

Earth Surf. Dynam. Discuss., referee comment RC2
<https://doi.org/10.5194/esurf-2021-103-RC2>, 2022
© Author(s) 2022. This work is distributed under
the Creative Commons Attribution 4.0 License.

Comment on esurf-2021-103

Dimitri Lague (Referee)

Referee comment on "Full four-dimensional change analysis of topographic point cloud time series using Kalman filtering" by Lukas Winiwarter et al., Earth Surf. Dynam. Discuss., <https://doi.org/10.5194/esurf-2021-103-RC2>, 2022

Winiwarter and co-authors propose a new method to analyze 3D point cloud time series (so called 4D data) by combining a spatial smoothing (the existing M3C2 distance measurement with a specific error model recently published by the authors M3C2-EP) and a temporal smoothing using Kalman filtering. Kalman filtering is typically used to interpolate and smooth the trajectory of moving objects (planes, vehicules...), and even extrapolate for short time periods their trajectory. Specific points of the scene (regular core points) record the complete temporal evolution of the topographic change which is smoothed and interpolated with Kalman filtering to create a time serie of topographic change with regular sampling. Following a string of recent papers describing spatio-temporal clustering of 4D data, the authors use various approaches to cluster the 2D map of features extracted from the time series, to create maps of clusters (e.g., timing of the first event, amplitude of the largest event....). They use a real dataset of a cliff monitored over several days with TLS.

Evaluation: while the general idea of smoothing temporally the signal to improve the signal to noise ratio and the detectability of potentially smaller events is interesting (but not new in itself, e.g., Komer et al., 2015), I find that the paper do not demonstrate clearly the benefits of the complex Kalman filtering and its associated error model compared to previous approaches (Kromer et al., 2015) or more simpler approach such as bi-temporal analysis, or simple linear interpolation when regular temporal sampling of data is needed. The paper also lacks information and discussion on key aspects of the clustering approach., and use a very complex set of features derived from time series without clear justification and in-depth analysis of the results.

The introduction is very good, but the result section is not well organized and many figures are not informative, or of limited quality, or not fully described in the text. A simple figure illustrating the principle of the method is also lacking.

I think it is possible for this MS to be published at some point, but it needs very significant work to better present the results (both in terms of figure quality and analysis), better demonstrate the advantages of the method compared to simpler approaches, which could be done for instance on synthetic data. Also focusing the clustering approach on one method with a meaningful set of features that would be easy to interpret would make the paper simpler.

General comment :

- 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 tend 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., $v = (P(t_2) - P(t_1)) / (t_2 - t_1)$ 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 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.
- The choice of the number of clusters 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.
- Some figures have poor quality, with details that are difficult to see (fig. 7,8)
- Figure 8 seems to miss 1 sub-picture that is mentioned in the text, but not shown
- The results section does not have a clear organization, and many figures are not described and exploited to their full extent.
- The discussion does 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.
- The discussion does not describe the benefit of Kalman filtering compared to the Kromer et al., (2015) approach.
- Also the fact that the clustering is done in 2D, while the core points are inherently 3D is not discussed.

Detailed comments

The introduction is very good, and states clearly the objectives of the paper with the necessary references to previous work.

L113 : please specify the typical point spacing. This is a critical information that is missing to understand why you are not able with bi-temporal analysis to detect a 5-10 cm change with a sensor with 0.005 m precision !

L127 : could you explain why you needed to realign the data if the sensor was on a fixed pillar, and arguably, all scans were acquired in the same reference frame ? or is it specifically related to using M3C2-EP and estimating the alignment uncertainty ? In that case, mention it in the text.

L136 : why 0.5 m ?

L138 : are there any correction for temperature effects on ranging measurement (that start to be significant over 800 m) ? Also, I suspect the 0.005 m ranging accuracy is certainly not at 800 m distance ! have you better constrained on the actual ranging accuracy at 800 m ?

Section 2.1 : could you give an estimate of the mean point density of the scans ?

Section 2.2 seems like an introduction to the algorithm you present to analyses PC series, with a bit of state of the art in spatio-temporal clustering. Then subsequent section (M3C2-EP etc...à) should be sub-section on this one (2.2.1, 2.2.2....) otherwise section 2.2 by itself is not part of the method.

L174 : while I know M3C2-EP, I suspect it would help less specialist readers to have a bit more explanation on the extra steps needed for the uncertainty calculation in M3C2-EP, and the benefits compared to the standard uncertainty model of M3C2. No need to go into too much detail, but the M3C2-EP paper being a tough one to read, it would help to have a self consistent paper.

L179 : you should specify how k is going to be defined, as it needs to be manually chosen for k-means clustering.

