TECHNICAL NOTE: SEDIDETECTION – DERIVING THE NATURE OF THE SEDIMENT BOTTOM BY ANALYZING GAIT DATA

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With 12 figures
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Summary: In order to comply with EU guidelines for monitoring the condition of the Wadden Sea, regular transect surveys are required. Those are done by taking point sediment samples to determine the near-surface sediment composition. However, these methods are expensive and time-consuming. Remote sensing analyses provide only limited information of the first millimeters of the surface. The results are influenced by interfering signals. The application of motion analysis based on smartphone sensors was investigated in order to draw conclusions about the sediment composition along transects. The aim was to identify homogeneous sediment areas and their boundaries along the transects, thereby significantly reducing the need for traditional sediment sampling. In addition, it was examined whether qualitative statements on sediment composition can already be made with sufficient accuracy. The results show that sediment softness and area boundaries can be measured with this method, but obstacles for practical applications remain.

Keywords: Coastal morphology, Schleswig-Holstein, North Sea Schleswig-Holstein Wadden Sea, sediments

1 Introduction

The European Wadden Sea has been protected as a World Heritage Site since 2009 (UNESCO 2009). It is a large, mainly undisturbed habitat, and determined by the tides. The core of the area consists of sublittoral drainage channels and interspersed sediment flats. These mudflats are mainly differentiated by the duration of the dry fall, the sediment composition, and the wave and current energy acting on them. They are the characteristic habitat of this World Heritage Site. The organisms at the surface and in the upper few centimetres of sediment form the basis of the food supply for most of the bird life and are in themselves a complex habitat for specific species.

Most areas of the Wadden Sea floor are composed of fine sand. Coarser sand can only be found in close proximity to the mouth of an estuary or due to transport by wind. Muddy sediments are rare and only exist near coastlines, in a distal position to the tidal channels. They may be hazardous to access. Shell detritus occurs sporadically. Other substrates occur in the submerged land areas of the North Frisian Wadden Sea, which contain fossil peat, gyttja, and clay.

In the Schleswig-Holstein Wadden Sea area, there are only a few large-scale surveys of tidal flat sediments. There are smaller surveys of sub-areas, such as the sediment distribution in Königshafen in 1932/33 (Wohlenberg 1937), in Meldorf Bay in 1978 (Gast 1980), or in the North Frisian Wadden Sea (Köster 1980, Köster 1998), and in 1989 by Austen (1994).

Large-scale surveys are based on satellite image analysis (Dennert-Möller 1983), ship grab samples, and, less frequently, ground surveys combined with remote sensing (e.g. Doerfer & Murphy 1989). Of particular note is the survey of fine sediments from 1964 to 1976, which resulted in a map of the fine sediments of the German Bight basing on a 1 sm to 0.5 sm grid of Van Veen grab samples, the fraction smaller than 0.063 mm slurried, the other sifted (Figge et al. 1981: 2f.). This was followed at the end of the 1980s by the recording of a sediment grid with mixed probes, wet screening and hydrometer (van Bernem et al. 1994: 45) as part of the oil sensitivity mapping of the Wadden Sea (van Bernem 1992, van Bernem 1998) with a broad database for satellite-based sediment mapping (Kleeberg 1990). The combination of remote sensing data and ground data to verify and adapt the image analyses is characteristic of large-scale approaches to mapping tidal flat sediments using optical remote sensing data, radar signals or a combination of methods (Müller et al. 2016, Wang et al. 2021).

In tidal flats situated at a considerable distance from the shoreline, the composition is primarily influenced by fine sand. There, the sediment composition frequently undergoes only minor alterations

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over distances of several kilometres. In the context of high tidal flats, where sediment accumulation is influenced by the presence of islands and other sediment bodies, and within the domain of seagrass beds, the deposition of finer sediments can extend over extensive areas, often spanning multiple hectares. However, it has been observed that "in areas that appear to be completely identical in terms of morphology and hydrography, sandy and 'silty' sediments can occur in close proximity to each other" (Figge et al.1980: 188).

The repositioning of tidal channels gives rise to variations in sediment of a small scale (order of magnitude 10^1 – 10^{-1}m). Structures caused by land use in the early modern period, like ditches in former cropland in what is now the North Frisian Wadden Sea, can also cause such small-scale disturbances of the larger-scale sedimentary patterns (Gade et al. 2017).

Especially areas with a higher patchiness are frequently covered with thin alternating layers of different sediment types. As a consequence, their characteristics cannot be easily observed by remote sensing and also not optical while defining sampling areas. They often only become noticeable when walking across them, as the ground gives way unexpectedly or the muddy layer is underlain by firm sandy mudflats.

The tidal flats in Schleswig-Holstein (higher LAT) covering 1520 km², are far too large for a dense sampling grid due to the effort and costs involved. Morphological considerations, such as those incorporated in the submarine extension and update of the map by Figge 1981 (Lauer et al 2014), can be helpful in creating an adapted sampling grid as a first approximation. On the high mudflats, transects can contribute to this, in particular the depth of subsidence conveys changes in sediment deposition and grain size.

The smoothness especially responds to the sediment composition of the upper, particularly biologically active centimetres. Differences in surface types can influence gait changes in pedestrians (Menz et al. 2003, Thies et al. 2005). Those gait properties may be measured by accelerometer and gyroscope sensors carried while moving. Surface type assessment studies with those sensors have been done while being mounted on a car (Allouch et al. 2017, Gupta et al. 2020) or a bicycle (Takahashi et al. 2015, Zang et al. 2018), focussing on road roughness and/or the identification of humps and potholes. Other studies are using the sensor data for the assessment of walkability of sidewalks (Kobayashi et al. 2020, Ng et al. 2022) using pedestrians. The sensors used were either dedicated wearable sensors for scientific measurements, or those integrated in smartphones. To our knowledge, no study as of now has been done to assess natural surface types outside the context of the human build environment.

