Exploring a Robots ability to Determine the Angle of Inclination, before Ascension, with a Proximity Sensor

Joanna Percival (1711066), Milan Vekaria (2086489), Matthew White (2074124), Hongyi Zhang (2031207)

***Abstract*—For safe traversal of an incline, a robot needs knowledge of its environment. This paper investigates if an angled proximity sensor can successfully detect a slope before the robot commits itself to traversing the gradient. Multiple different positive gradient angles were tested, with and without a low pass filter, at varying distances from the robot, to determine the possibility and accuracy of incline angle calculation.**

I. Introduction

Autonomous robots are becoming increasingly integrated into everyday life. A wide range of commercially available robots can perform tasks from delivering parcels, to vacuuming a home or mowing a lawn. While sophisticated, a shared issue that appears in the literature is their approach to inclines. For instance, many manufacturers of smart lawn mowers suggest not to purchase one for garden gradients steeper than 20°. They state that if a smart lawn mower encountered a slope steeper than this it would simply sit at the bottom unable to proceed upwards [1]. Current sensors present in devices such as these include a 'cliff sensor' (to detect sudden drops in the ground implying steps are nearby) [2] and gyroscopes (to determine the current angle of inclination that they are currently travelling at). However, none of these robots appear to receive prior information about an incline. Knowledge of an incline before ascension would allow a robot to alter its actions prematurely to ensure safe travel. This could mean reducing speed or changing its path entirely if the slope is too steep.

This project investigated whether a robot could accurately determine the angle of inclination of a slope prior to ascension. To carry this out, a VL6180X Proximity Sensor (VPS) was mounted above a robot, where it measured the distance from its position to the ground enabling identification of gradient changes. The noise of the sensor was a major obstacle identified which limited the success of this task. A baseline solution was created, with comparisons made against variants utilising a different sensor mode and a low pass filter, observing if noise was reduced and the accuracy of readings improved. The intended demographic for this research would be low-power systems, as discussed above, without high-performance negative feedback. In this case a low pass filter is suitable as the time-lag caused will pose no dangers to the system. In this experiment overestimations of ramp calculations are desirable compared to underestimations as they prevent danger to the robot and its surroundings. As such, the solutions were compared not only for their accuracy in angle but also the direction of error.

A. Hypothesis Statement

The VL6180X proximity sensor claims to have accurate results independent of the target's colour and surface, when perpendicular to that surface. However, as a time-of-flight sensor it suffers from noise both systematic (Returns on Reference, Crosstalk, Leakage [3]) and non-systematic (Photon Shot, Analogy to Digital Quantization, Light Scattering [4]). While systematic noise can be managed by calibration, non-systematic noise requires filtration. It is believed that the non-systematic noise will increase due to non-perpendicular angle of the sensor to the surface and with vibrations of the sensor when the robot is moving, causing larger variations of readings. A low-pass filter would provide a smoother form of the signal, removing short-term fluctuations yet preserving the long-term trend. From this knowledge a hypothesis can be formed:

"We hypothesise that the VL6180X proximity sensor (based on an angled sensor and a given distance) is capable of determining a sufficiently reliable angle of inclination for a robot to traverse. We further believe, that implementing a low-pass filter or utilising the continuous ranging mode of the sensor will improve the consistency of sensor readings and reduce the calculated angle of inclination error. Finally, we presuppose that the error in angle will increase linearly with the distance from the robot."

The hypothesis was investigated through a structured robotic experiment. A standard solution, allowing the robot to calculate the angle of inclination was set up using the VPS in its single ranging mode, taking static readings of the inclination angle. The error in the angle was then investigated by varying the distance from the robot to the incline. The effect of using the continuous ranging mode and applying a filter to the VPS was explored to see if it made a difference to the stability of the system or improved the accuracy of the inclination angle. The performance of each method was determined by its measurement of the angle of inclination of a gradient of a set height and the error associated. In addition to this, the consistency, time efficiency and direction of error produced for each method were compared.

II. Implementation

To conduct experiments in a reliable and reproducible manner, the construction and set up of the experiment must be standardised. The following section explains the steps necessary to replicate the method used and reproduce the findings attained in this report. The parts requiring construction have details outlined, and a calibration routine is defined and explained. Following this, a set of instructions dictate how the robot was intended to be used for the purpose of this experiment.

A. Construction of components

For this experiment, the VPS was mounted above the robot on a boom so that it faced downwards with an angle close to 45° to the horizontal. The boom assembly and incline constructions consist of the parts shown in Figure 1 along with a VPS with header pins attached, a nut and bolt (Length of 10 mm, M2) and 4 jumper wires.

