DEVELOPING A THEORETICAL ASSESSMENT METHOD FOR AN ASSISTED DIRECT GEOREFERENCING APPROACH TO IMPROVE ACCURACY WHEN MAPPING OVER WATER: THE CONCEPT, POTENTIAL AND LIMITATIONS

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ABSTRACT:

Drones offer a a unique survey platform that can operate below cloud cover and acquire very high spatial resolution datasets in near real-time. Studies have demonstrated that drones can be used for mapping over water using the Direct Georeferencing approach. However, this method is typically only feasible with high-end drones equipped with highly accurate GNSS/IMU systems. Moreover, placing targets over water to improve accuracy in post-processing can be challenging, further exacerbating this limitation. In this study, we developed an Assisted Direct Georeferencing method which combines the advantages of traditional Bundle Adjustment (BA) and Direct Georeferencing to overcome these challenges. Our approach utilizes BA over feature-rich segments of the drone trajectory, such as the shoreline, and DG in featureless areas, such as over water. To simulate a water-type environment or surface for our early tests, synthetic datasets have been created using Python for theoretical analysis. We then conducted a theoretical assessment of our approach under low and high variability attitude measurements. Our findings revealed that our methodology performs well under low variability attitude measurements, where wind conditions are close to optimal with an R-square value of 0.93. However, our model performs poorly under high variability attitude measurements, with an R-square value of only 0.028. These results suggest that Assisted Direct Georeferencing can serve as an alternative to high-end drones and Direct Georeferencing for water mapping applications in most standard. The findings from this theoretical assessment provide valuable insights into the achievable accuracy, error budgets, and limitations of the proposed model.

1. INTRODUCTION

Drones offer a a unique survey platform that can operate below cloud cover and acquire very high spatial resolution datasets in near real-time (Arango and Nairn, 2019, Kedzierski et al., 2019, Wu et al., 2019). Mapping over water surfaces using drones for applications such as measuring water quality is now a realistic alternative to use of satellite images (Knaeps et al., 2019, Maravilla et al., 2019, Wu et al., 2019). A drone approach provides a very high spatial resolution which can significantly improve the level of detailed information that can be obtained, and improve the quality of the water quality parameter being monitored (Lo et al., 2023). For instance, if a water quality monitoring approach uses very high spatial resolution, it will be able to detect and measure changes in water quality over small areas with a high level of detail. However in photogrammetry, the traditional Bundle Adjustment (BA) method faces an obvious disadvantage when mapping over water surface, due to the difficulty in finding ground features that can act as tie points for the image reconstruction (Essel et al., 2022, Knaeps et al., 2019, Windle et al., 2021).

In solving this problem, previous studies have shown that the only practical solution for reconstructing images over water is the use of the Direct Georeferencing method where the IMU and GNSS provide information on the pose of the drone(Román et al., 2023, Essel et al., 2022, Windle et al., 2021). However, the DG approach is only successful in 2D image reconstruction with high-end drones that possess a highly accurate RTK GNSS and IMU (Bláha et al., 2012, Ip et al., 2007) and hence its usage is not widely applicable due to the cost of purchasing such platforms. As a result, our study seeks to develop a method for low-end GNSS/IMU that combines the benefits of both Direct Georeferencing and Bundle Adjustment (BA). Integrated sensor orientation (ISO) is an established concept in photogrammetry where simultaneous image processing is done by combining the Bundle Adjustment and Direct Georeferencing (Heipke et al., 2002, Ip, 2005, Tanathong and Lee, 2014). Studies have shown that the accuracy that can be achieved from only the DG method is limited by the accuracy of the GNSS, the IMU and calibration errors (Mitishita et al., 2016, Stam, 2010) however with ISO technique, reliable and high accuracy measurements are achievable. Further, ISO can provide an opportunity to use low-cost IMU /GNSS which have less accuracy (Tanathong and Lee, 2014). In this study we propose combining the strength of both the DG and the BA methods in an adaptation of the ISO workflow for image reconstruction over a simulated water environment. Our approach proposes utilizing BA in feature-rich segments of the survey area, such as the shoreline, and DG in featureless areas, such as over water. Due to the difficulty of finding features over the water and also additional restrictions of placing GCPs over the water, the BA is used to stitch images over the shoreline and prop-

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agate the corrections over areas without features with the result of refining the accuracy of the images over the water.