During this project we investigated whether the sediment properties and their spatial changes can be derived from gait movements measured by smartphones, in order to be used to determine the placement of more expensive sediment sampling. The idea behind focussing on smartphone sensors was to explore the possibility of using crowd-based measurement of volunteers, increasing the area potentially assessed each year. Several challenges arise with this approach. As it would rely on equipment owned by the volunteers, a wide range of combinations manufacturer, operating systems and firmware versions are to be expected. In addition, as the main application of acceleration and gyroscope sensors in smartphones is to determine the orientation of the device, they are usually of low quality. Commonly used are Inertial Measurement Units (IMUs), as they are cheap to produce. Those are usually neither calibrated nor produce stable output over time often showing a drift or bias. Already after the first data recordings and analyses, it became clear that the chosen approach and equipment would not allow to classify sediments according to their absolute softness, let alone their grain size composition. Instead, we focussed on whether it was at least possible to recognise clear changes in the sediment softness in a comprehensible and reproducible manner.

The analysis follows the pre-processing and feature generation strategies developed in Human Activity Research (HAR), in which activities like walking, running, or climbing stairs are identified by using appropriate sensors positioned on the body. In recent years, many studies have been conducted using the sensors of smartphones carried during these activities (Dentamaro et al. 2024). Fields of interest are for instance health monitoring and fitness tracking. In this study, the aim was not to differentiate between the activities but identifying different substrates by detecting changes in walking behaviour. Thus, not many of the obstacles of HAR were faced, as the positioning of the smartphone as well as the activities allowed while taking data could be fixed. In addition, real-time prediction, a common requirement in many applications, like fall-detection, was not needed.

2 Methodology

The objective was the development of a crowd-capable method to survey the spatial variability of the sediment composition of the Wadden Sea to inform the placement of expensive sediment probes. For this, transects in areas with different sediment types were carried out (see Fig. 1). Hard fine sands were present close to Westerhever, where a transect was placed on a sand with longer dry time. Muddy sediments were tested mainly north of Nordstrandischmoor. Transitions from sandy to muddy sediments were provided by transects around the Eider estuary and north of Hallig Langeness.

Data was taken in roughly 10-minute-long transects by walking a straight line with a steady pace. In addition, comparative data was taken on asphalt in the same fashion. Any deviation from this pattern, e.g. an obstacle to resolve or an unexpected phone call, had to be marked with several seconds of standing still at the beginning and the end. The two most commonly used sensors in HAR, accelerometer and gyroscope, were used (Dentamaro et al. 2024). GPS data from the devices were used to localize both the sensor data as well as the truth data of the sediment softness.

2.1 Experimental setup

The following smartphone models were used for data acquisition: a Samsung Galaxy S22 Ultra SM-S908B, an iPhone XR, three iPhone 14, an iPhone 15, a Xiaomi Mi 10T Lite, a Fairphone 5, a Realme X2 Pro and a Oneplus Nord 3. Accelerometer, gyroscope and GPS data were recorded with Sensor Logger (Choi 2024, versions used: 1.24, 1.31, 1.34, 1.35, 1.36), which provided the data with the gravitational component removed.

The data of the accelerometer and the gyroscope was recorded in three dimensions x, y, z. GPS data was provided in geographical coordinates of the WGS84 ellipsoid. Their orientation within the smartphone is shown in the left section of Figure 2. Ng et al. 2022 studied the optimal placement of wearable sensors for assessing walking surfaces. They found the ankle location to be consistently

