson and Delen, 2008) on a (development) subset of the training data. That means the training data is randomly split into development set and evaluation set (random 50% subset for SVM and out-of-bag samples for RF). For a range of values for each hyper-parameter a grid search (testing all combinations of these values, Table I, Table II) is performed with a 5-fold cross-validation on
the development set. The combination of parameter values with the highest cross-validation score (fraction of correctly classified samples) is selected (Table I, Table II).

**Support Vector Classification.** Support vector machines (SVMs; Cortes and Vapnik, 1995) are non-parametric statistical learning techniques that are increasingly used for classification tasks, including remote sensing applications (Van den Eeckhaut et al., 2012; Ivanciuk, 2007; Mountrakis et al., 2011). SVM algorithms search for a hyperplane that separates two data classes with the maximum margin around that hyperplane, i.e. with the largest possible distance to the instances on both sides. Only the data points that are required to define this margin (support vectors) are used to set up the model. Thus, SVMs can deal with a large number of features and a limited number of training samples. A penalty parameter / slack variable $C$ controls the tolerance of the hyperplane and its margin towards training errors. For classification problems where the data is not linearly separable, a kernel function can map the data to a higher dimensional space (where it is linearly separable). Support vector classification is relatively tolerant towards irrelevant or redundant features (Kotsiantis, 2007; Mountrakis et al., 2011).

**TABLE I.** Support Vector Classification hyper-parameter optimisation on a random 50% subset of the training data (development set). $\gamma$ is the coefficient for the RBF kernel. $C$ is the penalty parameter of the error term. Details and empirically based recommendations on parameter ranges to test can be found in Hsu et al. (2003).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Parameter values tested</th>
<th>Parameter combination selected</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kernel</td>
<td>linear, RBF (radial basis function)</td>
<td>RBF</td>
</tr>
<tr>
<td>$C$</td>
<td>1, 10, 100, 1000</td>
<td>100</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>0.00001, 0.0001, 0.001, 0.01, 0.1</td>
<td>0.01</td>
</tr>
</tbody>
</table>

**Random Forest Classification.** Random forest (RF) is a non-parametric ensemble learner which can efficiently model non-linear relationships, handle a large number of
(potentially redundant) features and prevent overfitting (Breiman, 2001; Belgiu and Dragut, 2016). It aggregates the results of many randomized decision trees by the majority vote for the final results. Each tree is built based on a bootstrap sample of the training instances (subsampling with replacement) and each tree node is split using a user-defined number of randomly selected features (Max_features).

The data excluded from building a specific tree represent approximately one third of the original data and refer to the out-of-bag sample (OOB). Passing the OOB-data through the specific trees, and aggregating the proportion of misclassifications across all trees, results in an unbiased error estimate of the RFC model (Breiman, 2001). This can be used to define an adequate number of trees for the random forest classifier. The OOB error rate initially decreases with increasing number of trees. In our case, it stabilises with a number of trees $n_{estimators} = 700$. With this number of trees other hyper-parameters are optimised (Table II).

**TABLE II.** Random Forest hyper-parameter optimisation on a random 50% subset of the training data (development set). Max_depth is the maximum depth of the tree. If ‘None’, then nodes are expanded until all leaves are pure or until all leaves contain less than ‘min. samples split’ samples. Max_features is the size of the random subsets of features to consider when splitting a node. If ‘sqrt’, then max_features = sqrt(n_features). If ‘None’, then max_features = n_features. Min_samples_split is the minimum number of samples required to split an internal node. Min_samples_leaf is the minimum number of samples required to be at a leaf node. See scikit-learn documentation (http://scikit-learn.org/stable/index.html) for details and suggested parameter ranges to test.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Parameter values tested</th>
<th>Parameter combination selected</th>
</tr>
</thead>
<tbody>
<tr>
<td>max_depth</td>
<td>3, None</td>
<td>None</td>
</tr>
<tr>
<td>max_features</td>
<td>sqrt, None</td>
<td>None</td>
</tr>
<tr>
<td>min_samples_split</td>
<td>1, 3, 10</td>
<td>3</td>
</tr>
<tr>
<td>min_samples_leaf</td>
<td>1, 3, 10</td>
<td>3</td>
</tr>
</tbody>
</table>