To better understand the performance and limitations of our proposed method, a theoretical assessment was developed which allowed us to improve the model accuracy, reliability, assumptions and limitations of the model. We then identified areas of the model that require refinement or improvement to enhance reproducibility. Finally we assess the accuracy of the model, the sensitivity of the variables, and identify the underlying assumptions and limitations.

2. METHODS

2.1 Data

The process of generating synthetic data using Python typically involves using various image processing and computer vision libraries, such as OpenCV, NumPy, and PIL (Python Imaging Library). These libraries provide tools and functions that can be used to generate synthetic images by manipulating existing images or creating new images. It allows researchers and practitioners to generate large datasets and introduce diverse variations, which can be helpful in scenarios where real data is scarce or difficult to obtain. This is very useful for a study exploring the accuracy of a photogrammetric method over water - as we cannot place stationary targets for assessment and survey these using traditional GNSS RTK.

In this study, 40 synthetic images were created. Out of these, 5 images were selected as those that would have the shoreline in view, while the remaining images represented the featureless water environment with no shoreline in view as shown in Figure 1. Additionally, each synthetic image was overlaid with grid lines. Grid lines are commonly used in image processing for various purposes, such as image alignment, object detection, and measurement. In this case, the grid lines were added as a visual aid in assessing the accuracy and image misalignment. These grid lines can be generated using Python's image processing libraries such as OpenCV, which provide functions to draw lines, shapes, and other elements on images. The grid lines helped to evaluating the performance of our proposed model.

The synthetic images were created using defined parameters such as focal length of 3.75mm, image with of 1280 and image height of 980.

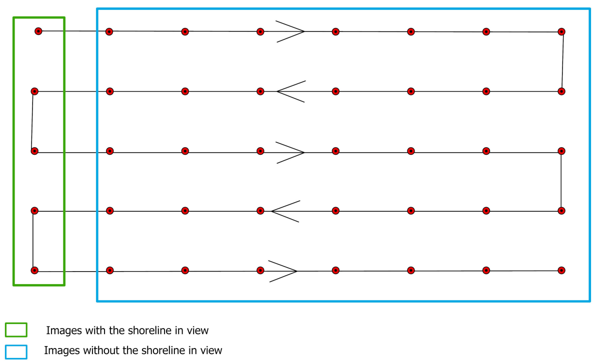

Figure 1: Image showing the flight plan for the synthetic data

2.2 Proposed Method: Assisted Direct Georeferencing

In this study, we propose a model called the Assisted DG model that aims at improving planimetric accuracy by using features from the shoreline. Our Assisted DG model combines benefits from both Direct Georeferencing and Bundle Adjustment. The DG approach is used to project all the images over the water surface unto the ground plane using the IMU/GNSS and the BA approach is used to process only the images with the shoreline in view.

Firstly, the images are separated into two: images with shoreline in view and images without the shoreline in view. The images that have the shoreline in view are then reconstructed using software that employs the Bundle Adjustment (BA) method such as PIX4D, Agisoft methashape etc. In this case, the overlaid grid lines were used as identifiable features during the BA process. A separate image reconstruction is done for images over the water without shoreline in view by using the DG method. The next step is to calculate the offset errors at a given point for the shoreline images by calculating the difference between BA and DG. These offset errors are then used to predict the errors and then used to calculate the predicted coordinates for a point over the water without shoreline in view. The last step is to perform an image transformation by using the predicted coordinate point and the observed coordinate point. This method is illustrated in Figure 2 where we describe the steps in processing the images and applying the prediction model for improving the planimetric accuracy.