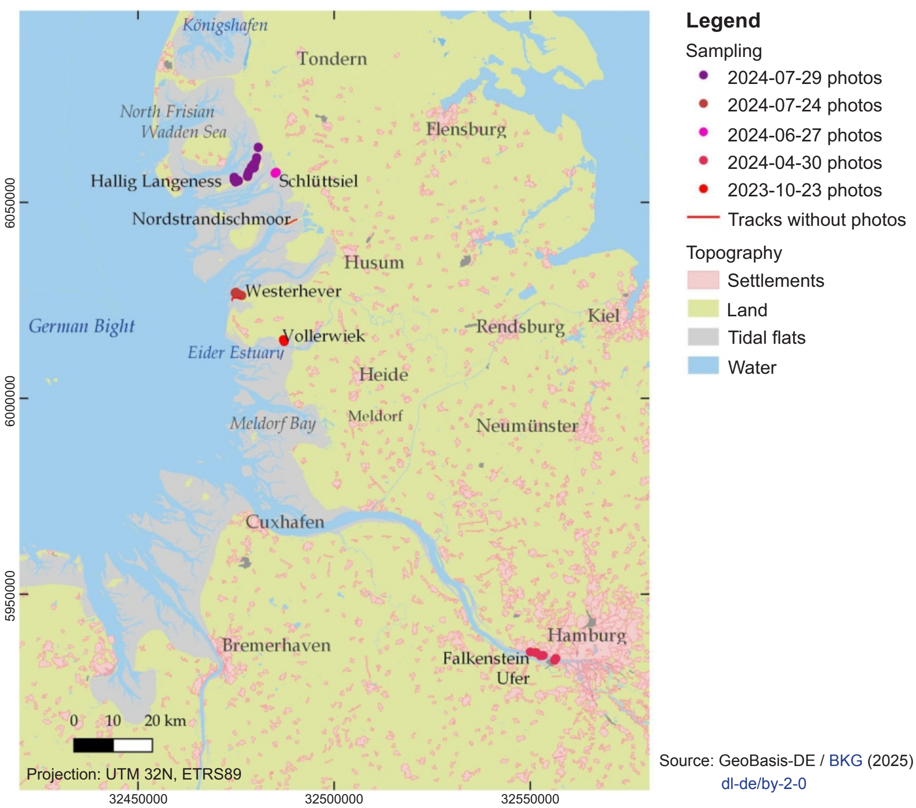

Fig. 1: Transects for data collection in the Wadden Sea

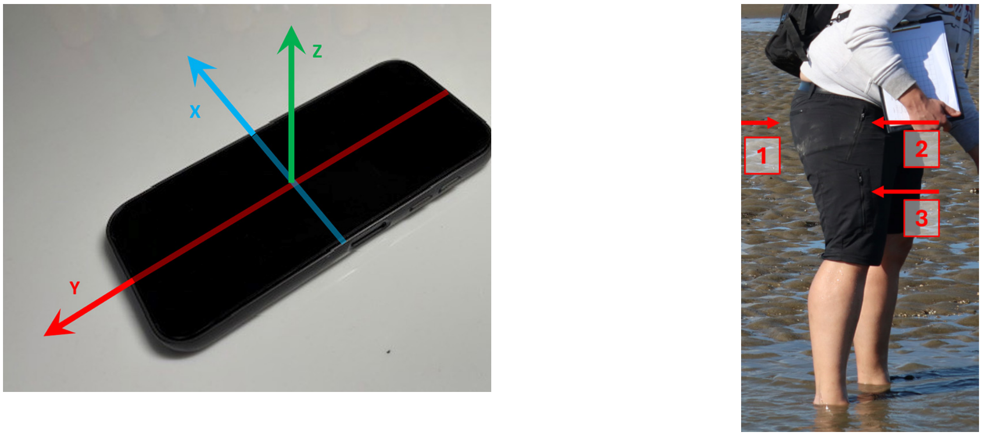

Fig. 2: Left: Orientation of the axes of both the accelerometer and the gyroscope. Right: The smartphones were either placed in the back pocket (1), main pocket (2), or side pocket (3).

better than the head and the hip locations, all commonly used to measure the effect of external environment on subjects' gait parameters. However, since the wet environment of the Wadden Sea does not allow the placement of non-waterproof sensors below the knee, the decision was made to place the devices in the upper leg area as a compromise. Without a dedicated wearable mount, there are three common options how the smartphone could be positioned: back pocket (1), main pocket (2), and side pocket (3) (see Fig. 2, right). In case multiple devices were used for measurement, they were placed in the same pocket if possible.

2.2 Truth tagging

In order to evaluate the results of the analysis, information on the actual property of the measured quantity ("truth") is needed. For this analysis, two different types of truth information were required.

Activity: To easily identify the walking activity, all other activities during data taking were separated by standing still for several seconds. After recording, walking was then annotated by hand (see Fig. 3).

Substrate: Truth information about the substrate was collected by taking photographs of the footprints every few meters (see Fig. 4) either by a person following the recording person(s), or, in very favourable conditions, directly after the transect was finished. The images were divided into six different classes depending on the depth of the tracks. These were 0 (barely recognizable tracks), 1 (recognizable tracks without depth), 2 (up to a sole's depth), 3 (deeper than a sole's depth, stable shape), and 4 (deeper than a sole's depth, deformed shape), plus one class for unrecognisable tracks. These classes provided a rough estimate of the softness of the soil, as a simple proxy for more complex properties of the substrate. The GPS localisation of the images was used to map the images (and thus the truth information) to the sensor data collected.

Since gaining the same coverage by taking quantitative samples would have been outside the available budged, we decided to evaluate the general performance of the methodology compared to the less accurate image method first. If proven to be viable, a comparison with properties like sediment grain size, soil bulk density, and water content could be made in a subsequent study.

2.3 Pre-processing

Sensor Logger was used to record the sensors, which allows for different target frequencies. However, despite setting identical target frequencies, the delivered frequency did not match for all smartphones. To get equidistant time intervals, linear interpolation of the raw datapoints was used, creating an output of the desired frequency of 100 Hz.

The data was recorded in three dimensions (x, y, z) for each individual sensor. In order to get data independent of the smartphone orientation, the magnitude v was used:

$$|v| = \sqrt{x^2+y^2+z^2} \quad \text{Eq. 1}$$

Figure 5 shows an example record of gyroscope data in three dimension (left) and as magnitude (right).

