The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XLVIII-2/W1-2022
7th International Workshop LowCost 3D – Sensors, Algorithms, Applications, 15–16 December 2022, Würzburg, Germany

WHY IT MAKES SENSE TO USE HIGH COST SENSORS TO DO LOW COST SENSOR RESEARCH

V. V. Lehtola[a,*], H. Hyyti[b], T. Malkamäki[c]

[a] Dept. of Earth Observation Science, Faculty ITC, University of Twente, Enschede, The Netherlands - v.v.lehtola@utwente.nl
[b] Dept. of Remote Sensing and Photogrammetry, Finnish Geospatial Research Institute (FGI), National Land Survey of Finland
[c] Dept. of Navigation and Positioning, Finnish Geospatial Research Institute (FGI), National Land Survey of Finland

WG ICWG I/IV

KEY WORDS: Low cost, Sensors, Point Clouds, Data analysis, lidar, camera, IMU, GNSS

ABSTRACT:

The question is highly topical in the world that is aiming to acclaim more efficiency through an omnipresence of sensors. The implication of the omnipresence of sensors clearly is that most of these sensors will be of the low-cost type. Hence, there is a call for research utilizing low-cost sensors. However, paradoxically, it often makes sense to use high-cost sensors to do this research. Here, we open up this apparent paradox and argue why high-cost sensors are not only greatly useful but also critically required in low-cost sensor research. We offer different examples that support this argument but discuss also limitations and cases where the argument does not hold.

1. INTRODUCTION

A low-cost sensor, we argue, is defined as a sensor for which the market price is significantly cheaper than for a sensor that is conventionally or traditionally utilized in some application. Because the definition is made through the market price, it does not automatically mean that the low-cost sensor would be of (significantly) lower quality than a high-cost sensor[1]. Nor does the definition automatically imply that a high-cost sensor would output data of high quality. However, in this work, the high-cost sensors we refer to, do output high-quality data, see Figure 1.

One core research theme in low-cost sensor research is the study of feasibility, i.e. whether an application is feasible with a named sensor and a named method. For example, feasibility studies may aim to test if new techniques succeed with certain quality data. In order to know what the quality needs to be, high-quality (usually also high-cost) sensors can be utilized to acquire data which is then artificially downgraded in quality (i.e., emulated low-cost sensor). This allows for straightforward determination of the quality of what the low-cost sensors must output, i.e., the requirements for the sensor specifications. Hence, high-cost sensors provide more information for feasibility studies.

High-cost sensors can also function as a state-of-the-art reference. A reference is almost always needed, regardless of whether low-cost sensor data or artificially downgraded data is investigated. In many use case scenarios, a high enough quality reference or ground truth is challenging, if not impossible, to acquire using low-cost sensors alone.

In order to keep our argument practical, we move on to discuss different examples related to the above-mentioned two main points.

2. EXAMPLES

We offer examples from research done with GNSS receivers (Global Navigation Satellite System), lidars, cameras, and IMUs (inertial measurement units). These sensor types are relevant for many applications.

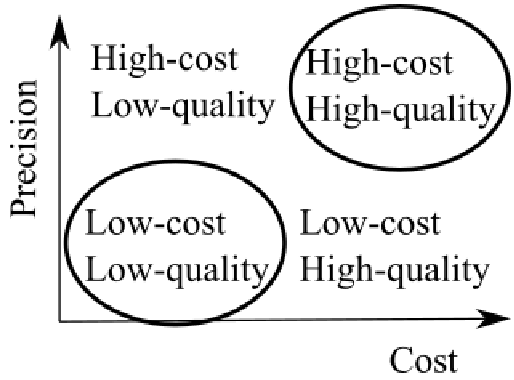

Figure 1: The circled entities are discussed in this work, and referred to as low-cost and high-cost sensors for brevity.

2.1 GNSS

Mapping the 3D distribution of water vapor in the atmosphere using crowdsourcing from low-cost GNSS receivers is an ongoing research direction [Lehtola et al., 2022]. One important thing to consider on this path is feasibility. Low-cost sensors, however, do not necessarily need to be physically used to draw conclusions about the feasibility of using them in an application, if the feasibility test is done with simulations [Marques et al., 2021, Lehtola et al., 2022]. These simulations, however, need error models based on experimental measurements.

