Advanced Image Analysis for Automated Mapping of Landslide Surface Fissures

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Abstract
Surface fissures are potential indicators of slope instabilities and considerably influence infiltration characteristics of the soil. The increasing availability of unmanned aerial vehicles (UAVs) enables the observation of surface features at unprecedented detail and this study develops an image processing method combining Gaussian filters and object-oriented image analysis to map such features in very-high resolution (VHR) aerial images largely automatically. At three different time steps the results of the technique are compared with expert elaborated maps.

Keywords
Line detection • Gaussian filter • Object-oriented image analysis • Landslide surface fissures • Unmanned aerial vehicle

Introduction
Surface features of slopes and rock cliffs reveal important information about the past and present patterns of deformation; their observation and interpretation can contribute to a better understanding of the controlling physical processes and help for the assessment of the related hazards (Fleming and Johnson 1989; McCalpin 1984; Purise 2003). Detailed mapping and analysis of structural discontinuities is a powerful tool to identify and characterize potentially unstable areas in hard rocks (Günther et al. 2004; Hock and Bray 1981; Jaboyedoff et al. 2004; Matheson 1983; Priest 1993; Selby 1993), and surface fissures may serve as a geo-indicator for initial failure states in soft sediments (Abramson et al. 2001; Chowdhury and Zhang 1991; Petley et al. 2006; Krauskopf et al. 1939; Shreve 1966).

The surface characteristics also influence hydrological processes, such as infiltration and drainage patterns, which in turn affect the ground-water system and the kinetic response of slopes to hydrological events (Malet et al. 2003, 2005; van Asch et al. 2009). Especially tension cracks and fissures modify the infiltration and pore-water response considerably, and their integration into physically-based models may yield more reliable kinematic forecasts and estimates of the hazard level (Baum and Fleming 1991; Corominas et al. 2002; Iverson 2000; Lindenmaier et al. 2005; Malet et al. 2005; van Beek and van Asch 1999).

Detailed maps of surface deformation features can be obtained by extensive field surveys either through the direct
observation of the topography (cf. Fleming et al. 1999; Meissina 2006) or indirectly through the analysis of seismic waves acquired in tomography set-ups (Grandjean et al. 2011; Bie`vre et al. 2011). The surface deformation pattern can also be obtained over larger areas from the analysis of VHR aerial images (especially those acquired from low-cost Unmanned Aerial Vehicles UAVs); (Niethammer et al. 2011). In this study, we targeted the development of a largely automatized image analysis technique to detect, map and characterize surface fissures from VHR aerial images. The developed method is based on a combination of Gaussian directional filters and object-oriented image analysis (OOA) and was tested on a set of multi-temporal VHR images acquired at the Super Sauze mudslide in Southeast French Alps. The obtained results were compared to manual mappings carried out by experts combining image interpretation and field surveys.

Study Site and Data

The Super Sauze mudslide is an active landslide located in the Barcelonnette Basin in the Southern French Alps (Fig. 1). It is a complex style movement that developed in clay-rich black marls since the 1970s and features highly variable displacement rates controlled by the local hydrological conditions (Malet et al. 2005). For this study we used subsets (≈14,000 m²) of three aerial images acquired with a UAV (Fig. 1) by Niethammer et al. (2011) in 2008/09 and a fourth image taken in July 2009 with a H4D-50 digital camera mounted on a helicopter. At the time of the helicopter survey an aerial LiDAR scan was also conducted and the resulting point cloud was rendered to a 0.5 m resolution raster to derive the general hydrological drainage pattern.

Methods

Fissure Characteristics and Special Challenges

The surface fissures observed at the landslide surface are essentially openings of the topsoil layer induced by lateral and/or basal shear, and the development of compression and extension features. In the field, fissure widths of 1–50 cm and lengths of typically above 100 cm are observed (e.g., Fig. 2a). In the images they can be recognized as dark curve-linear or angled lines as soon as their width approaches one pixel in size, whereas the highly textured landslide surface poses a noisy background that makes the visual and automatic mapping of the fine linear structures a challenging task; Further difficulties arise from variable illumination conditions and image resolutions among the different acquisitions.