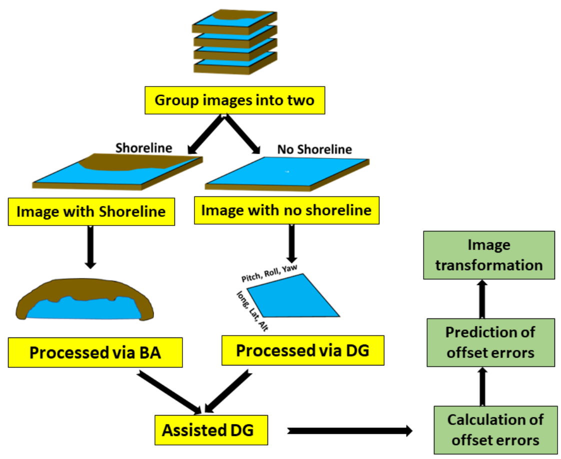

Figure 2: A flow diagram showing the proposed Assisted Direct Georeferencing process of improving the planimetric accuracy by combining BA and DG

2.2.1 Calculation of Offset Errors for Shoreline Images

The offset errors are determined from the images with the shoreline in view. These are calculated by finding the distance offset between the DG and the BA for a given point on the reconstructed image. Details and explanations of the DG workflow for image reconstruction from the object to camera, sensor and image coordinate system can be found in (Essel et al., 2022).

In the Equation 1 below, the offset error at a given point is denoted by $(\Delta X_r\ ,\ \Delta Y_r)$ in the image coordinate system and is calculated by finding the difference between BA which is denoted by ($\boldsymbol{X_{BA}}$, $\boldsymbol{Y_{BA}}$) and the DG which is represented as ($\boldsymbol{X_{DG}}$, $\boldsymbol{Y_{DG}}$). In any given image, the offset errors were calculated for at least four points using the grid lines and was done to have an even distribution across the image. The offset errors can only be calculated for images with the shoreline in view. This was because identifiable features are needed to calculate the difference in errors between the DG and the BA.

$$\begin{pmatrix} \Delta X_r \\ \Delta Y_r \end{pmatrix} = \begin{pmatrix} X_{BA} \\ Y_{BA} \end{pmatrix} - \begin{pmatrix} X_{DG} \\ Y_{DG} \end{pmatrix} \quad (1)$$

2.3 Prediction of Offset Errors for Water Images

Next, in building the model, the dependent variables required are the attitude angles in Roll and Pitch, the initial coordinate of a given point and offset errors derived from earlier images with the shoreline in view. From the model, A represents an image from the shoreline with Pitch and Roll values, X represent unknown offset error for images without shoreline in view and B represent Pitch and Roll values for an image without shoreline in view mutiplied by the measured offset error from image with shoreline in view as seen in Equation 1. From the model, ($\boldsymbol{\Delta X_U}$, $\boldsymbol{\Delta Y_U}$) represents the unknown offset error from an image without features (no shoreline in view). $\boldsymbol{\theta_{SL}}$ and $\boldsymbol{\varphi_{SL}}$ represents the Pitch and Roll values measured respectively for an image with the shoreline in view, $\boldsymbol{\theta_{FT}}$ and $\boldsymbol{\varphi_{FT}}$ represent Pitch and Roll values measured respectively for image without shoreline in view, ($\boldsymbol{P_w}$, $\boldsymbol{P_h}$) is denoted as the coordinate of a point measured in the image coordinate system and ($\boldsymbol{\Delta X_r}$, $\boldsymbol{\Delta Y_r}$) representing the residual/offset error at a given known point calculated from images with the shoreline in view. The next step was to perform an image transformation whereby the image was transformed using the original location of a given point in conjunction with the predicted coordinate point via an affine transformation.

