RESPONSE TO THE COMMENTS ON Ms. Preprint egusphere-2023-2596

Please note that in this rebuttal, reviewers' comments are denoted in *grey*, our detailed response is in black, and the new text of the revised version is in *italics*. Two different fonts are used for the reviewer's comments and the detailed response.

Response to REVIEWER #2

Referee's comments on the manuscript "**Evaluating the use of smart sensors in ground-based monitoring of landslide movement with laboratory experiments**"

The submitted manuscript aims to derive long-term rock movements and landslides through in-situ mounted sensors. Various laboratory experiments were carried out for this purpose.

The long-term goal of in situ-based landslide detection is socially relevant, and its achievement is scientifically desirable. However, how this manuscript is presented is not (yet) relevant for publication in its present form. The applied methods are per se to be embraced (smart sensors and the fusion of their gyroscope data with those of the magnetometer and accelerometer), but the validation presented (e.g. Fig. 11-13) are too far from the compared mental model, namely the center of mass of a rigid body (=single point). This raises both the questions of whether (a) the measured data and its fusion chain are not consistent or (b) whether the applied model is suited for the used complex cobble. Usually, favorable laboratory conditions are chosen. This has not been the case here, as the damping through the cotton pads around the sensors (which should protect them) creates an environment that is not comparable with the rigid body model.

So, in my opinion, the manuscript and its current results are not yet usable for the NHESS readership. On the one hand, the same results should be compared with a new comparison model. Instead of the cobble motions, the different movements of the sensors on its cotton pad are recorded. Therefore, the manuscript better fits in a signal processing journal, especially as the embedding in the natural hazards literature is not without some reservations (see specific comments). On the other hand, the experiments could be repeated with a rigid sensor attachment to the rock. Then, the simple single-point model can be applied, and the outcome will align with the NHESS scope.

<u>Response</u>

We thank the reviewer for their comments on the validation of the sensors in the lab for application in landslide movement tracking. We understand their reservation on the methods used here and we will try to explain the approach and the reasoning behind the submission of this manuscript to NHESS.

The use of MEMS sensors in earth science application is still at an early stage. Understanding how to effectively use these sensors for geohazard evaluation is of great interest and requires a cross-disciplinary effort. The potential and limitations of MEMS applications are of interest to all geoscientists who have been trying to use sensing technology on more and more lines of research (e.g. Mao et al., 2019; Hart, and Martinez, 2020; Wang et al., 2022). The novelty of the study is in the type of sensor, the phenomenon for which the sensor is tested in laboratory experiments, and the approach to couple sensor recordings and camera-based positions.

Aim. The present study is part of a larger project named SENSUM (smart SENSing of landscapes Undergoing hazardous hydrogeologic Movement). The aim of the research on SENSUM and by extension in this paper was to test a sensing technology to estimate the timing of hazardous movement, the magnitude of movement and the mode of movement of boulders embedded in slow-moving landslides. Moreover, the research on SENSUM wanted to test the transmission of movement-related data via LoRaWAN. The research project did not aim to measure any impact forces. The research goals on SENSUM are thus different from those in the existing body of work which performed more controlled experiments and wanted to measure physics and forces of processes such as rockfalls (Niklaus et al., 2017; Caviezel et al., 2018, 2019; Noël et al., 2023) or sediment transport (Maniatis et al., 2023). Regarding the motion of boulders embedded in a slow-moving landslide, Dini et al. (2021) managed to determine the timing of movement of using LoRaWAN but not the style or magnitude of movement as the sensor used was composed of just an accelerometer (i.e. not full IMU). The sensor used on SENSUM was a 9-axis device equipped with accelerometers (16-g range), gyroscopes (2000 °/s range), and magnetometers (16-Gauss range) that start recording when the acceleration exceeds a custom-defined threshold. This experimental study aimed to test this sensor to track cobble motion down an inclined plane as a preparatory investigation to monitor boulders embedded in slow-moving landslides. Sensors were thus used to find an overall estimate of the magnitude of the movement and understand the mode of movement. Moreover, the data transmission through LoRaWAN was tested under different thicknesses of sand layers to investigate how sand medium can affect data sending as it has not been tested before. Hence, beside trying to match with equation of motion, there are other ways the experimental data can be useful for the use of the sensor in field applications in slow-moving landslides.