Since most classical image processing techniques for the extraction of linear features return signals on both lines and edges (e.g., Sobel filter, Canny edge detector) and/or specifically target straight linear elements (e.g., Hough transform) they are not well-suited for the detection of the fissures.

Similar issues have motivated numerous studies in the field of medical image processing and a well-studied problem is the detection of dark blood vessels in photographs of the human retina. Based on the observation that the cross-profiles of the vessels approximate well a Gaussian distribution, Chaudhuri et al. (1989) proposed the use of a matched filter (MF) that is essentially a Gaussian convolution kernel subtracted by its own mean value. As Fig. 2 illustrates, the cross-sections of surface fissures can be approximated well with a Gaussian distribution. Since the fissures can take any possible orientation and the MF will only give a peak response when crossing the dark line at an angle close to 90°, in practice the filter must be rotated in all possible directions and only the maximum response is retained.

Combining Gaussian Filters

Since MF not only capture thin lines but still provide spurious responses at image features such as step edges (Fig. 3c), numerous extensions (Hoover et al. 2000; Sofka and Stewart 2006) and complex alternative approaches (Mendonca and Campilho 2006; Soares et al. 2006) have been proposed. Their enhanced results, however, incur considerable computational costs (which constitute a problem when the methods are to be applied on VHR remote sensing imagery easily containing 20 times more pixels than retinal images), and are based on assumptions applicable to vascular networks but not necessarily for the investigated fissure patterns. Recently Zhang et al. (2010) proposed a computationally efficient modification of the original MF filtering approach.
Fig. 2 Subset of the UAV image from October 2008 showing typical fissure patterns and grey-value profiles (green channel) approximated with Gaussian curve (a-d). Field terrestrial photograph taken in October 2009(e).

using additionally a first order derivative of a Gaussian function (FDOG) to locally adapt the thresholds separating dark line from non-target features. Inspired by their proposed method, a similar approach has been implemented in ENVI-IDL 4.8 (ITT Visual Information Solutions); the steps in the processing chain are described in the following.

The MF is a two dimensional kernel defined in the x-direction by an inverted Gaussian profile (Fig. 3b), and in the y-direction by replicates of the same profile. It may be denoted as:

$$MF = g(x, y; \sigma) = -\frac{1}{\sqrt{2\pi}\sigma} e^{-\left(\frac{x^2}{2\sigma^2}\right)} - m,$$  \hspace{1cm} (1)

for \(|x| \leq 3\sigma, |y| \leq L/2\),

where \(\sigma\) denotes the standard deviation of the Gaussian functions and relates to the width of the targeted feature, whereas \(L\) defines the extent of the kernel in the y-direction and can be related to the length of the fissures. As illustrated in Fig. 3c-d the matched filter still responds to dark and bright step edges. The spurious detection resulting from bright step edges can be addressed with a simple pre-filtering where every pixel value that is \(2\sigma\) above the mean grey level intensity of the image is replaced with the local median (Fig. 2).

Another more general strategy is to adopt the response of the FDOG to locally adjust the thresholds applied on the MF response to classify fissure and non-fissure structures. In analogy to 1, the first order derivative filter kernel may be denoted as:

$$FDOG = g'(x, y; \sigma) = -\frac{1}{\sqrt{2\pi}\sigma^3} e^{-\frac{x^2}{2\sigma^2}},$$ \hspace{1cm} (2)

for \(|x| \leq 3\sigma, |y| \leq L/2\).

Figure 3e shows that unlike the response to edges the FDOG signal yields a zero crossing in the middle of the idealized fissure structure. Convolving the FDOG response with a simple mean filter it is further possible to broaden the zero crossing to a plateau covering the whole width of the
fissure, whereas the high absolute values at the step edge are retained to later increase the thresholds locally at step edges.