$$A \, .\mathrm{X} = \mathrm{B} \quad (2)$$

$$\mathrm{X} = A^{-1} \, . \, \mathrm{B} \quad (3)$$

$$A = \begin{pmatrix} \theta_{SL} & \varphi_{SL} & P_w \\ \theta_{SL} & \varphi_{SL} & P_h \\ 1 & 1 & 1 \end{pmatrix} \quad (4)$$

$$B = \begin{pmatrix} \theta_{FT} & \varphi_{FT} & P_w \\ \theta_{FT} & \varphi_{FT} & P_h \\ 1 & 1 & 1 \end{pmatrix} \begin{pmatrix} \Delta X_r \\ \Delta Y_r \\ 1 \end{pmatrix} \quad (5)$$

$$\begin{pmatrix} \Delta X_U \\ \Delta Y_U \\ 1 \end{pmatrix} = \begin{pmatrix} \theta_{SL} & \varphi_{SL} & P_w \\ \theta_{SL} & \varphi_{SL} & P_h \\ 1 & 1 & 1 \end{pmatrix}^{-1} \begin{pmatrix} \theta_{FT}.\, \Delta X_r + \varphi_{FT}.\Delta Y_r + P_w.1 \\ \theta_{FT}.\, \Delta X_r + \varphi_{FT}.\Delta Y_r + P_h.1 \\ \Delta X_r + \Delta Y_r + 1 \end{pmatrix} \quad (6)$$

3. RESULT AND DISCUSSION

3.1 Simulation of Low variability Attitude Measurement

To better understand the performance and limitations of the proposed method, a theoretical accuracy assessment was conducted. This assessment was crucial for improving the accuracy and reliability of the model, as well as informing its appropriate use, identifying areas for refinement or improvement, and enhancing reproducibility. In this section, the theoretical assessment focused on evaluating the accuracy of the model under attitude measurements with low variability. This refers to measurements of the orientation that have little variation in Pitch and Roll.

The simulation was based on attitude measurements of which were found to have low variability, with a variance of 0.4 degrees. The R-squared method, a widely accepted and useful method for evaluating model performance was used to assess the accuracy of the proposed Assisted DG model as shown in Figure 5 (Teppati Losè et al., 2021). The theoretical assessment began by reconstructing the images using the Direct Georeferencing (DG) approach without any refinement, as shown in Figure 3. This benchmark scenario output revealed misaligned grid lines, indicating low accuracy in the reconstructed images. The Mean Absolute Error (MAE) measured for this initial reconstruction was 5m, indicating a significant level of error. The reconstructed images were then refined using our proposed Assisted DG (ADG) approach, as shown in Figure 4. A comparison of the outputs revealed that the grid lines in Figure 4 were aligned, indicating improved accuracy in the reconstructed images. The MAE was reduced to 2.2m, indicating a substantial reduction in error compared to the initial DG approach.

The visual comparison of the reconstructed images in Figure 3 and Figure 4 clearly illustrates the effectiveness of our ADG approach in improving the accuracy of the reconstructed images. The aligned grid lines in Figure 4 indicate that the ADG approach was able to significantly reduce misalignments and improve the positional accuracy of the images compared to the DG approach. The reduced MAE further supports the conclusion that improved accuracies are achieveable with our ADG approach.

In assessing the model accuracy, initial results also revealed a high R-squared value of 0.93, indicating a strong correlation between the predicted and observed values, as shown in Figure 5 below. This suggests that the Assisted DG model performed very well under conditions of low variability in attitude measurements.

These findings from the empirical assessment strongly suggest a capability of our proposed ADG model in refining and improving the planimetric accuracy of image reconstruction. The aligned grid lines and reduced MAE highlight the potential of the ADG approach for enhancing the positional accuracy of water-type environments in particular, and contribute to the overall understanding of the model's performance under low variability measurement.