Approach. In the present study, camera-based position and sensor data are fused into the Kalman filter. Hence, the approach is different from previous MEMS applications in rockfalls tracking (e.g. Niklaus et al., 2017; Caviezel et al., 2018, 2019; Noël et al., 2023) and granular flow experiments (Dost et al., 2020). In rockfall MEMS application, videogrammetric trajectory is aided by an accelerometer and gyroscope. Position and velocity are inferred by videogrammetric trajectory, acceleration is used to characterise the impacts with the ground and the number of block rotations over a given number of video frames. In recent granular flow experiments published on NHESS (Dost et al., 2020), the pebbles are not tracked by the camera since they are buried within the granular flow. Thus, in research papers mentioned, acceleration and position are not combined in the fusion algorithm.

Sensor. The sensor used in the present study is similar to that used in granular flow experiments (Dost et al., 2020), cobble tracking (Gronz et al., 2016), and debris tracking (Spreizter et al, 2019) in laboratory flume experiments. Differently from rockfall MEMS applications (Volkwein and Klette, 2014; Niklaus et al., 2017; Caviezel et al., 2018, 2019; Noël et al., 2023), the sensor used on SENSUM and by extension in the present work does not have a high-range IMU since the research does not aim to measure forces or study the impacts on the ground.

In industrial applications, there are different ways to clamp a sensor to a machine (e.g., stud, magnetic, wax, and adhesive mounting; Ewins 2000 - chp3). The sensor accuracy on high-frequency signals depends on the rigid attachment between the sensors and the object to monitor (e.g., Ewins 2000 - chp3). Indeed, the stiff mechanical connection between the inertial sensor and the object ensures that the motion of both bodies at all frequencies is the same. Therefore, any inertial force applied to the object is transmitted to the sensor due to the rigid attachment. High inertial force may require increasing the sensor range making the sensor sensitivity decrease (Dini et al., 2021). However, under high inertial (impact) forces, regardless of the range, MEMS sensors are likely not to be robust enough to withstand the impact and thus they can break apart or malfunction (Feng et al., 2023). To prevent damage to the sensors, soft buffers can dampen the impact overload and preserve the integrity of the sensors affecting its accuracy (Feng et al., 2023). Hence, the rigid attachment would be ideal for a comparison with a reference (numerical model, theoretical model, standard motion equation), but it is not ideal for sensor integrity.

Despite the limitations related to the cotton pad buffer and the nonfixed position of the sensor embedded in the cobble, the averaged values of motion variables computed by the data-fusion approach are within the range predicted by the standard motion equation (Table 2).

Table 2. Uncertainty estimation metrics for motion variables as derived from experiments on a 30º inclined. Uncertainty estimation metrics. μ, σ the sample mean, and standard deviation of experiments as described by camera and sensors considering all repeats, respectively. Maximum and minimum values computed for motion equation predictions.

			y (m)	z (m)	v_y (m/s)	v_z (m/s)	a_y (m/s^2)	a_z (m/s^2)
Rolling	Experiments	μ	1.933	0.096	1.040	-0.378	0.025	-2.977
		σ	0.181	0.019	0.410	0.220	2.285	2.586
	Standard motion equation	Max	3.7	0.547	2.714	0.0	3.287	0.0
		Min	0.088	0.060	0.0	-1.359	-1.281	-1.898
Sliding	Experiments	μ	0.786	0.229	0.974	-0.150	3.161	5.246
		σ	0.080	0.025	0.379	0.158	5.701	1.567
	Standard motion equation	Max	0.547	0.547	2.965	0.0	3.927	0.0
		Min	0.062	6.077	0.0	-1.428	-0.428	-2.267

The sensor integration involved in the filtering procedure described in this study addresses this problem. Recently, the sensor filtering procedure for granular flow experiments was published on this journal (Dost et al., 2020) without measuring position and providing validation. The present study builds on the filtering technique shown in their work and validate the overall motion magnitude using standard motion equations. Moreover, this study investigates the sensitivity of LoRaWAN data transmission to sand layers of different thicknesses which has never been studied before. The data transmission sensitivity to sand has important implications for the development and use of this technology in the field as part of the research on SENSUM. For these reasons, the present manuscript was not submitted to a sensor-focused journal. The method has some limitations that were openly discussed in the manuscript to favour a possible technological advancement and a scientific discussion. Despite the limitations indicated in the discussion, the range of camera-sensor motion is similar to that of the conceptual model.

Table 2 shown above was added to the updated version of the manuscript to improve the evaluation of the uncertainty of the data-fusion approach compared to the standard motion equation. Thanks to the reviewer's comment, the limitations related to the cotton pad buffer and the nonfixed position of the sensor embedded in the cobble are planned to be added to the discussion.

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Specific comments

L13:
process type instead of hazard

Response

We changed "***hazard***" with "***process type***" in the abstract. Thank you.

L28:
Sim et al. 2022 are talking rather about risks, not the hazard.