High- and low-cost GNSS receivers may be investigated experimentally in order to obtain appropriate error models and error parameters for simulations [Lehtola et al., 2019b]. In the experimental campaign, see Figure 2, low-cost receivers (smartphones) performed more poorly than the high-cost ones in several regards. The degraded performance was best visible in (Galileo) satellite tracking. In the reproduced Table 1, the smartphones suffer from a DLL and PLL noise levels that are over one level of magnitude higher. One major cause for this is without doubt the antenna, as

*Corresponding author.
[1] A radical innovation in the sensor design and/or how it is manufactured could be the explaining factor.

		GPS L1 (m)		Galileo E1 (m)		GLONASS L1 (m)	
Receiver	Clock σ_{dt} (m/s)	$\sqrt{2}\sigma_{DLL}$	$2\sigma_{PLL}$	$\sqrt{2}\sigma_{DLL}$	$2\sigma_{PLL}$	$\sqrt{2}\sigma_{DLL}$	$2\sigma_{PLL}$
Huawei P10	0.38	8.32	0.31	N/A	N/A	15.51	0.16
Samsumg S8	0.18	9.09	0.16	9.25	N/A	12.81	0.16
u-blox Patch	0.14	0.31	0.006	0.20	0.006	0.32	0.008
u-blox Leica	0.19	0.30	0.006	0.23	0.006	0.20	0.006
Septentrio	0.03*	0.07	0.004	0.04	0.004	0.11	0.005

Table 1: Table for the measured error model parameters for different GNSS receivers in open sky conditions, reproduced from [Lehtola et al., 2019b].

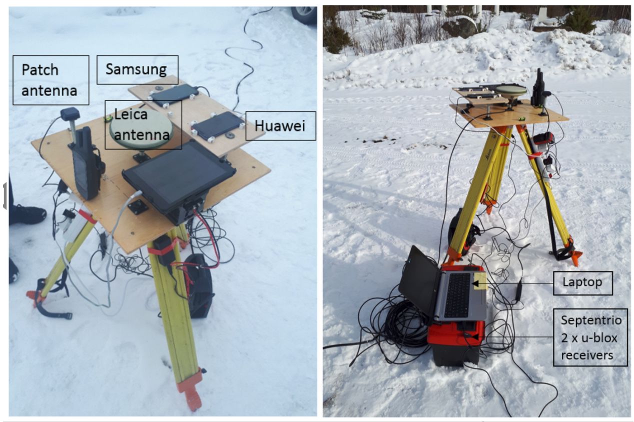

Figure 2: Experimental measurement campaign with four different GNSS receivers, one with two antenna configurations. Reproduced from [Lehtola et al., 2019b].

the smartphones have only small integrated antennas, while the other receivers have external antennas, see Figure 2.

There are limitations to this approach, however. Only the level of required performance can be evaluated, such as noise in the main observables. Specifically, in the case of smartphones, there are some errors that a dedicated GNSS receivers do not have. For example, the positioning application on a smartphone can be 'tombstoned'[2], e.g. if the system OS decides to prioritize the resources. This directly affects the positioning availability and would require a separate error model.

2.2 LIDAR

In lidar technology, the difference between high-cost and low-cost sensors is significant. We examine two cases with pulsed lidars; one for indoors and one for outdoors. Although other type of lidars do exist, pulsed lidars are currently the most common lidar type and portray the typical trade-offs in terms of e.g. pulse density, angular resolution and measuring range, all of which are highly correlated with sensor cost. In the future, especially single photon lidars may become part of the low-cost sensor research and could change some of these cost-performance characteristics, see e.g. [Lehtola et al., 2019a].

2.2.1 Indoors As demonstrated in Figure 3, a high-cost, high-quality Leica ScanStation P40 (A in Figure 3) can provide significantly increased point density compared to mid-price Velodyne VLP-32C (B) and low-cost Velodyne VLP-16 Puck Lite (C). The Velodyne sensors are multi-beam lidars which provide multiple parallel beams: 32 (Figure 3 B) and 16 (Figure 3 C) in a single scan around its main axis. The point cloud color is

[2] In technopedia: "An application is tombstoned if it is intentionally or unintentionally closed, halted or disturbed by a user, system or other operation", https://www.techopedia.com/definition/29091/tombstoned