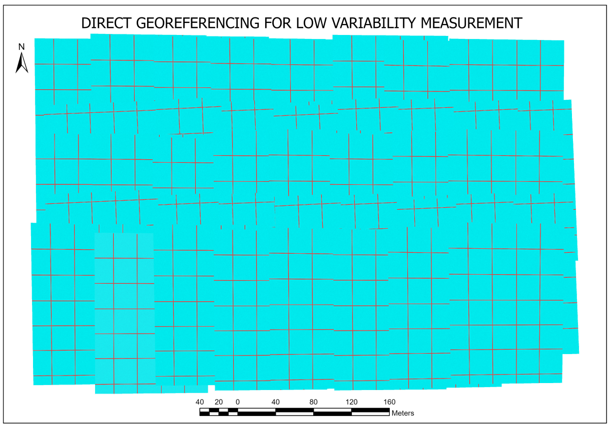

Figure 3: Initial result of the reconstructed images using the traditional DG approach with overlaid grid lines under low variability measurement

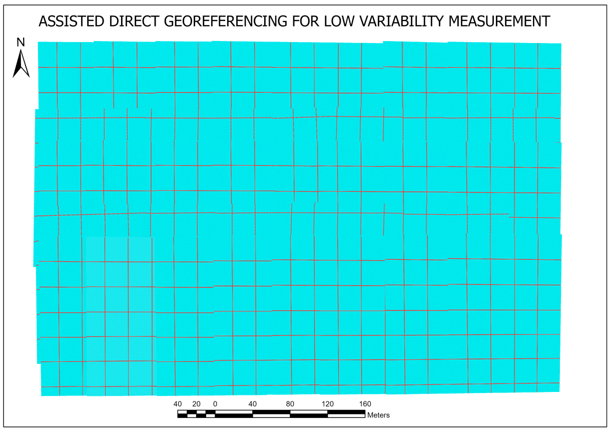

Figure 4: Improved result of the reconstructed images using our ADG model with overlaid grid lines under low variability measurement

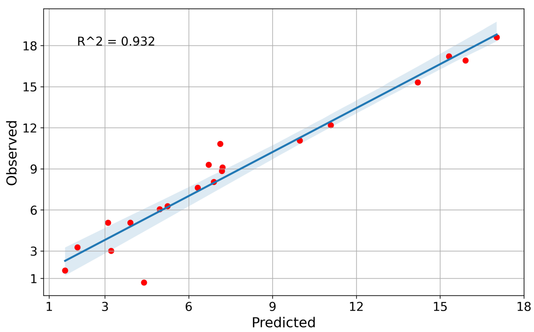

Figure 5: Theoretical accuracy assessment of the Assisted DG model with low variability attitude measurement

3.2 Simulation of High Variability Attitude Measurement

The performance of the proposed model was then tested to assess its ability to handle noisy measurements. This may be caused by factors such as high wind speed and strong magnetic interference affecting the readings from the IMU. To achieve this, a simulation was conducted using attitude measurements with high variability, represented by a variance of 6.5 degrees. Our simulation also enabled an analysis of the model's tolerance to high variability in measurements, which is important for understanding the consistency and accuracy of the model's results, especially in situations where the variability of the input data is high.

In Figure 9, the performance of the ADG model was tested by predicting under different level of variance. The results of the test revealed that the accuracy of the model decreased as the level of variance increased. Further, the results of the next simulation, as depicted in Figure 6, revealed that the Mean Absolute Error (MAE) for the Direct Georeferencing (DG) approach was 11.1m. Subsequently, our proposed ADG model was applied to the reconstructed images, and the MAE was reduced to 9.8m. It was evident from visual examination of the reconstructed images in Figure 6 and Figure 7 that alighnment of the grid lines was not significantly improved, indicating that the ADG model does improve the accuracy of the reconstructed images in the presence of high variability in the measurements. Furthermore, the R-squared value of 0.028 indicated a weak correlation between the predicted and observed values, further indicating isues with performance of the ADG model under noisy measurement conditions as shown in Figure 8.

Based on the results of the simulation, it can be inferred that our Assisted DG model exhibits reduced accuracy when dealing with noisy measurements. The visual misalignment of grid lines and the low R-squared value suggest that the accuracy of the model decreases as the variance of the input measurements increases. These findings highlight the limitations of the proposed ADG model in handling noisy measurements and provide valuable insights for understanding the performance characteristics of the model in different measurement conditions.