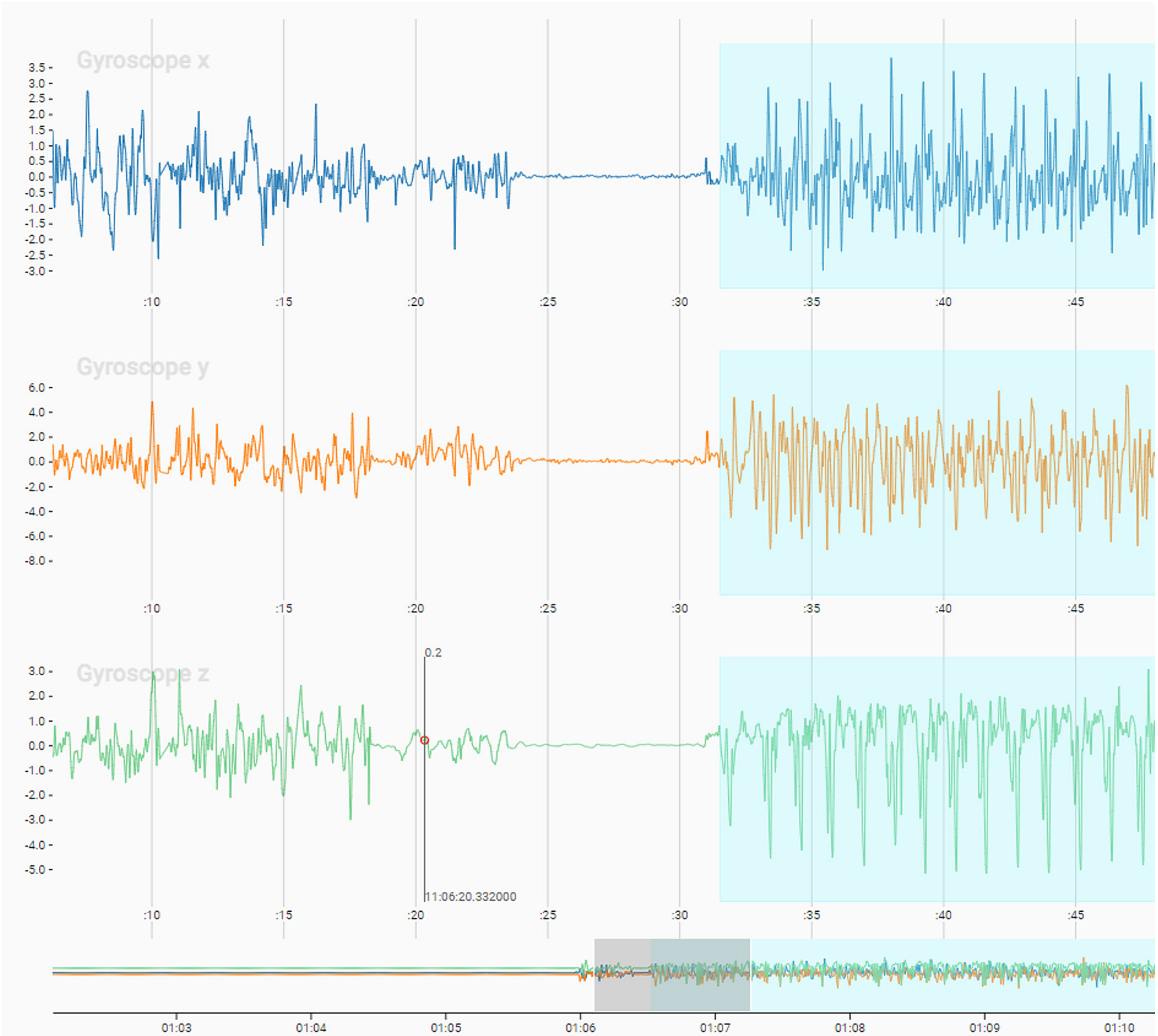

Fig. 3: Example for activity annotation in gyroscope data. The walking phase is marked in light blue. The two phases are separated by standing still for several seconds and are thus easily recognisable. It is separated from a phase of handling the smartphone during the start of the data taking by several seconds of standing still, and is thus easily recognisable.

2.4 Feature extraction

Feature extraction follows the most common approach in HAR (Dentamaro et al. 2024). Also in surface assessment studies, features are widely used (see e.g. Allouch et al. 2017, Kobayashi et al. 2020, Park et al. 2025). The time series of the magnitude is divided into windows of 2 seconds, each with an overlap of 1 second to the neighbouring windows. Within these windows, features like the mean or standard deviation of the included sensor data were calculated. For both the activity as well as the softness information, the most common occurrence is considered the truth value of the window.

In HAR, many different features from the time domain, frequency domain, and time-frequency domain are used (Bennasar et al. 2022). In this study, it was decided to focus on the energy as a single predictive variable. It is defined as:

$$E = \sum_{i=1}^{n} m_i^2 \qquad \text{Eq. 2}$$

With m the magnitude of the three-dimensional sensor data measurement and n the number of entries within the window. It is expected that walking on a hard substrate will produce higher energy measurements than walking on a soft substrate, as the majority of the vibration produced by the im-

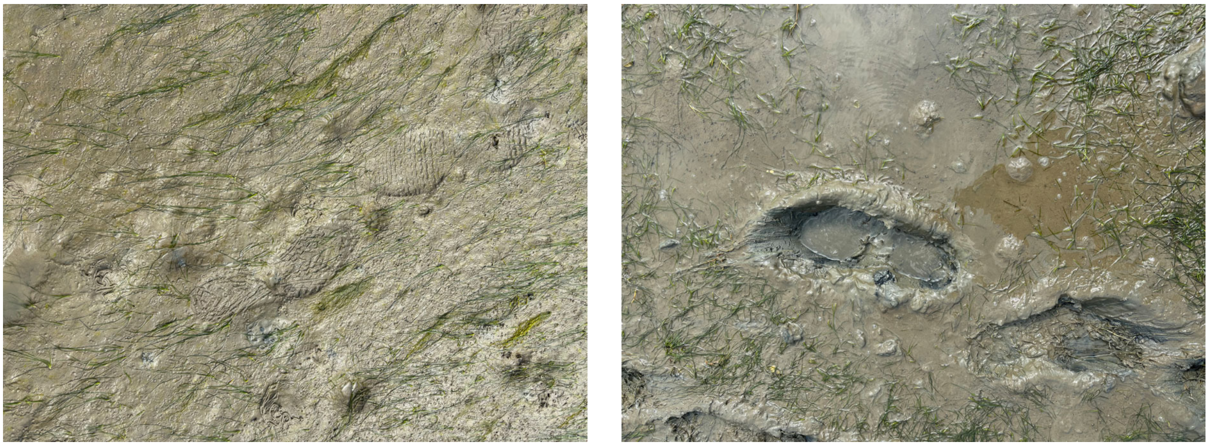

Fig. 4: Examples for tracks in different soil softness. The mapping of the sensor data and the softness was done on these documentation images. Left: softness 1. Right: softness 3.

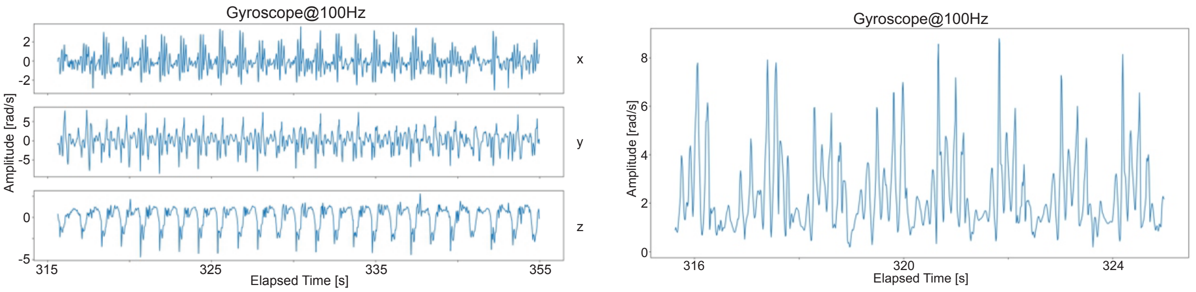

Fig. 5: Example of gyroscope data of a walking person versus time. Left: shown for the three axes x, y, z. Right: resulting magnitude.

pact of the foot on hard substrate will stay within the body and be recorded by the sensors. For soft substrates on the other hand, a larger proportion of the energy produced will be absorbed by the deformation of the substrate. Due to time constraints, in this study we focussed on a cut-based approach with a single feature expected to be sensitive to the softness of the walking surface as a proof of concept. Such a simple analysis can provide a baseline more sophisticated methods like a combination of several variables or machine learning can be measured against.