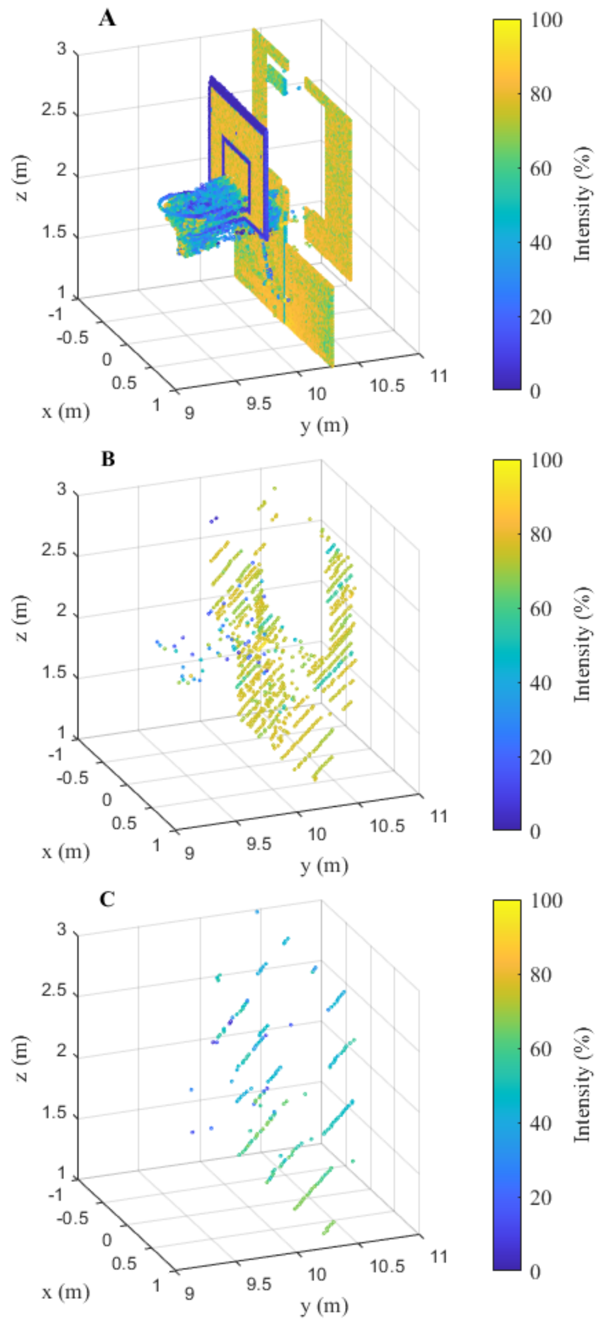

Figure 3: Lidar data comparison between Leica ScanStation P40 (A), Velodyne VLP-32C (B), and Velodyne VLP-16 Puck Lite (C). All point clouds are a single scan, collected from the same position 10 meters away from the target (a basketball hoop). Velodyne sensors are mounted on a 45° tilted platform.

determined based on the reflection intensity measurement and shown as percentage between 0 and the sensors maximum value. The maximum values are set the same for both Velodyne sensors so that their measurements would be comparable. In the example, the Velodyne sensors are mounted on a tilted platform such that the sensors are tilted sideways 45°. See the platform details from [Putkiranta, 2020].

In Figure 3, only single scans are shown from the Velodyne sensors to bring out their natural scanning patterns, data resolution, and quality of ranging and intensity values. The vertical resolution (in the scanner's frame) of low-cost sensors is visibly low since the angle between the laser beams is large, for example, 2° for VLP-16, see Figure 3 (C). Horizontal resolution on the other hand depends on the set rotation speed of the sensor. Note also that the low-cost VLP-16 has the least accurate reflection intensity measurement of the returning pulse.

The scanning pattern is heavily sensor dependent, and the lower cost sensors usually measure less points producing a sparser point cloud. Both of the Velodyne sensors produce significantly different point cloud patterns (see B and C in Figure 3). The lowest-cost VLP-16 sensor has the sparsest result while the mid-range VLP-32C is able to provide significantly denser result. Only the high-quality sensor in Figure 3 A is able to provide a point cloud form which the basketball hoop can be visually easily recognized, although it also has severe challenges in measuring the net of the hoop. Note also that the ranging precision for the low-cost sensors, in Figure 3 (B) and (C), is significantly smaller than for the high-cost sensor. This can be seen as larger randomness in the positions of the points.

Sensor calibration plays a significant role with the lower-cost sensors. The geometric calibration is important to define the elevation of each lidar beam to produce exact 3D data as shown in [Putkiranta, 2020]. Also as demonstrated in Figure 3, the intensity values of Velodyne sensors have a lot of variation between laser beams (i.e. between different stripes in the point cloud). A calibration procedure might be able to improve the quality of the intensity measurement.

The high-cost sensors are needed to provide ground truth point cloud data from the environment since low-cost sensors sample the object only sparsely and thus remain heavily dependent on their orientation, placement, and calibration, as shown in the example of Figure 3. When these sensor model properties are used, the high-quality point cloud can be used to generate simulated versions of the low-cost sensor's output by sampling only on the locations where the low cost sensor measures and by adding some measurement noise according to the sensor model. For example, the point cloud of Figure 3 (B) could be sampled out of the one in Figure 3 (A).