**Classifier Fitting and Evaluation.** The performance of the selected hyper-parameters and the trained classifier is assessed on the evaluation set (random 50% of the training data) that was not used during grid search and model fitting. Moreover, the overall classifier accuracy (fraction of correctly classified samples) is calculated for the validation data set (containing the smaller landslide). Additionally, the accuracy metrics precision/correctness, recall/completeness and the F1-score (Olson and Delen, 2008) per class and overall are calculated from the true positive (TP), false positive (FP) and false negative (FN) counts as

$$\text{precision} = \frac{TP}{TP+FP},$$  \hspace{1cm} (7)

$$\text{recall} = \frac{TP}{TP+FN},$$  \hspace{1cm} (8)

and

$$F1\text{-score} = \frac{2\text{(precision}\cdot\text{recall})}{\text{precision}\cdot\text{recall}}.$$  \hspace{1cm} (9)

Based on the results of this evaluation (section Results - Supervised Classification) the machine learning classifiers with optimised hyper-parameters are trained on the entire
training data set (containing the larger landslide). Subsequently, the performance of the trained classifiers is evaluated with the validation data (smaller landslide). Based on this performance, one of the two classifiers is selected to classify all point clouds of the time series (the RF classifier, see Results section).

**Landslide Shapes and Rule-Based Reclassification of Point Cloud Segments**

To correct errors from the supervised classification, topological relations between landslides and their surroundings are established. Landslide processes are gravitational mass movements and have a clear tendency to move in downslope direction. The highest part of the resulting landslide form is at the scarp. We use this as a reasoning to automatically construct a landslide model from the classified point cloud segments. The number of landslide per scene \( n_{LS} \) and their approximated minimum separating distance \( \text{dist}_{LS} \) must be provided by the user. The landslide models establish a spatial context for the segments within the scene (inside/outside the landslide) and help to employ rules for reclassification.

**Extraction of Landslide Shapes.** First, all segments labelled as scarp are extracted and small and isolated scarp segments are removed (false positives (FPs) from the supervised classification). The remaining scarp segments are grown to main scarp candidates if they are spatially contiguous. This is a recursive procedure which considers also the segments’ elevation relative to the current main scarp candidate. This is based on the assumption that, due to their recurrent geomorphic activity, the top sections of the scarp tend to be the most prominent and least diffuse ones and thus are recognised easier than some other parts located lower down. Consequently, the relative elevation criterion allows the scarp growing procedure to prefer lower segments over higher segments. This proved beneficial because it resulted in more complete main scarp models while rejecting FPs above the main scarps which resisted the previous filtering. Such FPs result for instance from terracettes in the terrain created by livestock trampling. These can have similar morphometric characteristics as parts of the scarp. Finally, only the \( n_{LS} \) largest main scarp candidates are extracted. This excludes any remaining FPs, like small rock cliffs misclassified as scarp.

In the next step, the downslope area from these main scarps is defined by a raster based hydrological flow routing (deterministic 8 (D8) algorithm by O’Callaghan and Mark (1984)). The point sets that represent the main scarps and the flow paths are used to construct the approximated landslide polygon outlines as alpha shapes (Edelsbrunner et al., 1983; Fig. 4, Fig. 8). The parameter \( \text{dist}_{LS} \) is used to discriminate the individual landslides for treatment as separate objects.
Rule-Based Reclassification of Point Cloud Segments. Based on simple topological relations between the labelled point cloud segments and the landslide shapes, misclassified segments are reclassified according to a rule-set (Fig. 5). The rules are inferred from the assumption that eroded area and deposit do not exist outside the landslide and (undisturbed, low or high) grass does not typically occur inside the landslide. The respective misclassified segments are relabelled as the class considered the most likely alternative, also with respect to a visual control of the classification results in all scenes and to the confusion matrix (Fig. 6) which highlights the most severe misclassification types (for the validation data).