3 Results

Several impediments appeared during data taking. While Sensor Logger was running smoothly on most of the models, it was not possible to log GPS data together with the sensor data on the iPhone 15, although the localization worked fine while taking images. In addition, the older iPhone XR did not provide enough memory to export the data from transects more than 10 minutes long. Both models were excluded in the further study.

The accuracy of the GPS localization in current smartphones is mostly within 10 meters of relative accuracy. During swaps of satellites, jumps in the localization can occur. In case of the Xiaomi Mi 10T Lite it was observed that a large divergence to the true position can also happen without such a swap. Figure 6 shows the recorded transect (red line) of the Xiaomi and the images (yellow dots) taken as softness truth documentation. A second device, a Samsung Galaxy S22 Ultra SM-S908B, placed in the same pocket as the Xiaomi, recorded transect GPS coordinates similar to the coordinates of the images. A single image in the lower left corner shows a jump consistent with a satellite swap. The transect recording shows a plausible route difficult to identify as incorrect if no comparison data is taken. This behaviour only occurred once for the Xiaomi, all other transect data were located reasonably close to the comparison data of other models. During data taking, another problem with GPS location in the Xiaomi was found. When taking softness truth data, it is imperative to have a GPS localization on the images in order to match the truth with the sensor data. While the presence of a GPS tag on an image can be easily tested in the field, it is not immediately obvious whether it corresponds to the

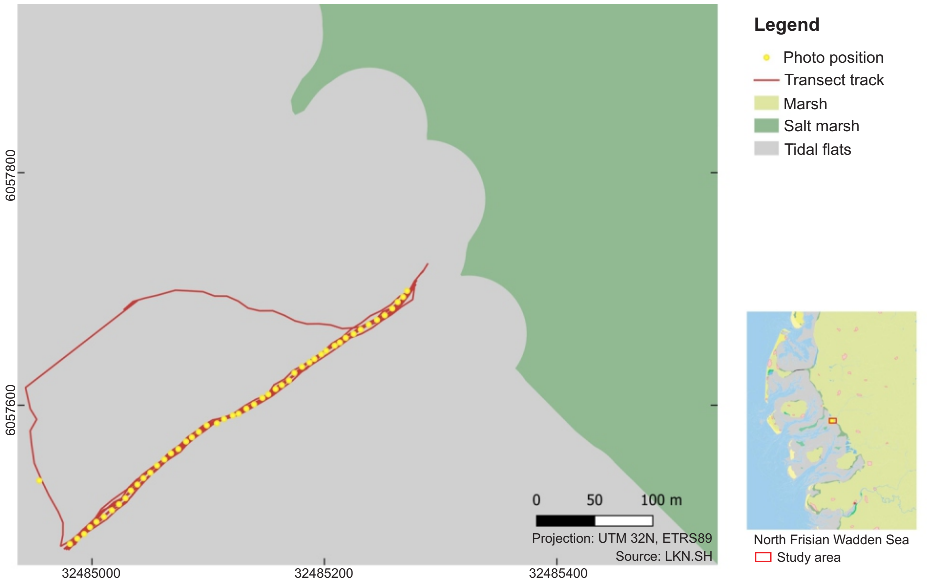

Fig. 6: Wrong, but plausible localization of sensor data of the Xiaomi Mi 10T Lite more than 50 meters apart from records of other smartphones (redlines) during the same run. The yellow dots mark the positions of the images taken for truth documentation. The Samsung Galaxy S22 Ultra SM-S908B placed in the same pocket during data taking recorded data close to the images.

recorded tags in the sensor data. Figure 7 shows the localization of the images taken with the Xiaomi Mi 10T Lite. Apparently, while perfectly capable of logging the proper GPS location in the sensor data, due to an "convenience" update, the GPS location written to the image metadata is changed to one of a close postal address, rendering it useless for this kind of task. We consider this not a feature, but a bug. In addition, even if correct, the GPS localization of two recordings (or a recording and the images) might differ by several meters. The information of the sediment softness is matched to the gait recording by choosing the closest image. As data taking by image is much less dense than data taking by recording, and because the GPS recordings may differ, the resulting match between truth and recording might not be entirely accurate and the transition between softness classes may be smeared.

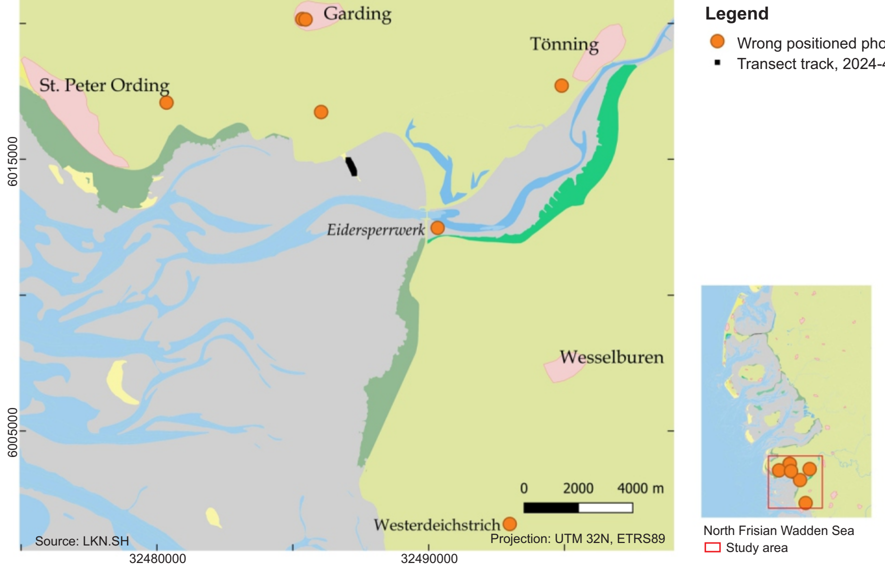

Fig. 7: Failed localization of the softness truth images taken with the Xiaomi Mi 10T Lite. The black dots mark the actual place of data taking, the orange dots are the mis-located images.