Construction of the boom required two pieces of cardboard cut out to the dimensions shown in Figure 1a. A hole (ISO M2) was made in the top left-hand corner of piece 1 (P1). The VPS was placed against the top of the back face of P1, with the VPS facing outwards and a nut and bolt fixing the two. P1 was placed under the front of the main circuit board of the robot into a grove and supported by P2, such that the VPS looked towards the ground at the front of the robot.

Jumper wires connect to their respective pins, while caution was taken to ensure connection did not cause the head of the boom to twist. The height (L1) was measured from the ground to the middle of the VPS for reference. The individual heights and angles of the proximity sensors following this set up may vary, but the calibration routine was designed to reduce the variance in data due to this.

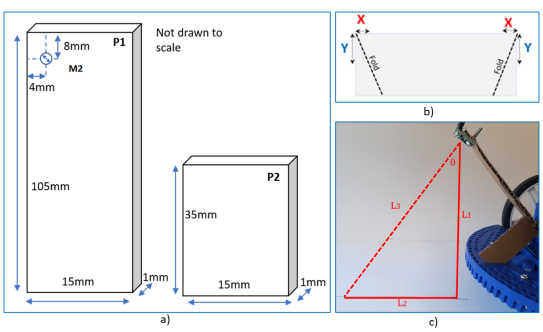

Fig. 1. This figure contains (a) a sketch displaying the dimensions of two pieces of cardboard (P1 & P2) required for construction of the boom, (b) an illustration for building the inclines and (c) an image displaying the setup and calibration routine.

Construction of the incline ramps required 1-2mm thick by 300mm x 180mm card board. The construction of individual incline ramps is shown in Figure 1b, where Y is 50mm and X can be calculated using the tangent trigonometry function.

B. Calibration

The robot was calibrated to a flat surface allowing the calculation of the individual angle of the VPS from the vertical axis (θ). This was essential to eliminate systematic noise in the sensor and make the setup reproducible. As the sensor is not located behind glass, Cross Talk Compensation calibration is not required but calibration will be performed to average out the Returns on Reference noise [3].

For the calibration routine, the height of the VPS above the ground (L_1) was manually inputted (to the nearest millimetre). Then the robot was placed on a flat smooth surface and 100 readings from the VPS were taken. From these values the mean was calculated and stored as the sensor beam length (L_3). A diagram for this calibration can be seen in Figure 1c. The angle θ was determined by:

$$\theta = cos^{-1}(\frac{L_1}{L_3}) \tag{1}$$

C. Angle of inclination

The robot calculated the angle of inclination (α) of a plane through a static approach. This meant that the robot took readings from the proximity sensor at a fixed distance from the ramp, to determine the inclination angle. The diagram sketched in Figure 2 displays the setup with the proximity reading labelled SR_1. L_1, L_3 and θ are all constants that were determined during calibration and d is the distance between the robot and the ramp. The angle of inclination of a slope can then be determined by:

$$\tan(\alpha) = \frac{L1 - SR_1 \cos(\theta)}{SR_1 \sin(\theta) - d} \tag{2}$$

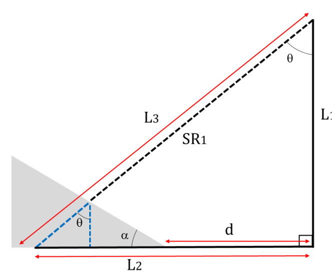

Fig. 2. A sketch of the parameters used to determine the angle of inclination, α, of a ramp at distance d from the robot. L_1 is the vertical height of the proximity sensor, L_2 is the focal point length of the sensor and L_3 is the sensor beam length. θ is the angle of the proximity sensor and SR_1 is the reading from the sensor.

D. Baseline Implementation

For the baseline solution, the VPS was placed on the angled boom (see section II-A) at the front of the robot. The sensor was configured to run with default range resolution and single shot range polling. From the VPS data sheet [5], in Single-shot mode, the VPS performs a synchronous single range measurement returning on completion. This configuration was used to obtain the angle of inclination through a series of experiments. A 100 sample average sensor reading was used for throughout the investigation.

E. Improved Implementation

In the hypothesis two variants were proposed to reduce the noise in the sensor and were compared to the baseline solution. The first was operating the sensor in continuous ranging mode; continuously sampling range values which are converged to a reading. This convergence of multiple values was believed to improve the accuracy of results. The VPS performs back to back range measurements at a user configured rate until the stop command is issued. The continuous mode is limited to 10Hz [5].