![Diagram of two-step classification strategy with supervised classification and rule-based reclassification.](image)

**Fig. 4.** Two-step classification strategy with supervised classification and rule-based reclassification.

![Diagram of topological rules for reclassification.](image)

**Fig. 5.** Topological rules for reclassification.
Extraction of Geomorphological Objects and Change Analysis

Finally, a connected component analysis grows adjacent segments of the same class to discrete scene objects and labels them with a common object ID. This creates the possibility to analyse changes of specific object classes or to identify changes of individual objects. For example, the cloud-to-cloud distance \(d_{C2C}\) can be aggregated as mean and/or standard deviation per object or per class. Moreover, the volume of eroded material can be calculated, for example restricted to the scarp (Fig. 9).

### Results

**Segmentation and Supervised Classification**

The segmentation procedure results in a couple of ten thousand segments per scene, representing the instances to be classified. Around 100,000 points of each point cloud are not grown into any segment and excluded from further analysis. These points do not meet the criteria for region growing (not enough neighbours (with similar properties) within the search radius) and are almost exclusively points in the vegetation. They can either be classified as such in post-processing or omitted, depending on the application requirements.

Table III shows the per-class accuracy metrics obtained for the training data set with an SVM and an RF classifier respectively. The model was trained on the development set (random 50% of the training data). The scores are computed on the evaluation set (other 50% of the training data). In this respect, the overall performance of the two machine learning classifiers is similar, with the random forest classifier slightly outperforming the support vector classifier for the class landslide scarp in terms of precision.

<table>
<thead>
<tr>
<th>Class</th>
<th>SVM</th>
<th>Recall</th>
<th>F1-Score</th>
<th>Segments</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 – Landslide scarp</td>
<td>0.54</td>
<td>0.69</td>
<td>0.69</td>
<td>216</td>
</tr>
<tr>
<td>2 – Eroded area</td>
<td>0.59</td>
<td>0.74</td>
<td>0.60</td>
<td>701</td>
</tr>
<tr>
<td>3 – Deposit</td>
<td>0.72</td>
<td>0.79</td>
<td>0.75</td>
<td>1106</td>
</tr>
<tr>
<td>4 – Medium and high vegetation</td>
<td>0.94</td>
<td>0.93</td>
<td>0.93</td>
<td>2269</td>
</tr>
<tr>
<td>5 – Low grass</td>
<td>0.90</td>
<td>0.76</td>
<td>0.85</td>
<td>2325</td>
</tr>
<tr>
<td>6 – High grass</td>
<td>0.65</td>
<td>0.70</td>
<td>0.68</td>
<td>734</td>
</tr>
<tr>
<td>7 – Rock outcrop</td>
<td>0.71</td>
<td>0.52</td>
<td>0.60</td>
<td>46</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td><strong>0.82</strong></td>
<td><strong>0.80</strong></td>
<td><strong>0.82</strong></td>
<td><strong>46</strong></td>
</tr>
</tbody>
</table>

The random forest classifier (RF) also obtained only a slightly higher mean accuracy score for the validation data than the support vector classifier (SVM) (78% vs. 76% fraction of correctly classified segments). Fig. 6 compares the results of the two classifiers for the validation data (containing the smaller landslide). They accurately recognise medium and high vegetation but other classes are prone to errors. Scarp is partly misclassified as deposit. Eroded area tends to be misclassified as deposit, low grass or high grass. Deposit is sometimes recognised as low grass or high grass.
Similar patterns of misclassification are evident from visual inspection of the other scenes. Fig. 7 visualises the results for both classification steps in three different scenes. One of the scenes was acquired with the Optech scanner (Fig. 7 a + b), the other two scenes with the Riegl scanner. With respect to the transferability of the trained classifier, the accuracy of the supervised classification is better for the unseen part of the same scene where the training data is from (PC_07; Fig. 7 c + d). For scenes (scans) acquired at another point of time, the classification tends to perform worse but still recognises major parts of the scene correctly. The instrument used for acquisition tends to influence the classification as well (depending on which data was used for training).