Figure 8 shows a comparison between accelerometer (left) and gyroscope (right) energy measurements using two different devices on the same data collection run. Data from the Samsung Galaxy S22 Ultra SM-S908B are shown as filled area, data from the Xiaomi Mi 10T Lite are shown as line. Both devices were worn in the same pocket at the same run. For both devices, the different activities "standing" (blue) and "walking" (orange) can easily be distinguished in both sensor types. In case of the accelerometer, however, the sensors of the different devices record a different energy distribution for the same run. While it is possible that the time series of the recordings are shifted against each other due to internal time measurement inaccuracy, overall, the average energy recorded in each window over the full run should be the same. The difference is much less pronounced for the gyroscope. Such behaviour has been observed in other device pairs as well.

While this difference may not be a problem when trying to identify human activities, trying to glean the substrate softness from the different walking patterns is another matter. Thus, as the accelerometer has been found to be unreliable, only the gyroscope was used in the following analysis.

In Figure 9 the energy distributions for walking on a transect with four different Wadden soil softness classes (colour coded) is shown. On the left, the device was placed in the right back pocket, on the right it was placed on the left side pocket. Although there are only a few entries for soil types with softness class 2 and above, it is obvious the energy distribution is sensitive to the different softness classes, which is more pronounced in the data recorded with the device carried in the side pocket.

While it does show the influence of the different substrate softness, the absolute energy is also influenced by the walking style and weight of the individual person taking the data. In addition, external factors

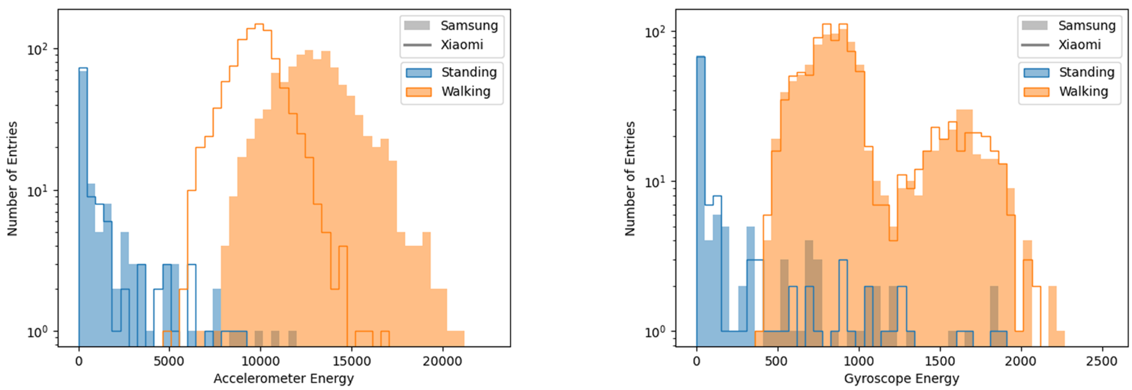

Fig. 8: Comparison of the energy between the accelerometer (left) and the gyroscope (right) during a recording on asphalt. Marked in blue is the activity 'standing', in orange is 'walking'. The filled areas denote a recording of a Samsung Galaxy S22 Ultra SM-S908B, while the lines show the data for a Xiaomi Mi 10T Lite. Both devices where positioned in the same pocket at the same time.

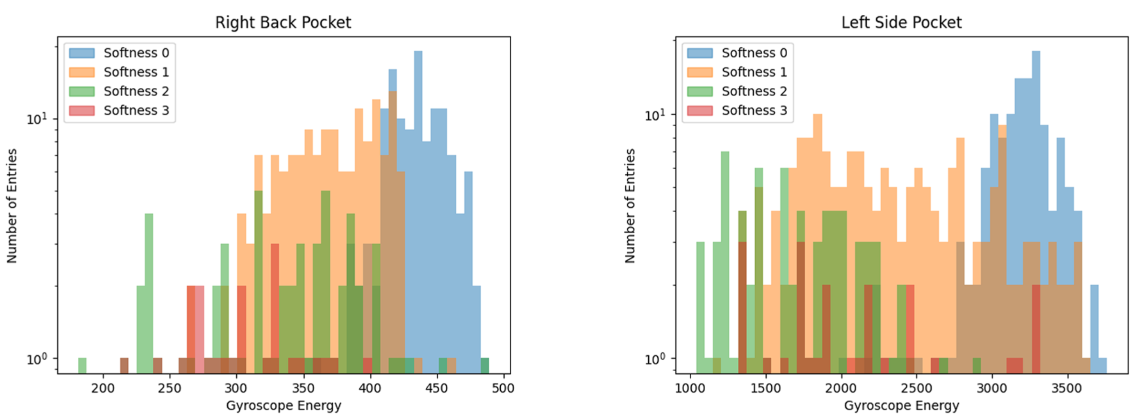

Fig. 9: Energy distributions for walking on a transect with four different softness classes present. Left: the device was positioned in the right back pocket. Right: the smartphone was carried in the left side pocket. In both distributions, the difference between the soil types is clearly visible, while for the side pocket, it is more pronounced.

like weather can impact the measurement. Figure 10 shows the energy versus time on a transect taken close to Westerhever on hard sand walked back and forth while continuously taking data. One direction was walked against strong wind, the other with the wind. A strong impact on the absolute value of the energy can clearly be seen. This behaviour was seen in data taken by two different people.

regularities in gait, e.g. due to tripping, may produce a marked spike in the energy slope mimicking a signal. To avoid this, a transect should be walked several times by different people using different smartphone models (more than one per person if possible). By averaging over the recorded energy, the unwanted influences can be suppressed and the areas of interest enhanced.