The second variant was the addition of a low pass filter; low pass filters provide a smoother signal, removing short-term fluctuation and leaving the longer-term trend. Discrete Fourier transforms were used to find the amplitude of the signal under different frequencies, a graph of the results is shown in Figure 3. This graph confirmed the need for a low pass filter as the desired signal is concentrated at a low frequency area. The function of a low-pass filter is to retain the signal lower than the cut-off frequency, known as the pass band, and to remove the signal at higher frequencies than this, the stop band. Taking account of data collected from the moving and stationary robot, an estimate is that useful information is contained in the lowest ten percent of Bandwidth. Based on these tests, the ideal parameters of the filter were a cut-off frequency (pass band) of 0.2Hz and total bandwidth of 5Hz. This satisfys the Nyquist-Shannon sampling theorem, $B < \frac{f_s}{2}$ for adequate signal fidelity, where B is the guaranteed band limit.

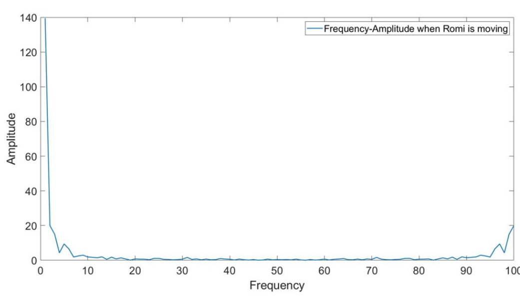

Fig. 3. A graph displaying the amplitude of the signal under different frequencies for the robot

A Butterworth filter was chosen as the final filter as it is designed to have a frequency response as flat as possible in the pass band, which can preserve the property of a target signal [6]. In addition, it is also easier to design compared to other filters such as epsilon and Chebyshev filters. The linear difference equation for this filter is:

$$\sum_{k=0}^{N} a_k Y(t-k) = \sum_{k=0}^{N} b_k X(t-k) \tag{3}$$

III. The Experiment

This section defines the methodology and variables used for the experiment. This is followed by an outline of the motivation for the choices made to ensure a robust and consistent experiment.

A. Setup and Ground Truth Measurements

For the calibration routine the height of the sensor was required. Using a set square, the vertical drop from the centre of the sensor to the floor was measured, in millimetres, then implemented into the software. A line was drawn parallel to the front of the robot, which passed through the point directly beneath the sensor. This parallel line was marked as 0 (ground), from this ground line parallel lines for ramp distances (d) of 40mm and 80mm were made (Figure 4). At this point the robot must not be moved.

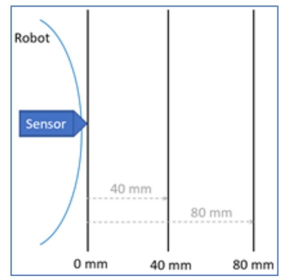

Fig. 4. Top View - Robot and Guidelines

B. Methodology

As highlighted in Section I-A, the experiment focused on understanding how a noisy sensor can be used when determining an incline presented to a robot. Specifically, the performance was assessed between the implementations described in Section II-D and II-E to understand the suitability of low pass filtering when the sensor operates in its two modes, single range and continuous. To acquire data for these variants, the experiment was carried out as follows:

1) The robot was placed on a flat, level white surface.
2) The robot was calibrated to the surface and set to single range/no filter mode.
3) A $5°$ ramp was placed in front of the robot on the 0mm line.
4) 10 Static measurements of the inclination angle of the ramp were taken.
5) This was repeated for $0°$, $10°$, $15°$, $20°$, $30°$ and $40°$.
6) Steps 3-5 were repeated for $d = 40mm$ and $80mm$.
7) Steps 2-6 were repeated for the continuous ranging mode and again with the presence of a filter.

This method was followed exactly and results were collected separately by four different individuals creating a total of 40 data samples for filter mode of each incline measured.

C. Independent and dependent variables

The primary independent variable in this experiment was the mode of the sensor; whether it was in single range or continuous mode and if a filter was present (as stated in Sections II-D and II-E). The dependent variable was the incline angle derived from the sensor reading and the error associated. An additional independent variable was the distance of the robot from the ramp. This was used to assess the system's performance as a robot approached an incline and to determine at which distance would be most appropriate to stop and measure the ramp.