**Rule-based Reclassification**

Fig. 7 and 8 show point clouds classified with the random forest classifier and the same point cloud reclassified with the topological rule set and the extracted landslide shapes. The differences between scenes are reduced by the second classification step (rule-based reclassification), leading to a more consistent classification of point cloud objects through the time series. Basically, the landslide shapes are reconstructed correctly in all scenes. In the depositional zones, however, the shapes partly differ. Moreover, the results after the rule-based reclassification tend to overestimate the class deposit at the cost of eroded area because all segments classified as grass are reclassified as deposit if they are anywhere within the landslide. On the other hand, the reclassification improves the accuracy score (fraction of correctly classified segments) for certain classes considerably. For the validation data (left, unseen part of scene PC_07), scores for deposit and high grass increase from 63% to 77% and from 59% to 71% respectively.
Fig. 7. Top view of three different point cloud scenes after supervised (RF) classification (a, c, e) and after rule-based reclassification (b, d, f).
Object-based Changes

An example for change analysis on the level of landslide objects is presented in Fig. 9. It shows the 3D alpha shapes constructed from the scarp points of two successive point clouds. This can be used to visualize and estimate the volume of eroded material that was lost at the scarp between the two scans (approximately 1.7 m³).
DISCUSSION

In the previous sections, we presented a point cloud classification and object extraction approach for landslide monitoring, as well as the results from testing this approach with a time series of nine point clouds from a test site. The results of the accuracy analysis indicate that the two different machine learning classifiers can perform similarly well for a supervised classification of the scenes with morphometric features (overall accuracy metrics differing by maximum 2%). Thus, we conclude that in practice either of the two algorithms support vector machine and random forest is suited to accomplish this first part of the proposed approach, provided that the hyper-parameters are tuned properly and enough training data is available.

For this machine learning classification on a standard desktop computer the object-based approach is an advantage because it reduces the number of objects (instances) to classify from several million points in the raw point clouds to a maximum of 36 466 segments per scene. This reduces memory consumption considerably, in particular during the training phase, making a proper grid search for optimisation of hyper-parameters feasible.

Nevertheless, such a supervised classification restricted to geometric features has limitations (see the description of common errors above). Some classes of a natural scene are difficult to separate because (i) their patterns in a morphometric feature space are similar and (ii) the morphometric signature can be variable within a class. Therefore, the rule-based reclassification, integrating topological relations between objects of a scene, is an important component of the proposed classification approach. This improves the classification accuracy considerably. In particular, errors that are not tolerable from a geomorphological point of view (such as segments outside the landslide misclassified as eroded area) can be eliminated.

On the other hand, some classes are overlapping. Most landslide deposits at the test site, for example, are grass-covered, either because clods of turf and soil were displaced and deposited or because of vegetation regrowth already taking place in the less active parts of the landslide. Hence, it depends upon definition if that should be classified as grass or deposit.

Reclassifying all initial grass segments inside the landslide as deposit, results in an overestimation of deposit at the cost of eroded area. One reason can be that less smooth parts of the eroded area (with relatively large particles at the surface) tend to be misclassified as grass. Another reason can be that vegetation succession is already occurring in some parts of the eroded area. Again, this results in an actual overlap of classes and a conflict of definitions, which is also a question of scale. In this respect, the applied topological rules are not capable to accommodate the complexity of the scene in all cases. Improving the rule-set accordingly would require a method to subdivide the landslide shapes into eroded area and depositional zone. This is challenging due to their rather diffuse transition. A soft classification strategy could be an appropriate approach to accommodate the vagueness of these natural objects, also considering constraints to multi-temporal object-matching and change analyses.