As noted above, a fissure may be aligned at any orientation and in practice matched filters at multiple directions are evaluated and for each pixel only the maximum response value is retained. This can also be considered as finding the angle \( \theta_{\text{max}(x,y)} \), which maximizes the filter response at a given position \((x,y)\) and can be denoted as:

\[
\theta_{\text{max}(x,y)} = \arg \max (I(x,y) \otimes MF_{\theta})
\]

for \( 0 < \theta \leq \pi \)

where \( I \) denotes the image, \( \otimes \) the convolution operator and \( \theta \) the orientation of the MF. The calculation of the maximum value at each pixel in the MF response image \( R \) can be expressed by:

\[
R(x,y) = I(x,y) \otimes MF_{\theta_{\text{max}}}
\]

and the response of the FDOG filter \( D \) can be denoted accordingly by:

\[
D(x,y) = I(x,y) \otimes \text{FDOG}_{\theta_{\text{max}}} \otimes M
\]

(5)

In the latter expression, \( M \) denotes the mean filter used to convolve the response of FDOG filter oriented at the same direction where the MF provided the maximum response. While Zhang et al. (2010) suggested a fixed and very broad mean filter we suggest to use a kernel size that matches the width of the Gaussian kernel \((6\sigma)\) and is consequently close to the width of the fissures.

The response of the FDOG filtering is used to locally adjust the threshold \( T \) that is applied on \( R \) according to the following formula:

\[
T = (1 + \bar{D}) \ast \mu_R \ast c
\]

where \( \bar{D} \) denotes \( D \) after a normalization to a value range between 0 and 1, \( \mu_R \) is the mean of the response image \( R \) and \( c \) is a user-defined parameter that typically range from 2 to 3 and influences the sensitivity of the detection.

In summary, the user needs to specify four simple parameters, namely (1) the scale of the filter kernels in terms of \( \sigma \), (2) the length \( L \) of the kernel, (3) a constant \( c \) to adjust the thresholding, and (4) the number of orientations \( (\theta) \) at which the filters are calculated. An adjustment of the latter, however, is only relevant with very large kernels and/or images where the computational time may become an issue. In our experience 12 angular steps are already sufficient to capture linear features at all orientations.

The smallest visible fissures at the coarsest resolution are approximately 10 cm wide, and extracting several cross profiles on the smallest elements, standard deviations \( \sigma \) between 0.6 and 0.7 are observed for the best fitting Gaussian function. In our experience, \( \sigma \) establishes the lower bound for the width of the targeted features, whereas the filters still remain sensitive to features which are up to five times larger. For \( L \), the minimum length of the fissures is chosen, which is typically at least 1 m. \( \sigma \) and \( L \) were kept the same for all experiments and only scaled according to the pixel size of each image (Table 1). In all experiments the green channel was used because it provided the best contrast between the surface fissures and the background.
Object-Oriented Post-Processing

The filtering process generally performed well in detecting the dark linear structures, whereas several visually similar surface features such as erosion features (rills, smallthalwegs) and elongated shadows induced by the microtopography andvegetation still yield numerous false positive detections. Theirremoval requires a higher level understanding of the scene context. In order to put spatial reasoning into an explicit form and to automatize the post-processing we propose an object-oriented approach implemented in eCognition 8.64 (Trimble 2011).

First, the ratio of shadow around each detected element is evaluated and the element is removed as false positive if the area ratio is larger than 0.33. Vegetation generally shows a higher reflectance in the green and red compared to the blue channel, whose contribution to the sum of all channels is generally less than one third. The exact threshold may, however, depend on illumination conditions and the season, and Otsu’s method (Otsu 1979) was adopted to automatically determine the threshold constraining the search space to ratio blue values below 0.33. Fissure candidates covered by the resulting vegetation class, or having a relative border length larger than 0.15, were subsequently removed.

