Authors’ comment: ESURF-2021-103

Full 4D Change Analysis of Topographic Point Cloud Time Series using Kalman Filtering

This authors’ comment is a response to the reviewer comments by (1) Dr. R. Lindenbergh and M. Kuschnerus, and by (2) Dr. D. Lague. On behalf of all authors, I want to express our gratitude for taking the time to read and comment on our manuscript.

The two reviews give many helpful suggestions to improve the quality of both our research and the presentation of the results. As both reviewers indicate that the topic is of relevance to the community, we will prepare a revised version of the manuscript in the coming weeks. For now, we wish to respond to the main points of criticism (indicated as “Major comment” or “General comment” by the reviewers) and outline our revision approaches in the following.

We hope the reviewers and the editors agree that once these changes are incorporated into the manuscript, the quality is improved sufficiently for final publication in ESurf.

April 24, 2022, Lukas Winiwarter (on behalf of all co-authors)

---

1. Review by Dr. R. Lindenbergh and M. Kuschnerus

Major comment #1:

The Kalman filter is one way of interpolating a time series. Directly related is Kriging, which aims at assessing and exploiting spatial and/or temporal correlation. Kriging also enables error propagation. Time series could also be approximated using Fourier or B-Spline polynomials. This could be better discussed in the Intro (as it is related work).

We will make sure to give appropriate consideration to Kriging and Fourier/polynomial approximations in the introduction of the revised paper, as well as to discuss similarities and differences to Kalman filtering.

Major comment #2:

In your Kalman filter implementation you use three parameters, location, velocity and acceleration. First it should be clearly stated somewhere that you use these parameters to model change in the vertical direction (right?). That said, using velocity and acceleration to model change at a location that changes due to digging is not directly intuitive to me, as such change would better modeled as a step function, please comment. Or more general, how should instantaneous change be incorporated in your setup? And do you really need acceleration as a third parameter, would location and velocity not provide similar results in an easier way?

It is correct that the Kalman filter using the Newtonian model (cf. Eqs. 1 and 2) is unfit to represent sudden changes, such as those induced by the excavator works and other large episodic events including rockfalls. This is reflected in the large sum of squared residuals of the Kalman smoother results. The effect is very similar to the global test in adjustment computation, where a large residual sum can suggest an unfit functional model.

In the revision, we will add more explanation on how this sum of squared residuals could be used to detect areas/timespans where the model is unfit and how a piecewise model (re-initializing the

Kalman filter at a break point) could lead to a better estimate. Furthermore, and in accordance with comments by Dr. D. Lague, we will exclude the area of excavator work from the analysis.

Major comment #3:

I find Figure 1 difficult to understand at first sight, would be good to also include a photo or point cloud colored by height as a fist impression of the site.

We will add a better visualization of the study site in the revision.

Major comment #4:

Sect. 2.5, from line 263 onwards and Sect. 2.6: Looks like you are trying many different methods at once. Why not choose one clear method of (1) pre-processing (2) uncertainties with M3C2-EP (3) smoothed time series with Kalman filter (4) feature extraction (5) clustering. Where you choose one set of (most relevant) features for the clustering. In my understanding the main goal of this paper is not to compare different features and/or clustering algorithms but to introduce the two previous steps and highlight the improvements that they yield during clustering. Possibly also add the workflow chart as shown in the readme file that comes with your code on Github. The comparison with clustering on unfiltered time series and without feature detection can then be part of the discussion.

We agree that we might have included too many unrelated methods/results. We will revise the paper to focus on more clearly showing the benefit of (a) smoothing the time series for feature extraction (also cf. the comment by Dr. D. Lague on finite differences) and (b) kMeans clustering. We realize that the Gaussian Mixed Models are adding too many additional thoughts for a single article (weakening the focus). A workflow chart is a good suggestion and will be incorporated.

Major comment #5:

It would be good if some or all of the features in Tables 1 to 4 could be illustrated on 2 two 3 example time series (e.g. RTS-SE-0.5) of representative locations, one in the excavation area, one in a rockfall gully and some third one.

We will add some more representative locations instead of going into detail in the clustering. As for the features, we will survey inputs to common geophysical models (e.g., erosion models) and extract these from the time series instead of the current ones presented in Tab. 1-4.