Inaccuracies of the final classification appear in the lower part of the depositional zones due to incomplete landslide shapes (Fig. 8). Here, the diffuse appearance of the depositional zone in reality is limiting both an automated and a manual delineation. Moreover, limitation of the flow routing at the data extent border can influence the landslide shape reconstruction. This can be tolerated, with respect to a landslide monitoring
because of the reduced activity in these parts of the scene. The more active parts (which are more prominent in terms of morphology, e.g. the scarp) are recognised more consistently (Fig. 7).

With regard to its transferability, the supervised classification is validated on an independent data set (unseen, left part of the scene, containing the smaller landslide). Moreover, the final results from the scene containing the training data are compared with those from other scenes. Moreover, the presented methods have been tested with point clouds from a different TLS device. Limitations for transferring the classifier that was trained on one scene to other scenes of the test site can result from (i) variabilities in vegetational properties and morphology (phenological state) and (ii) differences in point cloud properties (cf. Fig. 7). The latter are related to the use of two different scanners and to different point densities due to inconsistent scan settings. However, in our series of nine point cloud scenes the scarp is recognised and the landslide shapes are constructed correctly. Integration of these key objects with simple topological rules (inferred from basic geomorphological knowledge) is shown to enhance the final classification and object extraction considerably, in particular regarding its consistency through the time series.

CONCLUSIONS

We presented an approach to extract geomorphological objects from a time series of terrestrial laser scanning point clouds. The experimental results show that the point clouds contain valuable information about the complex morphological characteristics of landslides and their surroundings. Discrete geomorphological objects can be identified and readily used for geomorphological interpretation and process analysis in a multi temporal framework. Thereby, the detailed, three-dimensional geometric information of the point cloud can be jointly used with semantic information.

Our work demonstrates that this information can be exploited to extract geomorphological objects (i) automatically, (ii) in a point cloud based workflow and (iii) using exclusively the geometric data. This has several advantages. The high degree of automation makes the analysis reproducible, objective and efficient. This is an important prerequisite for a landslide monitoring (i.e. with repeated measurements of a scene) on the basis of geomorphologically meaningful and consistent objects. Constraining the analysis to a point cloud data representation (no raster conversion) conserves the high level of geometric accuracy and three-dimensionality inherent in the original point cloud. A brief example demonstrates that this is beneficial for a subsequent change analysis to support detailed geomorphological process investigation.

From a methodological point of view, we conclude that the combination of a supervised classification with a rule-based reclassification using simple topological relationships between objects can yield good results. A machine learning preclassification (support vector machines and random forests) preclassified point cloud segments into geomorphologically meaningful object classes. This classification, however, contains certain types of errors, due to ambiguities of certain classes in a purely morphometric feature space. The reclassification step can correct the majority of errors from a machine learning preclassification (support vector machines and random forests). This increases the fraction of correctly classified segments per class by up to 14%.

The results indicate that the automated classification procedure can be transferred to
other landslide scenes with similar morphology and point cloud characteristics (such as point density). Future work should test the transferability to other monitoring sites where landslides occur in a similar natural environment (in terms of morphology and vegetation).

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The Photogrammetric Record


MAYR et al. Object-Based Classification of Terrestrial Laser Scanning Point Clouds for Landslide Monitoring


Résumé

L’histoire de l’appariement d’images remonte à plus de cinquante ans, lorsque les premières ...

Zusammenfassung


Resumen

La correspondencia de imágenes tiene una historia de más de 50 años, desde los primeros ...

摘要

影像匹配技术在模拟摄影测量中首次应用开始，已经有50年的发展 …