2.2.2 Outdoors In maritime environments, detection of navigational aids[3] via sensors in order to improve situational awareness and safety is an interesting and emerging development direction paving the way for autonomous maritime operations. An example of such a maritime NAVAID is depicted in Figure 4. This is a cut-down segment of an actual NAVAID used across Finnish territorial waters. An outdoor experiment was carried out, where this NAVAID segment was measured at short and long range, using both a low-cost and a high-cost lidar [Malkamäki et al., 2021].

[3]"A navigational aid (NAVAID), also known as aid to navigation (ATON), is any sort of signal, markers or guidance equipment which aids the traveler in navigation, usually nautical or aviation travel.", https://en.wikipedia.org/wiki/Navigational_aid

(a) (b)

Figure 4: Pictures of a cut-down segment of a navigation aid in natural lighting (a), and with an illumination source placed in front of the NAVAID cylinder to illustrate the retroreflective strips (b).

The NAVAID is cylindrical and has a highly retro-reflective material embedded in recesses around the surface (illuminated in Figure 4b).

For short range, the cylindrical target shape, together with the embedded retro-reflecting strips can be observed in the point cloud captured with a high-cost lidar, see Figure 5 (c). Although the low-cost lidar is already averaging over the reflector strip area due to higher beam divergence and consequent spot size, the retro-reflecting area is still distinguishable, while individual reflectors have already been blurred, see Figure 5 (a).

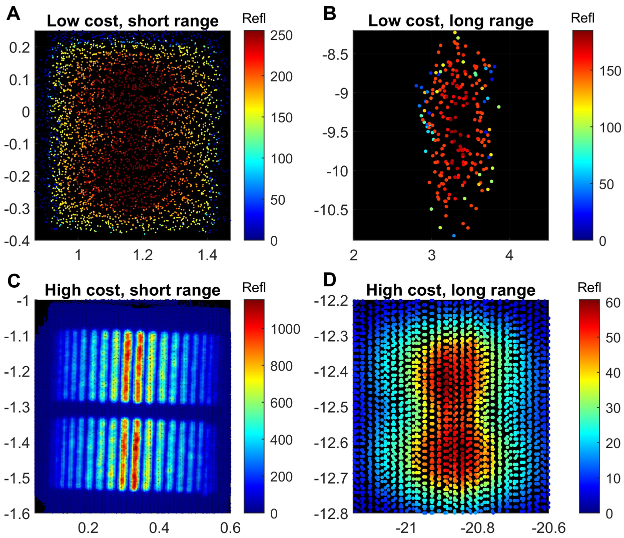

Figure 5: Point clouds obtained from lidar measurements on maritime navigational aids. Short range equals to 50m and long range equals to 500m. The x and y axes are in meters. Note that the intensity scales are not identical. The sensors have roughly two orders of magnitude difference in price, but this is at least partially attributable to highly sophisticated software for the high cost sensor. Based on data from [Malkamäki et al., 2021].

The fundamental problems of the low-cost lidar become visible at long range, where the target shape and size become severely distorted due to, amongst other things, the relatively large spot size and low angular precision of the scanning mechanism. Of particular interest in this example is the difficulty to qualify and quantify the errors for the low-cost sensor. The blurring of the point cloud could follow from angular errors, but it could as well com-

https://doi.org/10.5194/isprs-archives-XLVIII-2-W1-2022-137-2022

Figure 6: A panoramic Ladybug5+ camera mounted on a multi-sensor backpack system designed by the first author at the University of Twente (left). Images acquired with the Ladybug5+ camera array outdoors (top) and indoors (bottom) show an overlap and barrel distortion. Camera direction is up, right, front right, front left, left, back.

prise of ranging errors or intensity measuring errors (in which the intensity errors are further mixed with possible range calibration errors). The consequence of the lumping and magnitude of these error sources is the difficulty in assessing how the target is distorted and which particular error source would need to be addressed in order to improve performance. For example, when comparing the low-cost and high-cost lidar images at long distance, see Figures 5 (b) and (d) respectively, one can make an educated assumption that the angular resolution is the main cause for distortion, but it is difficult to quantify the relative impact of beam divergence and angular precision to the resulting point cloud. Furthermore, low-cost lidars, such as the one used in this example, suffer from low numerical precision in the processing chain, which can be observed in e.g. saturation of high intensity values at short range, which makes it difficult to observe and model the real attenuation of the signal strength for a given target.