D. Control Variables

The reliability and reproducibility of this experiment rested upon the consideration of control variables. The following is a list of the identified control variables and procedures put in place to either eliminate their impact or reduce it as much as possible.

Hardware:

- Robot: The Polulu Romi 32U4 was used throughout.
- Sensor: ST's VL6180X proximity and ambient light sensor was used throughout.
- Experiment used USB cable as its power source eliminating the effect of varying battery power. New batteries were required when the robot utilised the experimental results and attempted autonomous navigation.
- Sensor mounting: Instructions on boom construction written in Section II-A.
- Pins usage: Other sensors were detached and unplugged. Consistent pins and wires used throughout.

Software:

- No. of sensor data samples set to 100 for all experiments.
- Butterworth Filter parameters: a filter of order 3 with coefficients of $a = \{1.0, -1.647459981, 0.7008967812\}$, $b = \{0.01335920003, 0.02671840006, 0.01335920003\}$.

Environment:

- Experiment surface: Flat, level and white/light surface was consistently used.
- Inclines: Made of 1-2mm thick brown non corrugated card.
- Lighting: office lighting used, well-lit and diffused.

Procedure:

- Robot placement: The robot was static and did not physically move through the experiments.
- No. of experiment executions: Each experiment, with variant, was executed 10 times.
- Data collection: The USB cable was permanently attached during the experiment. Commands were sent to the robot via the serial port to change experiment as required resulting in no movement of the robot.

E. Discussion of Metric(s)

The aim of this report was to compare different modes of the VPS sensor to decide if it was possible to use a proximity sensor to determine the angle of inclination of a ramp and if so, which mode was most suitable. Once the angle of inclination was calculated, a robot could autonomously decide whether it was safe enough to proceed upwards or to turn around. The inclines were concentrated around the $13°$, as at this angle the robot would ground out i.e. the drive wheels lost contact with the ground. Therefore, a suitable sensor mode is one which determines accurately whether the incline is above or below $13°$. Underestimating the angle could result in a robot travelling up an incline too steep leading to slip and potential damage to the robot. An ideal sensor would have a small absolute error acting as an overestimation.

To compare each method successfully the following metrics were used. Firstly, the standard deviation, σ, was calculated to determine the spread of the 30 repeats of the measurement. It is a measure of the precision of the method which finds the root mean squared difference between each measured value (x) and the mean measured value (μ). The formula for standard deviation is:

$$\sigma = \sqrt{\frac{\sum(x-\mu)^2}{N}} \tag{4}$$

To compare the accuracy of each method the absolute error was found for each data set. This is the average difference between the mean calculated angle (μ_i) of ramp and the true angle (X_Ti). This metric tells us on average how much each data point deviates from the true value. It was calculated using:

$$E_A = (\mu_i - X_{Ti}) \tag{5}$$

The next metric splits the absolute error into over estimates and under estimates using the following equations:

$$E_{over} = \max(\mu_i - X_{Ti}, 0) \tag{6}$$

$$E_{under} = \min(\mu_i - X_{Ti}, 0) \tag{7}$$

Using these equations, an average, overestimated error and average underestimated error are calculated.

The final metric is the time cost of measurements. This is the average amount of time it takes to determine a single value for angle of inclination. It is a measure of the efficiency of the mode.

IV. Results

In this experiment, four complete sets of data were collected individually with separate, yet identical setups. Each setup used a different robot, with booms constructed from the instructions above. To ensure validity when combining these results, it was essential to eliminate systematic errors between the different data sets. Therefore, all robots were calibrated to a flat surface, which determined the individual sensor angles allowing uniform calculations of the angle of inclination. The error in calculated inclination angles, due to inaccurate sensor readings, varied due to different proximity sensor angles (θ) between different setups. However, these variations had an insignificant magnitude of $< 6 \times 10^{-4\circ}$ and therefore could be neglected. It could then be concluded that there were no systematic errors due to the set up, *between* the four different data sets, allowing them to be combined freely. However, errors in overall results still occurred due to the setup and design of this experiment.

	Single/No Filter (S/NF)	Continuous/No Filter (C/NF)	Single/Filter (S/F)	Continuous/Filter (C/F)
Mean Standard Deviation	0.717°	0.866°	0.678°	0.781°
Mean Absolute Error	1.086°	1.064°	0.655°	0.651°
Mean Overestimated Error	0.640°	0.741°	0.296°	0.358°
Mean Underestimated Error	0.447°	0.323°	0.359°	0.294°
Time cost of measurement	0.177 seconds	1.44 seconds	0.178 seconds	1.40 seconds

TABLE I

A TABLE DISPLAYING A COMPARISON OF THE AVERAGE VALUES FOR EACH METRIC FOR EACH SENSOR MODE. FOR EACH METRIC THE TWO BEST PERFORMING MODES ARE HIGHLIGHTED GREEN AND WORST TWO PERFORMING MODES ORANGE.