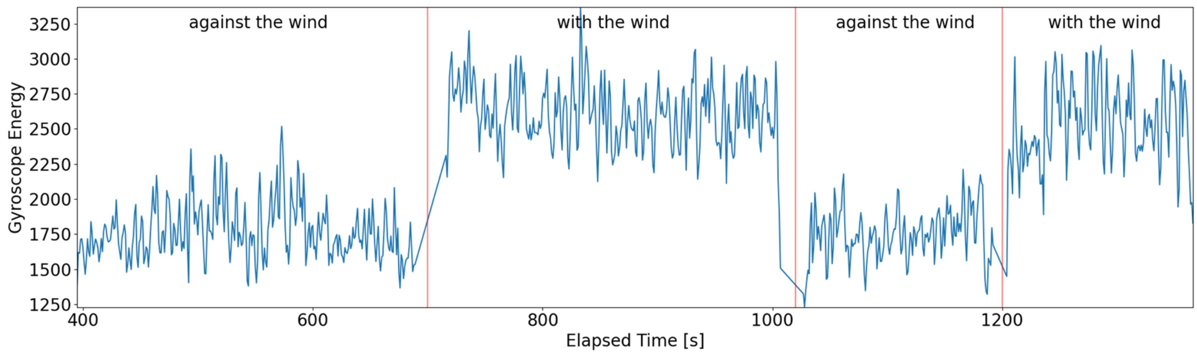

Fig. 10: Influence of the wind on the energy distribution vs elapsed time since start of the record. The phase before the start of the walking activity has been removed. The soil type was hard sand. The same transect was walked four times with continuous data taking. One direction was walked against a strong wind, the other direction with it, with short standing phases between them. The direction walked is clearly correlated with the measured energy. This behaviour was seen in data taken by two different people.

To mitigate the external influences on the absolute value of the energy, one can try to normalize the distribution. One possibility would be to use independent transects on defined substrate, like asphalt. However, due to both difficult to control weather changes as well as the internal drift of the sensors, this normalization would not be stable. Another possibility would be to divide the energy distribution of a run by the overall mean of the run, i.e. normalizing it onto itself. This way, both influences are suppressed, as long as the transect is not too long and the wind direction during its recording does not change. While the information about the individual soil softness classes is lost this way, the information on where they change is retained. Thus, individual runs on the same transect become comparable, regardless of the direction of travel.

Figure 11 (top) shows the energy distribution for a transect recorded near Vollerwiek. On the bottom, the corresponding slope is shown. It is calculated on the linear interpolation on 10 points before and 10 points after for each point. Areas of strong changes in energy can be selected by choosing a threshold on the absolute slope value.

Since the sensors in smartphones are neither gauged nor standardized across models, they may differ in accuracy, resulting in slightly different behaviour while recording the energy. In addition, irregularities in gait, e.g. due to tripping, may produce a marked spike in the energy slope mimicking a signal.

This is shown in Figure 12 for another transect from near Schlüttsiel with variable, but generally high, softness in the beginning (mainly softness classes 3-4), and a continuously less soft substrate in the second half (mainly softness classes 0-1). A tidal channel separates those two areas and acts as a showcase of an extremal signal for our analysis. The slope for the energy distribution of a single recording of the transect is shown on the top. The transition from generally soft to harder substrate with the tidal channel in between is seen in the centre with high absolute values of the slope. However, in the continuously hard substrate area the slope exceeds the chosen threshold several times, leading to a fake signal. This behaviour is suppressed if averaged over several runs (bottom), while preserving both the signal of the transition area as well as some of the signals in the more versatile soft area. The energy distribution with matched softness classes is not shown, as in this case, the conditions were not optimal and the measurement did only weakly pick up on the softness.

4 Discussion

The original idea for this study was to provide a simple and cost-effective method of measuring the substrate softness to gain insight on the soil distri-

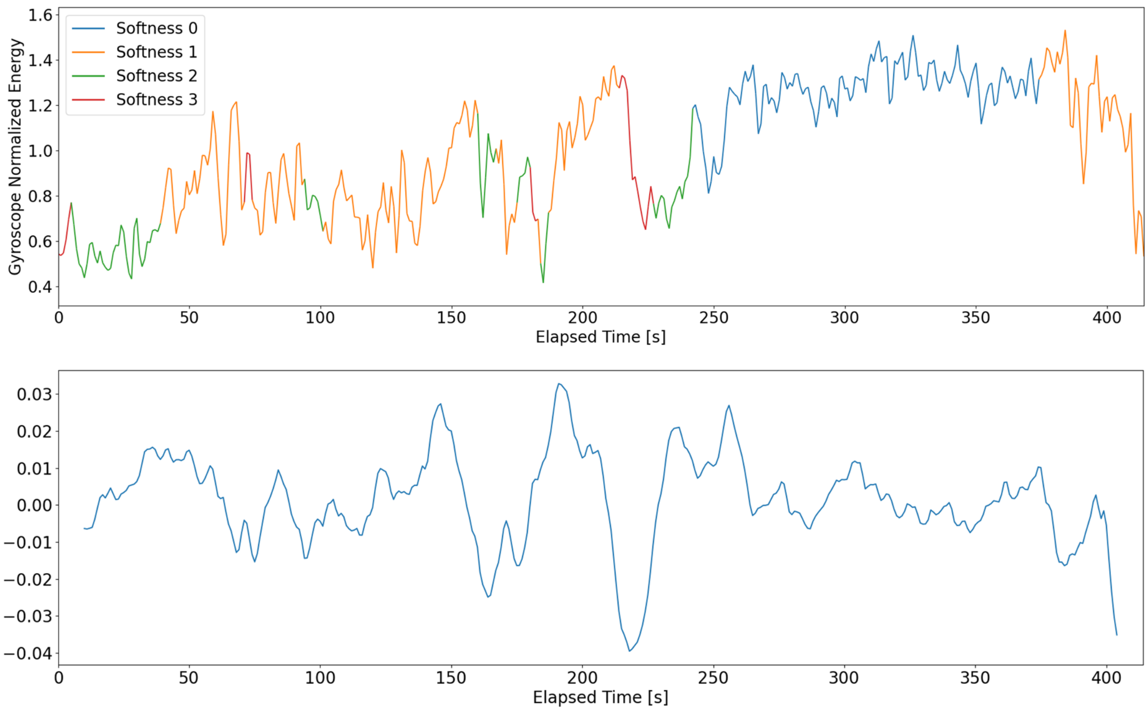

Fig. 11: Top: Energy distribution over time for a transect with different softness classes. Bottom: Slope of the same distribution. Large absolute values of the slope indicate sudden changes in the relative energy value, which correlate with soil softness changes.