In this particular case, the existence of the retro-reflecting strips on the target causes both instruments to detect high intensity return signals, even at atypically long ranges. Therefore, this type of application is limited by sensor characteristics other than the range, which is generally considered to be one of the main problems for lidars in maritime domain. In order to optimise and design low-cost lidars for maritime use and particularly for the the detection of navigational markers, one would need to address the contribution of individual error sources, which requires high-quality data.

The application matters. If the measurement focuses solely on detecting the existence of a highly reflecting target, a low-cost sensor may be sufficient. However, if the application also requires an estimate on, e.g., the shape or the exact location of the target, a low-cost lidar will not provide adequate data beyond a certain range. This will make target identification difficult, regardless of the fanciness of the algorithm. In practice, collecting low quality data from a low-cost lidar for the purpose of training a neural network-type object classifier will very likely be a lost cause. It is hence less risky to acquire training data with a high-cost sensor and then artificially downgrade the data quality for feasibility testing. Furthermore, adding simulated errors to the data will allow for the evaluation of how different error sources in low-cost sensors impact the AI training.

2.3 CAMERA

Images come with different perceptual quality [Zhai and Min, 2020]. Some cameras are designed to yield specific type of quality while sacrificing some other type of quality. Therefore, it is hard to talk in generic about low-quality and high-quality cameras. Hence, we focus our discussion on the argument in the context of frame cameras and panoramic cameras, see Figures 6 and 7.

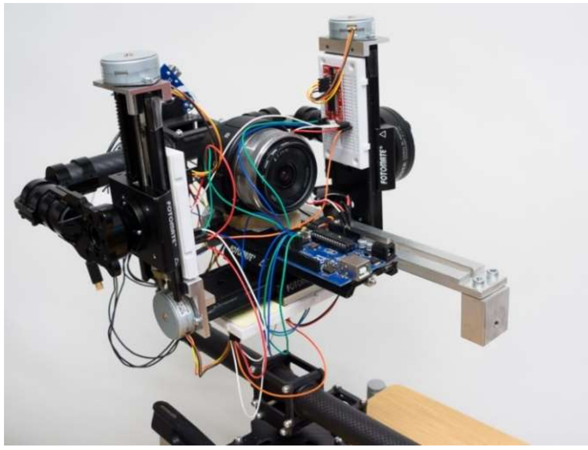

Figure 7: A low-cost frame camera on a motorized mount can automatically calibrate its principal point to be on top of the rotation center of mount, effectively imitating a more expensive 360 panoramic camera. Reproduced from [Kauhanen et al., 2016].

A low-cost frame camera can replace a high-cost panoramic camera, for example, when set on a motorized mount [Kauhanen et al., 2016]. The mounted camera can capture panoramic images automatically so that the projection centre of the camera is located at the rotation centre of the mount. However, such a low-cost system comes with limitations, because it must be kept in place during the data acquisition. While on motion, panoramic images may still be properly acquired by a high-cost camera system mutually positioned to obtain a 360-view, e.g., Cyclorama [Van Den Heuvel et al., 2006]. Arguably, a compromising solution is to have the camera principal points close to one another, such as in the Ladybug5 six-camera system [Lichti et al., 2020]. These camera images are provided with overlap, see Figure 6 for images from Ladybug5+, but need to be fused together or with the lidar data.

Sensor fusion between photogrammetric computer vision and mobile laser scanning (MLS) has its baseline on RGB colored point clouds and in lidar-corrected depth images, e.g. [Lehtola et al., 2017]. We shall discuss these two baseline approaches. First, a

This contribution has been peer-reviewed.
https://doi.org/10.5194/isprs-archives-XLVIII-2-W1-2022-137-2022

point cloud is colored by projecting lidar points on an image and inheriting the RGB color values of the associated pixel(s). We can immediately see that a higher resolution image acquired with better optics (e.g. less lens distortion) yields more accurate information. However, a task may be also completed with a low-cost sensor if its specifications satisfy the applications needs. Second, lidar-corrected depth image is calculated by benefiting from the lidar scan resolution, or local point density. Here, a higher density is better in terms of accuracy. Depending which approach is selected, the importance of having high-cost equipment for the primary measurements is important.

Low-cost depth cameras, or RGB-D sensors, may be seen as a replacement for lidars for geometry measurement purposes [Ingman et al., 2020]. However, here also, the focus in examining these low-cost sensors is to assess the quality of their output, so that the feasibility of using a specific low-cost sensor in a specific application with a specific method can be known. The general study about the overall feasibility of the methodology is left to be done with the high-cost sensors.