Major comment #6:

Results section and Figures 4-8: some subsections are needed here to make it more accessible. The first part deals with the results of processing steps 1-4. From line 300 it goes into feature extraction and comparison/visualization of different features. As mentioned above: better focus on one set of features. Then a subsection called 'comparison' is needed. Here it should be clear, what is 'your own presented method' and what other methods do you compare with. I would suggest to only compare end results and not different steps in between. Make a selection out of Figures 4 to 8 and show the most relevant results.

This is in line with our planned revision of focussing on the kMeans clustering and removing the large number of feature-based classifications. Furthermore, this allows for a better presentation of the representative locations, the choice of the physical model, and the Kalman filter in general.

Major comment #7:

P14, Fig 7 is hardly discussed, discuss if relevant, or omit the figure.

We will omit this figure in the revision.

---

2. Review by Dr. D. Lague

Major comment #1:

Kalman filtering is used for predicting system states that vary smoothly. I do not see why it would apply to an excavator removing rocks, rockfall or climate-driven surface erosion given that these events tends to be highly discrete in time, and thus inconsistent with a smooth evolution. Moreover, the use of a backward pass limits the ability of the method to accurately detect the timing of an event. Why can't you simply define local velocities or accelerations from a finite-difference calculation (e.g., v=(P(t2)-P(t1))/(t2-t1) where P is your point location. You'd get a better temporal localization of events, at the expense of a lower detectability of small events. As for the clustering, as you mention in the discussion, a simple linear interpolation would suffice.

The Kalman filter is limited by the choice of functional model, which needs to be differentiable and therefore continuous. To that extent, it is true that discrete events are not well represented by the model, which is also visible in the areas of excavator work. However, while the dataset shows a rockfall-affected area, the changes that are observed represent rill erosion rather than episodic rockfalls. In the revised version, we will focus on such examples of change happing over multiple epochs, and disregard the anthropogenic change by excluding this area from the dataset.

To our understanding, the backward pass does not limit the accurate detection timing of changes. In fact, only using a forward pass would bias the detection towards later points in time (cf. the blue line in Fig. 2). This effect is removed by using the backward pass in addition. In contrast to a difference calculation, noise is effectively reduced, which is especially important if thresholding is undertaken in subsequent steps (e.g. by means of a statistical test). Taking numerical derivatives drastically increases the signal-to-noise ratio as uncertainties are amplified in the differencing. We will take care to clearly demonstrate this in the revised manuscript.

To identify the timing of events using the Kalman filter, one can, e.g., take the argument maximum of the absolute velocity (i.e., the turning points of the smoother estimate). For all choices of q, they perfectly estimate the location (cf. Fig. 3, the peak of the red curve is exactly aligned with the change event). Of course, the backward pass is only available in post-processing/offline filtering, and not fit for predictions into the future (i.e. online monitoring). We will make this distinction clearer in the revised manuscript.

Major comment #2:

The part of the paper using features extracted from time series is quite superficial. There is no discussion on which features are actually important in the clustering.

In alignment with the comments by Dr. R. Lindenbergh and M. Kuschnerus, we will remove the clustering using extracted features from the manuscript.

Major comment #3:

The choice of the number of cluster is not discussed at all. This is a critical point as the issues of over or under-segmentation are critical in clustering, and not addressed at all here in the paper.

Our experiments showed that the number of clusters used in the GMM do not have a large influence on the result in the area of the debris cone (i.e. target area). We assume this to be because of the larger variability of data (detected changes) within the surrounding forest areas, where the additional clusters were formed. In the revised manuscript, we will take care to show these considerations and also discuss the number of clusters for the kMeans clustering.

Major comment #4:

Some figures have poor quality, with details that are difficult to see (fig. 7,8)

We will take care to improve the figures and include them in high quality.

Major comment #5:

Figure 8 seems to miss 1 sub-pictures that is mentioned in the text, but not shown

Figures will be reworked in the revised manuscript. We apologize for the incorrect reference to Fig. 8c.

Major comment #6:

The results section does not have a clear organization, and many figure are not described and exploited to their full extent.

As also suggested by Dr. R. Lindenbergh and M. Kuschnerus, we will thoroughly revise the results section, omit the clustering using GMM and the derived features, and focus more on the Kalman filter results as well as the kMeans clustering and differences to the state of the art. This will allow us to make better use of the more prominent results and figures.