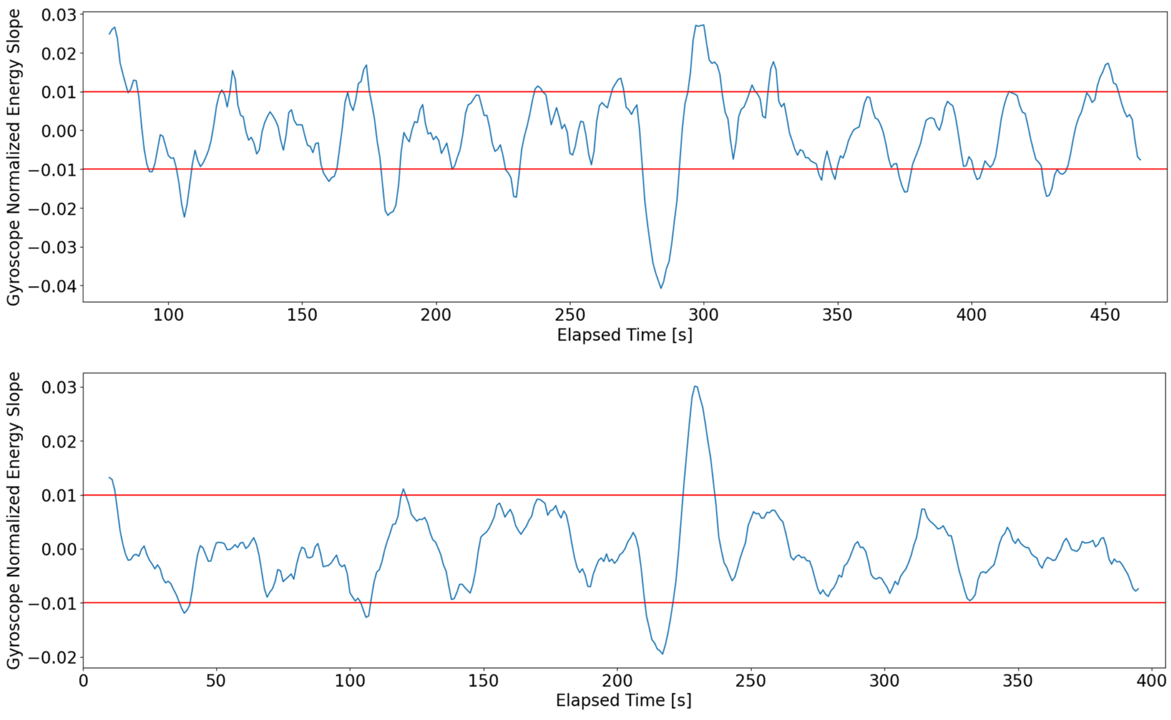

Fig. 12: Slope of the normalized energy distribution of a single recording of a transect (top) and averaged over seven recordings (bottom). For averaging, the recorded points of the different runs are matched by geolocation. The shown elapsed time is the one from the first used run. The sediment softness up until ca. 300 seconds of elapsed time is variable, but generally soft. After that, it changes to be consistently low in softness. A (arbitrarily chosen) threshold of +- 0.01 on the slope selects changing areas before and after the transition. For the averaged transect, the peaks are suppressed.

butions in order to determine the placement of the more expensive soil probes. While it has been shown in this study that measuring the gait with smartphones can pick up on the soil property softness, this is only feasible under very favourable conditions. To mitigate this, instead of deriving the softness class of the soil directly from the gait measurement, changes in the average slope of several measurement can be used to detect major changes in softness. Because of the strong influence of external factors, like wind or tide, no further investigation on the repeatability (same transect, at a different time) and transferability (transect at a different location) were made.

Due to the differences in accuracy as well as their technical issues, some smartphone models are more suitable for the measurement task than others. In addition, walking a transect several times restricts the coverable area severely, since the time available to access the Wadden floor is limited. Other studies focussing on identifying surface types instead of just anomalies like bumps and potholes find that differentiating between similar types is challenging with smartphones (Kobayashi et al. 2020), or use dedicated high-quality sensors (Ng et al. 2022, Shimizu et al. 2025) placed on defined places on the body or even inside shoes. Thus, one remedy to the unreliability of the measurements due to uncalibrated sensors would be to avoid using smartphones in the first place and instead using high-quality sensors placed on predefined places on the lower extremities. Additionally, such placement would avoid the versatility of trouser design which defines where a smartphone can be placed for each volunteer differently. Due to time and budget restrictions, it was not possible to test whether significantly better results could be achieved in this way.

Another possibility is to eschew measuring the gait at all by instead using computer vision techniques on the control images of the tracks made for collecting the truth information of the substrate softness. A similar approach is widely studied for road damage assessment, using either traditional computer vision methods or machine learning (see e.g. Ranyal et al. 2022 for an overview) to successfully classify a range of different road conditions. An image classification based on machine learning could likewise be used to identify the different sediment softness classes used in this study. Instead of the elaborate method developed in this study, data taking would consist of taking top-down GPS-tagged images of tracks in a transect. While not being as convenient as the original idea, it would still be feasible to be done by non-experts.

5 Conclusion

While in principle it is possible to use a smartphone to measure gait in such a way that conclusions can be drawn about soil properties, successful verification, however, has only been achieved under very favourable conditions due to interference from external factors like wind and internal factors like device properties. In addition, a considerable effort must be made in data taking such that no other activities like surveys of other Wadden properties are possible at the same time. The distance covered is also limited with this approach. Thus, we conclude that the usage of gait data recorded by smartphones to measure the sediment softness in the Wadden Sea to gain insight on the distribution of sediment properties is currently not feasible in practice.

On the other hand, first tests of using computer vision methods to determine the softness class(es) within an image has been shown to be a promising approach. Its application is simpler than using the smartphone gait sensors, but still requires the involvement of at least two persons, such that the resulting reduction in sediment sampling effort compared to the desired one has to be reassessed. It also remains to be seen in a further study whether those methods remain stable under the broad use of people of different weight on different types of substrates and conditions, whether this softness classification corresponds to quantitative soil properties like grain-size distribution or bulk density, and how it compares to the results from the remote sensing data.

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