Response

The sentence was rephrased as (lines 27-29):

"The higher frequency and intensity of extreme weather conditions under climate change have increased global landslide hazards (e.g., Gariano and Guzzetti, 2016) leading to the development of different approaches in landslide risk management (e.g., Sim et al., 2022)."

L34:
https://doi.org/10.1038/s43247-023-00909-z is also an important source here.

Response

Thank you for bringing this very recent publications to us. I added it as you suggested in Line 34.

L65/557
Citing EGU-General assembly abstracts is not the best practice.

Response

Field investigations using MEMS sensors to monitor boulders embedded in a landslide and LoRAWAN to transmit data are rare because the technology has just started being deployed in geoscience applications. We mentioned the two most recent abstracts on this topic.

L74-76:
The data of pressure sensors were barely used in these studies.

Response

We wanted to highlight the sensors composing StoneNode (Niklaus et al., 2017; Caviezel et al., 2018, 2019) which are different from those composing the device used in our study. We rephrased the sentence as:

"*The sensor was equipped with accelerometers, gyroscopes, and a pressure sensor. The linear and angular motion were tracked by the accelerometers and the gyroscopes respectively. Both sensors helped to detect and characterise the collision with the ground. Conversely, the pressure sensor was used to measure altitude differences."*

L78:

The cited sources here make no sense: They were all published before the smart sensors publications (L74-76) and the mentioned 3D rockfall modeling approach was already validated with the publication by Dorren (2005).

Response

True, the sentence is misleading and thus was rephrased as

"This provides a new tool to collect a dataset to further improve and validate modelling frameworks on rock falls that had been previously calibrated only through case studies (Caviezel et al., 2018, Dorren et al., 2011; Dorren, 2016)."

L94-97:

This section is unnecessary. If you use meaningful sub-titles (as you do), the reader can easily navigate without this section. However, if you want to add this section, add at least the purpose and content of section 4.

Response

Thank you for this comment. We rephrased that part at the end of the introduction. The amended lines read as follows (lines 97-100):

"This study shows the results from LoRaWAN data transmission tests and the findings on raw and processed data for the cobble motion (Section 3). After comparing experimental results to simple conceptual models (Section 4), the study discusses the strengths and weaknesses of the smart sensor technology in monitoring boulders and the challenges awaiting to be addressed to improve the technology (Section 5). "

L107:

The squared, inclined board was hinged to the rectangular, horizontal board along its shorter side.

Response

We changed the sentence following your suggestion. Thank you.

L108:

Synchronized recordings to what?

Response

True, the sentence is misleading. We rephrased the sentence as *"The GoPro camera was paired to a remote controller via Wi-Fi to start and stop the recording remotely"*.

L155:

How many different training images?

Second, in each training image, …

Response

The training images were 390. I added this detail in the text. Then, I made the amendments in the sentence following your suggestion.

"First, different training images of the object were collected (i.e. 390 images). The images were the ground truths to train the model. Second, in each training image, …"

L162:
Which one is the suitable built-in function in OpenCV?

<u>Response</u>

The rectification was carried out using the built-in Python functions *cv2.initUndistortRectifyMap* and *cv2.warpPerspective*. We plan to add this detail between brackets in the updated version of the manuscript.

L165:
Missing "." after "occurred"

<u>Response</u>

True. We corrected the oversight. Thank you.

L228-234:
Belongs rather to the methods section.

<u>Response</u>

We moved this part to the method section (lines 222-226) following your suggestion. Thank you.

L248-250:
Belongs rather to the discussions section.

<u>Response</u>

We moved this part to the method section (lines 575-578) following your suggestion. Thank you.

L280, Fig. 5:
Better comparability if the x-axis comprises in all subplots (a-f) the same interval (e.g., 0.0 s – 2.8 s). The same would also be nice for the y-axis in the corresponding subplots (a and d; b and e; c and f).

<u>Response</u>

We made changes to Figure 5 following your suggestion. Please find below the corrected figure.