2.4 IMU

Inertial measurement units (IMUs) measure acceleration and angular velocities in three orthogonal axes but may include also other capabilities. Often, they also include magnetometers to aid heading estimation. The sensor fusion study for these sensors has already continued for 40 years, but still the development is ongoing [Nazarahari and Rouhani, 2021]. One of the main challenges is the quality of the low-cost sensors, which is attempted to be compensated using more complex estimation algorithms. While high-cost sensors come with a promise of stability regarding the changing biases or other calibration parameters, the low-cost sensors usually have a lot of variation in their calibration parameters over temperature changes, see e.g. [Hyyti and Visala, 2015].

In [Hyyti and Visala, 2015], a low-cost SparkFun 6DOF Digital IMU breakout board (which combines an ADXL345 accelerometer and an ITG-3200 gyroscope chips) was compared against a two orders of magnitude more expensive MicroStrain Inertia-Link IMU, which could still be considered as a low-cost sensor compared to any navigation or tactical grade IMUs. The comparison was performed using a KUKA Lightweight Robot 4+ and KUKA Fast Research interface for measuring the pose of the two IMUs that were fixed to the tool of the robot arm. The setup is shown in Figure 8, where the orange colored KUKA robot with 7 degrees of freedom has a custom tool mounted in place of its gripper, which contains both compared IMUs mounted on opposite sides of the same aluminium plate. The SparkFun breakout board was constructed inside the aluminium block in the previous work in order to use it in outdoor tests. The robot enabled the authors to collect an accurate reference trajectory for a complex but reproducible motion around the robot. Although the robot was able to provide a good reference trajectory, it was still unable to provide a good reference for linear accelerations, and a high-cost navigation-grade IMU would have given a more suitable reference, if it had been available.

Other key difference between high-cost and low-cost IMU sensors is the amount of noise in their measurements. As seen in Figure 5 of [Hyyti and Visala, 2015], the low-cost sensor has a significantly increased amount of noise in acceleration measurements as compared to slightly more costly sensor used in the comparison. Furthermore, in high-cost sensors, such as navigation or tactical grade IMUs, the noise can be very low, even multiple magnitudes lower than in consumer grade low-cost sensors [Stanisak, 2022]. However, there is also ongoing development in micro-electro-mechanical systems (MEMS) to provide less noisy sensors which would behave more stable in terms of their calibration parameters [Langfelder et al., 2021]. This would allow also simpler algorithms to be used for attitude and heading estimation effectively.

Figure 8: A high-cost 7 degrees of freedom KUKA Lightweight Robot 4+ used to actuate low-cost IMUs mounted on top and to collect a reference trajectory.

3. DISCUSSION

We define a low-cost sensor as a sensor for which the market price is significantly cheaper than for a sensor that is conventionally or traditionally utilized in some application. Simultaneously, the high-cost sensors we refer to, do output high-quality data and are good investments for a research laboratory.

We set out to find answers to the question, why does it make sense to use high-cost sensors to do low-cost sensor research. Figure 9 encapsulates our findings. A sensor with precision below the feasibility threshold T_h, e.g. low-cost A, indicates that the task is not feasible with that sensor, but it does not give insights whether the task is feasible with some other, i.e. better, sensors. Instead, sensors with precision above the feasibility threshold T_h are not only suited for the given task, but in addition, these high-cost sensors allow for the overall study of the feasibility. Feasibility can then be studied over multiple applications and methods (each having their own T_h), and sensors. Furthermore, high-quality data can be used to evaluate cost-quality optimization in sensors. In many applications, a preferably regime in data quality can be found,

https://doi.org/10.5194/isprs-archives-XLVIII-2-W1-2022-137-2022 |

beyond of which increasing the data quality brings very little, if any, improvement in the end result.

A low-cost sensor, *per se*, is useful mostly when doing feasibility testing of a specific high technological readiness level (TRL) solution for that sensor, or when determining a specific error model for that sensor. However, the latter case may pose caveats in certain regimes where the errors may get mixed so badly that determining proper error models for a low-cost sensor becomes impossible. This was observed in the outdoor lidar case. Mixed error sources could also include sensor calibration issues, thermal dependencies, measurement resolution (e.g., lidar spot size, or camera resolution), altering noise profiles, certain non-linearities, motion during measurement leading to blurriness, and inaccuracies in measurement time synchronization.