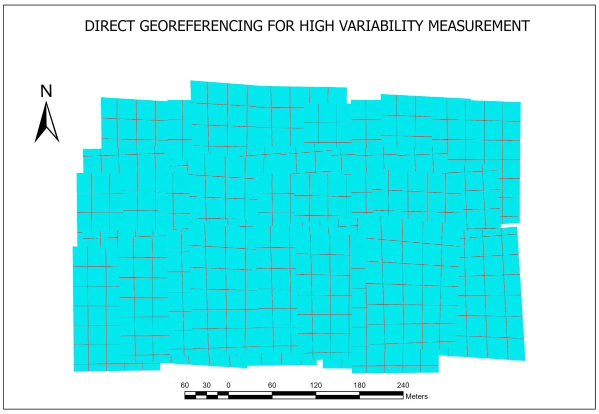

Figure 6: Initial result of the reconstructed images using the DG approach with overlaid grid lines under high variability measurement.

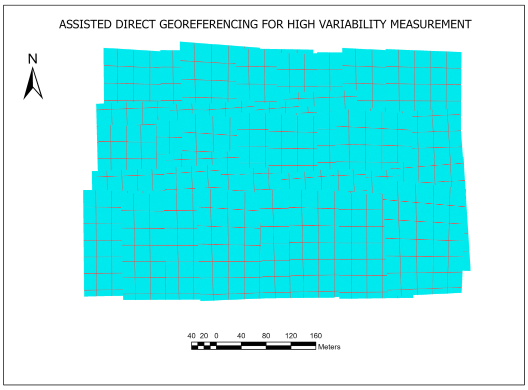

Figure 7: Result of the reconstructed images using the ADG model with overlaid grid lines under high variability measurement

measurements will tend to propagate into the predictions. In order to assess and quantify the potential errors introduced during the measurement of offset errors, an error budget was conducted. One factor that can introduce errors in the offset measurements is the accuracy of the Bundle Adjustment at the shoreline. The Bundle Adjustment is a process used to refine the positions and orientations of the images in the model, including the shoreline. If the Bundle Adjustment at the shoreline is not accurate, it can result in errors being propagated into the final output. Figure 10 provides a visual representation of the error propagation that can occur when there is an error or uncertainty in the offset errors used in the ADG model. It illustrates that even a small error of 1 meter in the offset measurements can result in an error of 0.67 meters in the refined reconstructed image, which is the output from the ADG model. This highlights the importance of accurate Bundle Adjustment at the shoreline to minimize errors in the offset measurements and ultimately improve the accuracy of the ADG model predictions.

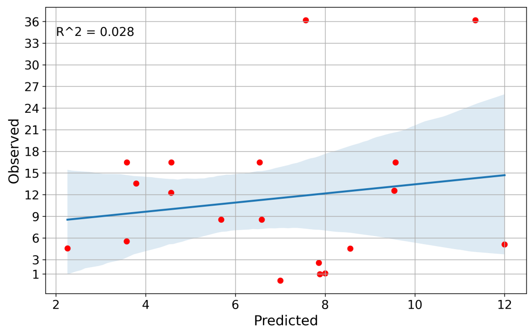

Figure 8: Theoretical accuracy assessment of the Assisted DG model with high variability attitude measurement

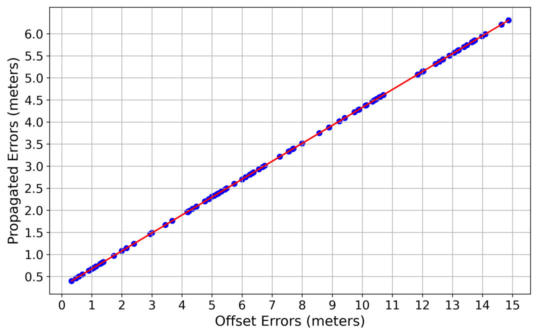

Figure 10: Error propagation showing the effect that errors in offset measurement in the BA and will have on the output