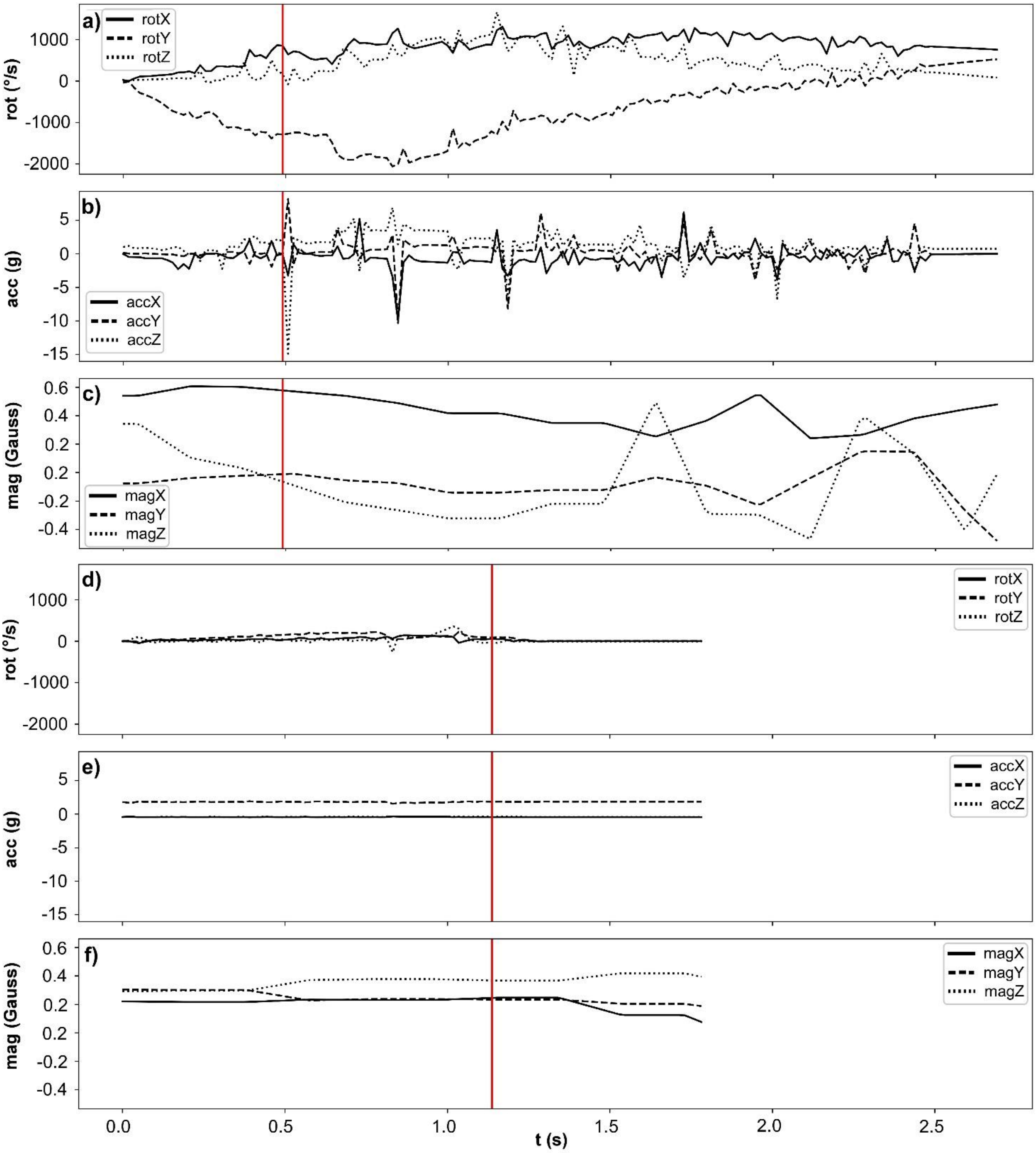

Figure 5. Raw recordings of the three sensor types on a 30° incline for (a, b and c) a rolling experiment and (d, e and f) a sliding experiment. (a, d) gyroscopes data, (b and e) accelerometers data. (c, f) Magnetometers data after upsampling. The solid line refers to the x axis, the dashed line to the y axis and the dotted line to the z axis. The solid red line shows the time when the cobble passes over the slope break.

L306-310:
A procedure description belongs to the methods section.

Response

We moved this part to the method section (lines 236-240) following your suggestion. Thank you.

L320:
“We speculate” belongs never in a result section.

Response

We deleted the sentence from the result section. The concept is already described in the discussion section. Thank you.

L324:
Wrong sub figures mentioned (7 c,d instead of 7b,c)

Response

True. We corrected the oversight. Thank you.

L365:
From where do you have the linear velocity? Pronounce it (again) that this is from the video footage analysis.

Response

The linear velocity is not inferred from the video analysis, but it is computed by the Kalman filter fed by the camera-based position and the sensor-based linear acceleration. We rephrased the sentence to make this point clear. Thank you.

“The linear velocity is computed through the Kalman filter fed by the camera-based positions and sensor-based linear accelerations, whereas the angular velocity is evaluated from the orientation angles (Section 2.3, Figure 3).”