Our discussion has, so far, mainly addressed single sensors. However, multi-sensor systems could mount a combination of high-cost and low-cost sensors of different types. Then the feasibility of the whole system for a task would depend on this combination. For instance, mobile mapping is a task usually done with multi-sensor systems, e.g. [Liu et al., 2010, Lauterbach et al., 2015, Karam et al., 2019, Blaser et al., 2018]. For multi-sensor systems, one can think that each sensor must fulfill its role for the combination to be successful. Hence, one can argue that a feasibility threshold still exists for each individual sensor. The deciding factor is again the application but also the way in which the information fusion is done. For the multi-sensor system shown in Figure 6, it is possible to fuse the data with multiple ways using simultaneous localization and mapping (SLAM) techniques. One way is to first do a lidar-inertial fusion with the two Velodyne VLP16 lidars and the Xsens MTI-630R IMU mounted under the horizontal lidar [Karam et al., 2021, Xu et al., 2022]. After that the Ladybug5+ camera may be used to color the acquired point cloud for a baseline data output. Here, the lidars would play a critical role while the camera would be an auxiliary sensor. Another way is to use the camera for SLAM and then refine the acquired 3D map with the lidar data [Blaser et al., 2019]. Yet another way is to do visual-lidar-inertial fusion [Lin and Zhang, 2022]. Either way, if the primary localization method is SLAM, then a GNSS receiver would act in an auxiliary role offering geopositioning capabilities when the system is under open sky conditions. For example, the system in Figure 6 benefits from a Trimble BD990 GNSS receiver.

4. CONCLUSION

Paradoxically, high-cost sensors may often be more useful in low-cost sensor research than low-cost sensors themselves. This can be a hard point to argue when applying for funding and/or for the procurement of high-cost sensors for a low-cost research project. We hope that this work supports those arguments.

We argue that all research should always begin with high-cost sensors because (i) then the general feasibility of the methods can be examined, i.e., whether some application is plausible in the first place and (ii) then the detailed specifications of a sensor with which the application is plausible can be explored and become known. In other words, the sensor should be of high enough quality to reside well above the feasibility threshold. When using a low-cost sensor, the only added value to this is to obtain the specific error model or the feasibility result for that specific sensor make. Finally, in any case, the ground truth or reference must be available from a high-quality sensor.

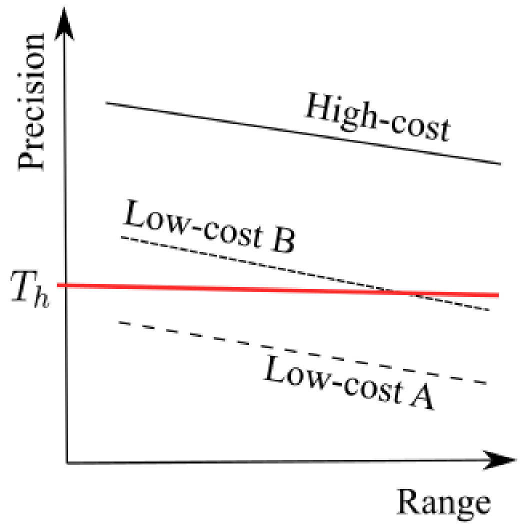

Figure 9: Schematic on the benefits of high-cost sensors. The 'Range' axis is connected to the sensor resolution, i.e., a high-cost sensor may yield the same resolution from a long range than what a low-cost sensor yields from short range. The feasibility threshold T_h can be well examined from above by artificially downgrading the data quality from a high-cost sensor, but not so with case A or case B low-cost sensor.

ACKNOWLEDGEMENTS

This study has been done with H.H. having an affiliation to the Academy of Finland Flagship, Forest-Human-Machine Interplay - Building Resilience, Redefining Value Networks and Enabling Meaningful Experiences (UNITE) (decision no 337656, `https://uniteflagship.fi`).

REFERENCES

Blaser, S., Cavegn, S. and Nebiker, S., 2018. Development of a portable high performance mobile mapping system using the robot operating system. ISPRS Annals of Photogrammetry, Remote Sensing & Spatial Information Sciences.

Blaser, S., Nebiker, S. and Wisler, D., 2019. Portable image-based high performance mobile mapping system in underground environments–system configuration and performance evaluation. ISPRS Annals of Photogrammetry, Remote Sensing & Spatial Information Sciences.

Hyyti, H. and Visala, A., 2015. A dcm based attitude estimation algorithm for low-cost mems imus. International Journal of Navigation & Observation.

Ingman, M., Virtanen, J.-P., Vaaja, M. T. and Hyyppä, H., 2020. A comparison of low-cost sensor systems in automatic cloud-based indoor 3d modeling. Remote sensing 12(16), pp. 2624.