False detections may originate from small elongated elements nested in larger features such as gullies, whereas fissures can be distinguished from false positives as soon as their orientation significantly deviates from the main orientation of the larger linear feature. To exploit this relationship the Gaussian filtering was repeated with the settings indicated in Table 1, but with a two times increased scale $\sigma$ and on a five times coarser image representation. Resampling was performed with a bilinear interpolation scheme. The resulting large linear features were overlaid with the map containing the fissure candidates, and the difference of their main angles was calculated. An intermediate result is illustrated Fig. 4. We tested angular thresholds of 10°–45° and selected a rather conservative cut-off value of 13°. All candidates overlapping a larger feature and differing in their main direction less than 13° were consequently removed (Fig. 4).

The same operation was performed once more using the main drainage lines extracted from a LiDAR surface model (0.5 m raster resolution) instead of the coarse scale linear features.

A final clean-up step was implemented removing all candidates not longer than 0.4 m, an area smaller than 0.1 m², and a fissure class density lower than 1 % in a surrounding neighbourhood of 10 m². Table 2 displays that most adopted thresholds were kept the same among all scenes, whereas the classification rule for shade areas had to be adopted to compensate for the different illumination conditions (direct sunlight in July vs. diffuse light in October).

![Fig. 4 Illustration of an intermediate processing step in the object-oriented post-processing routine. Fissure candidates that are overlapped by larger linear features and aligned with them (±13°) are excluded](image)

| Table 2 Summary of the thresholds adopted in the object-oriented post-processing routine |
|-----------------------------------------------|---------------|---------------|---------------|
| Shadows                                      | July 2008     | July 2009     | October 2009  |
| Shadow ratio                                 | $\leq 0.33$   | $\leq 0.33$   | $\leq 0.33$   |
| Rel. border to vegetation                    | $\leq 0.15$   | $\leq 0.15$   | $\leq 0.15$   |
| Min. angular difference                      | $>13°$        | $>13°$        | $>13°$        |
| Min. length (clean up)                       | $\geq 0.4$ m  | $\geq 0.4$ m  | $\geq 0.4$ m  |
| Min. length (clean up)                       | $>0.1$ m²     | $>0.1$ m²     | $>0.1$ m²     |
| Min. fissure class density                   | $>1 %/10$ m²  | $>1 %/10$ m²  | $>1 %/10$ m²  |

Results and Discussion

The imagery acquired in July 2008, July 2009 and October 2009 was processed with the parameter setting described above where at the highest spatial resolution ($\approx$ 5 Megapixel) the routine required less than 5 min to complete (Intel Core Duo 2.8 GHz, 4 GB RAM). Relative good agreement of the general fissure patterns was found by comparing the results obtained with expert maps based on field surveys and those obtained from visual image interpretation (Fig. 5).
Especially in areas with an abundant occurrence of fissures the visual appearance of expert and automatic mappings is similar, whereas most remaining mismatches originate from features detected by the proposed technique but not registered in the expert maps.

In order to obtain a quantitative estimate of the match between both mapping, line densities were calculated from the original maps varying the kernel size and the resolution of the output raster between 2 and 6 m. Figure 6f shows that for all time steps the agreement between expert and automatic maps is higher at coarser spatial scales. This is in agreement with the observed similar spatial patterns in both mappings, whereas there are still significant differences at the scale of individual fissures.

While it is important to note that also the manual mappings comprise a yet not quantified degree of uncertainties, a significant number of false detection can still be clearly attributed to cast shadows that resemble the elongated shape of fissures. Somewhat counter intuitive this leads to a more robust performance of the proposed mapping technique on low contrast images acquired under cloudy conditions because cloudy sky yields a diffuse and more uniform illumination of the surface. Indeed the best match was achieved with the UAV images acquired in October 2009 (Fig. 6a–e).

Besides quantitative differences it should also be noted that the original expert map comprises information about the type of the fissure which at present cannot be resolved with the proposed technique, whereas the automated mapping yields information about the vegetation cover as by product.

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References


Tribble (2011) Tribble cognition 〝 Release Notes