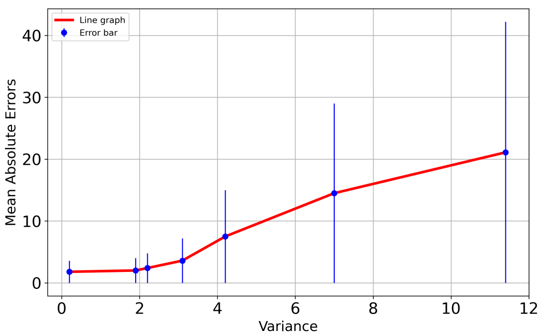

Figure 9: Performance of the ADG model under varying level of variance

3.3 Error Budget

The accuracy of our ADG model is dependent on the accuracy of the offset errors that are measured from the shoreline. These offset errors are crucial because they are used to predict errors in images where the shoreline is not visible and use them to refine the images without shoreline in view. If the offset errors are measured with high accuracy, it means that the observed points are close to the true values on the ground. In such cases, the model can provide accurate predictions. However, errors in the offset

3.4 Sensitivity Analysis

The sensitivity values presented in Figure 11 provide important insights into how the proposed model responds to changes in input variables. Specifically, the sensitivity values for Pitch and Roll are found to be 0.6, while the sensitivity value for point location is only 0.2. These sensitivity values indicate the magnitude of change in the model's predicted output in response to a unit change in the corresponding input variable.

A sensitivity value of 0.6 for Pitch and Roll implies that even a small change in the values of these variables would result in a relatively larger change in the predicted output of the model. This suggests that Pitch and Roll are highly influential factors in determining the accuracy and reliability of the model's predictions. Any variations or errors in the measurements of Pitch and Roll could significantly impact the model's output, highlighting the need for low variability measurement.

On the other hand, the sensitivity value of 0.2 for point location indicates that changes in the input variable of point location would have a comparatively smaller effect on the model's predicted output. This suggests that the accuracy of the point location measurement has a relatively lower impact on the overall performance of the model, compared to Pitch and Roll.

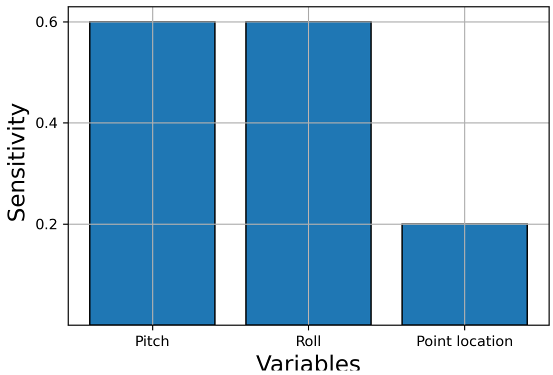

Figure 11: A graph showing sensitivity analysis of the input variables for the model

4. CONCLUSION

A theoretical accuracy assessment of our proposed Assisted DG (ADG) model was conducted to evaluate its performance and limitations under attitude measurements with both low and high variability. These results demonstrated potential for significant improvements in accuracy and reliability compared to the Direct Georeferencing (DG) approach under low variability attitude measurement. This was evidenced by the aligned grid lines in the reconstructed images and a reduced Mean Absolute Error (MAE) of 2.2m compared to 5m in the initial DG approach. Also, it was evident that an error in the offset measurement will lead to an error in the refined reconstructed image. Future work will encompass real world tests in an area of flat terrain to further assess the accuracy and reliability of the proposed approach. Nevertheless, our study contributes to the understanding of the potential of Assisted Direct Georeferencing in overcoming the limitations of traditional Direct Georeferencing for mapping over water and provides a foundation for future studies in this area. Our findings provide a solid foundation for future studies in this area, and highlight the need for continued research and validation to refine and optimize the ADG model for accurate and reliable water mapping applications.

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