Karam, S., Lehtola, V. and Vosselman, G., 2021. Simple loop closing for continuous 6dof lidar&imu graph slam with planar features for indoor environments. ISPRS journal of photogrammetry and remote sensing 181, pp. 413–426.

Karam, S., Vosselman, G., Peter, M., Hosseinyalamdary, S. and Lehtola, V., 2019. Design, Calibration, and Evaluation of a Backpack Indoor Mobile Mapping System. Remote Sensing 11(8), pp. 905.

Kauhanen, H., Rönnholm, P. and Lehtola, V., 2016. Motorized panoramic camera mount-calibration and image capture. ISPRS Annals of Photogrammetry, Remote Sensing & Spatial Information Sciences.

Langfelder, G., Bestetti, M. and Gadola, M., 2021. Silicon mems inertial sensors evolution over a quarter century. Journal of Micromechanics and Microengineering 31(8), pp. 084002.

Lauterbach, H. A., Borrmann, D., Heß, R., Eck, D., Schilling, K. and Nüchter, A., 2015. Evaluation of a backpack-mounted 3d mobile scanning system. Remote Sensing 7(10), pp. 13753–13781.

Lehtola, V., Hyyti, H., Keränen, P. and Kostamovaara, J., 2019a. Single photon lidar in mobile laser scanning: The sampling rate problem and initial solutions via spatial correlations. International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences.

Lehtola, V. V., Kaartinen, H., Nüchter, A., Kaijaluoto, R., Kukko, A., Litkey, P., Honkavaara, E., Rosnell, T., Vaaja, M. T., Virtanen, J.-P. et al., 2017. Comparison of the selected state-of-the-art 3d indoor scanning and point cloud generation methods. Remote sensing 9(8), pp. 796.

Lehtola, V. V., Mäkelä, M., de Oliveira Marques, T. and Montloin, L., 2022. Tropospheric wet tomography and ppp: Joint estimation from gnss crowdsourcing data. Advances in Space Research.

Lehtola, V. V., Söderholm, S., Koivisto, M. and Montloin, L., 2019b. Exploring gnss crowdsourcing feasibility: combinations of measurements for modeling smartphone and higher end gnss receiver performance. Sensors 19(13), pp. 3018.

Lichti, D. D., Jarron, D., Tredoux, W., Shahbazi, M. and Radovanovic, R., 2020. Geometric modelling and calibration of a spherical camera imaging system. The Photogrammetric Record 35(170), pp. 123–142.

Lin, J. and Zhang, F., 2022. R3live: A robust, real-time, rgb-colored, lidar-inertial-visual tightly-coupled state estimation and mapping package. In: 2022 International Conference on Robotics and Automation (ICRA), IEEE, pp. 10672–10678.

Liu, T., Carlberg, M., Chen, G., Chen, J., Kua, J. and Zakhor, A., 2010. Indoor localization and visualization using a human-operated backpack system. In: 2010 International Conference on Indoor Positioning and Indoor Navigation, IEEE, pp. 1–10.

Malkamäki, T., Khatun, A. and Kaasalainen, S., 2021. Research report on lidar detection performance of maritime navigation aids equipped with auxiliary reflectors. Publications of Finnish Transport Infrastructure Agency (338).

Marques, T. D. O., Mäkelä, M., Montloin, L., Lehtola, T., Thombre, S. and Lehtola, V., 2021. Towards tropospheric delay estimation using gnss smartphone receiver network. Advances in space research 68(12), pp. 4794–4805.

Nazarahari, M. and Rouhani, H., 2021. 40 years of sensor fusion for orientation tracking via magnetic and inertial measurement units: Methods, lessons learned, and future challenges. Information Fusion 68, pp. 67–84.

Putkiranta, P., 2020. Geometric calibration of rotating multi-beam lidar systems. Master's thesis, Aalto University. School of Engineering.

Stanisak, M., 2022. inertial technology: Sensors, algorithms, and integration,". In: Proceedings of the 2022 International Flight Inspection Symposium (IFIS).

Van Den Heuvel, F. A., Verwaal, R. and Beers, B., 2006. Calibration of fisheye camera systems and the reduction of chromatic aberration. In: ISPRS comission V Symposium, Citeseer, pp. 25–27.

Xu, W., Cai, Y., He, D., Lin, J. and Zhang, F., 2022. Fast-lio2: Fast direct lidar-inertial odometry. IEEE Transactions on Robotics.

Zhai, G. and Min, X., 2020. Perceptual image quality assessment: a survey. Science China Information Sciences 63(11), pp. 1–52.