Major comment #7:

The discussion do not address the choice of the number of clusters. Also it does not discuss the limits of the approach, when it comes to the reduced temporal resolution, the need to choose a state variance, and the general complexity of the approach. In particular, it is ill adapted to detect precursors which can be critical in real-time monitoring because of the smoothing effect of the signal. In general, I find that there is a tendency in the discussion to assume that because the method is more complex, it is better. However, it is not clearly supported by the evidence shown in the paper. Apart from one figure (fig. 3), the superiority of the new approach compared to a simple bi-temporal approach is not clearly demonstrated (and I actually have doubts on the results of fig. 3). The benefits in terms of lower level of change detection are not obvious and would benefit from synthetic data simulation to evaluate quantitatively how each method is able to recover a known change.

Our aim is to present the method as an extension to bitemporal change detection in the temporal domain. The notion of improving bitemporal methods is not based on the more complex model, but the increased complexity allows for the introduction of uncertainties to the analysis. We may see it as "more complex is not worse", which allows us to consider additional information in the analysis (i.e., reducing uncertainties).

The main point of doubt concerning Fig. 3 seems to be the bitemporal uncertainty quantification. We will make sure to analyse the components of uncertainty resulting from M3C2, and will present this in the updated manuscript. A first analysis showed that the LoDectection of ~8 cm at these locations is mainly a result of uncertainty in the rotation of the coordinate systems. It is yet to be determined if there is an actual rotation/tilt of the measurement pillar, e.g. due to sun irradiation, or if this is a (temperature-induced) atmospheric effect. In either case, while the changes are systematic, they cannot fully be alleviated by a rigid Helmert transformation (otherwise the ICP would solve this problem). Therefore, the residuals are treated as errors, resulting in a higher LoDetection.

In response to the comments by Dr. R. Lindenbergh and M. Kuschernus, we will extract more examples from the dataset to visualize the full time series. This will more clearly demonstrate the results of Kalman filtering at different locations. As the reviewer correctly points out, the example locations only show parts of the benefits of a Kalman filter. We therefore welcome the suggestion of synthetically altering the data. We will subsample the 4D dataset both spatially and temporally (including irregular intervals). This will result in different M3C2-EP uncertainties for different epochs, as the number of points will not be the same in each epoch (due to different subsampling). Then, we expect to show that the Kalman filter still provides an adequate fit, whereas more simple averaging or the method presented by Kromer et al. (2015) cannot use this information in the same way. With this approach, we believe that a fully synthetic dataset (e.g., by using Virtual Laser Scanning) is not required after providing clear evidence from the examples outlined above.

Finally, in contrast to simple moving window averaging of the time series, the Kalman filter combines the information about the measurement uncertainties with temporal uncertainty (as given by the q value). In consequence, the estimate of filter states between measurements is also attributed by an appropriate uncertainty value depending on how large the timespan between the surrounding measurements is. We will include these considerations in the revised manuscript.

Major comment #8:

The discussion does not describe the benefit of Kalman filtering compared to the Kromer et al., (2015) approach.

We will more explicitly mention the benefit of being able to use uncertainty information in connection with temporal smoothing (cf. response to previous comment).

Major comment #9:

Also the fact that the clustering is done in 2D, while the core points are inherently 3D is not discussed.

We guess that this is a misunderstanding. Clustering was done on the feature dimensions, and fully excluded spatial information. We will make sure to clearly explain this in the revised manuscript. Thanks for hinting to it.

Below follow two of the specific remarks we further want to address:

- *Ranging accuracy:*
  There are additional stable reflectors in the scene which were also scanned by the laser scanner. We will derive a ranging uncertainty value/model from these reflectors.

- *Comments on "discrete erosion events" and "temporal detection" vs. "prediction":*
  We understand the critique on the Kalman filter not being the best solution for discrete erosion events, and agree that the exemplary time series shown in Fig. 3 suggests we employ the Kalman filter for detection of such a discrete event. In fact, the slow but steady change after 2020-08-23 06:00 until the end of the time series much better shows the type of change the Kalman filter should be employed for.
  In the revision, we will take two steps to tackle these issues:
  1) Locate better examples in the dataset and
  2) More clearly discuss in which cases (i.e., for what types of change) Kalman filtering is an effective way to reduce the LoDetection, and when and where other methods of change detection and quantification are better suited. Moreover, we will clearly state that Kalman filtering is not "the holy grail", but rather adds to the toolset of existing 3D/4D change quantification methods.

References:

Abellán, A., Jaboyedoff, M., Oppikofer, T., and Vilaplana, J. M.: Detection of millimetric deformation using a terrestrial laser scanner: experiment and application to a rockfall event, Nat. Hazards Earth Syst. Sci., 9, 365–372, https://doi.org/10.5194/nhess-9-365-2009, 2009.