L180 : I'm roughly familiar with Kalman filtering owing to airborne LiDAR data processing,

however, I suspect many readers won't, and they may have trouble following this part. Maybe a sketch of the basis of kalman filtering applied in your specific case would help.

L220 : see major comment 1. I really have trouble reconciling the smooth nature of Kalman filtering with the highly discrete nature of erosion events

L241 : this sentence is not clear to me. How do you turn the 4D data into 2D ?-> ok I get it, it's an introduction to the subsequent section. Maybe rephrase to make things clearer.

L254-258 : making sense of the attributes in relation to the expected geomorphic processes would be great. For instance, it is not obvious at this stage why the total curvature is importante (compared to a more straightforward measure such as cumulative change) ?

L263 : FFT on a signal which is have periodic pattern does not really make sense especially if you're not detrending the signal and using filters to account for the finite dimension of the time series. Maybe theres's a reason I don't see, but in that case it seems important to give a little intuition as to why you suggest such features. Wavelet analysis might make more sense as it combines temporal location (when an event happen) and frequency analysis (\sim duration of an event), but it's hard to come up with simple integrative features to be used for subsequent clustering.

L275 : I do not see at all, how the clustering based on the features, which are potentially very numerous and do not contain any relation to "physics" or "drivers" of cliff erosion (precipitation, local cliff geometry,) can actually lead to a more "physical interpretation" than analyzing the estimated change directly. The authors need to back this statement.

L277 : you should mention that the number of clusters need to be specified, in case non-specialist readers think that unsupervised clustering is just pushing a button and getting a result. An you should explain here, how you choose the number of clusters (as you did for GMM. It's critical.

L293-299 / figure 2 : the description of the figure needs to be improed. You're first sentence stating "appropriately filters daily effects" gives a sense that 0.005 m/day^2 is initially the best value, while indeed you choose 0.05 m/day^2 . Also for such an important parameter, your search of the optimum is rather qualitative. I don't think plotting acceleration helps at all. You do not discuss the occurrence of clear oscillations in the signal prior to the change. Are they real signal, or variations of the scanner position ($\pm 2 \text{ cm}$, that's huge) ? It seems that another criteria for choosing σ is that it must be large enough to not trigger a detection for these oscillations.

Fig3 : It is hard to tell without having the information on the point cloud spacing, but I'm extremely surprised that a bi-temporal analysis is not able to detect change in the channels where distances more than 5 cm are measured by the multitemporal approach. It might be that the ICP registration has an issue on the two epochs used for testing for significant change and translated into a large registration error increasing the LoD. But 5 cm over a few cm² should be detected easily with a sensor with 1 cm ranging error (an estimate at 800 m) and a 1 cm registration error. It's very odd.

Fig 4b: use also greyed color for the area with non significant change to facilitate comparison with 4a. It would be interesting, following fig. 3 to show if the onset of change detection differs significantly from the bi-temporal approach compared to the multi-temporal approach. This would better emphasize the interest of your method.

L318 : which "value" ? it's not clear

L321 : I fail to grab the interest in showing fig. 5. What do you learn and how important it is ?

L325 : Ok, figure 6 tells us you use 50 clusters in one case and 100 in the second case, but it is not even mentioned in the text and you do not justify your choices. It's a critical point to discuss. Also why can't you simply create a linear interpolation between two epochs to fill in the gap for your clustering ? it would solve your problem of temporal spacing without having to rely on a complex Kalman filtering.

Question: is there correspondence between the large pink area and the area where no change is detected ?

L330 & fig 7 : this description of figure 7 is insufficient. It is not up to the reader to analyze the results. You must highlight much more key results, otherwise it means the figure is useless (actually I'm not convinced it's actually useful, because the quality of the visualization is poor, and we don't know why you 150 clusters and not a lower or larger number).

L334 : the whole subsequent section is really hard to follow.

L340 : How dependent are the so-called "distinct" features on the number of cluster. As

you are using a large number of cluster, you are artificially producing many features. But this may simply result from over-segmentation. Here the choice of your number of cluster should be discussed in depth.

Figure 8 : the visualization is extremely poor, and this figure is not really usable.

L343 : Fig 8c is missing

L345 : this last statement seems to contradict previous sentences in the very same paragraph. So in the end, your method detect the same things than the others. What is really its interest beyond interpolating slightly (which could simply be done with linear interpolation between 2 epochs...) ?

L355 : smoothing of the time series is debatable advantage, as it decreases the temporal resolution of event detection. Also "predicting" future states when it comes to natural environments seems hardly feasible, especially when considering rockfalls or rain-related erosion which are by nature not really predictable.

L362 : velocity and acceleration are meaningful for estimating a plane trajectory as it by nature smooth, however it is not useful, and probably not desirable, for interpolating the occurrence of discrete erosion events.