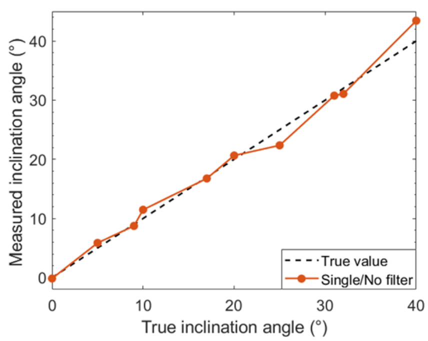

Fig. 5. A graph displaying the mean measured inclination angle against the true inclination angle for different measurements using the single range proximity sensor without a filter and a ramp distance of 0mm.

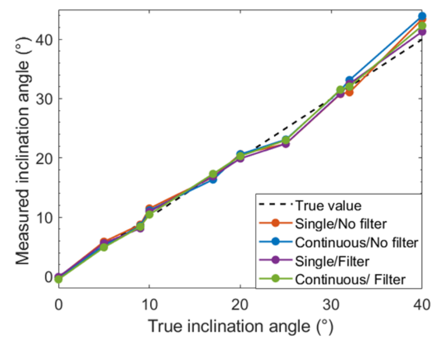

Fig. 6. A graph displaying the mean measured inclination angle against the true inclination angle for different measurements using the four different sensor modes and a incline distance of 0mm.

The baseline method, of having the VPS in single ranging mode without a filter (S/NF), was used to determine a range of ramp angles from 0° to 40° with $d = 0mm$. The results from this are plotted in Figure 5. It can be seen from Figure 5 that the measured inclination values sit close to the true ramp angle values, with the highest deviation occurring for the largest incline of 40° where the robot returned a value of 43°. Individual readings from the sensor were observed to vary on average by ± 2mm resulting in a fluctuation of the calculated sensor angle due to sensor noise. The improved implementations were tested to see if these fluctuations reduced.

The method was repeated for the other three modes of the sensor, continuous range without a filter (C/NF), single range with a filter (S/F) and continuous range with a filter (C/F), with 'd' maintained at 0mm. The results from this are plotted in Figure 6. All of the modes produced values following the same overall trend with deviations less than 3° from the actual angle of the ramp. The metrics discussed above were used to compare the performance of the different modes. Table I displays a summary of the results with the best two performing modes for each metric highlighted in green and two worst performing in orange.

From Table I, it can be concluded that operating the sensor in single range mode reduced the standard deviation of the results, meaning the S/F and S/NF modes are more precise than C/F or C/NF. The addition of a filter increased accuracy of the data. The S/F and C/F have a 40% reduction of absolute error compared to the modes without a filter, S/NF and C/NF.

The mean overestimated and underestimated error gave a breakdown of the proportion of measurements which fell above or below the true value. Comparing filtered modes it shows that the majority of the error for S/F is underestimated whereas C/F is overestimated. The ideal performance of a sensor mode would be one that overestimates error, since it would be preferable for a robot to over judge a ramp and not ascend than to under judge it and damage itself. The final metric, time cost of a measurement, represents the efficiency of the sensor mode. S/F and SN/F have a lower time cost than C/F or C/NF, meaning operating in the single range mode is more time efficient.

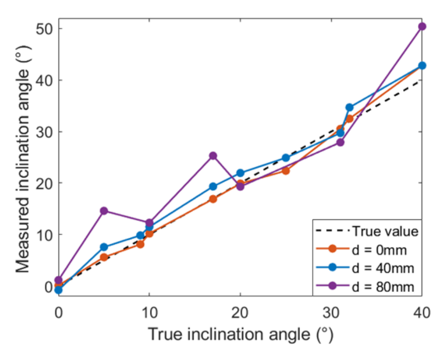

Fig. 7. A graph displaying the mean measured inclination angle against the true inclination angle for distances between the robot and the ramp, with the sensor mode set to S/F.

The next part of this experiment was investigating how varying distance to the ramp affected the calculation of the angle of inclination. The results showed that a robot was capable of determining the angle of inclination with d anywhere within the limits of the sensor focal length (typically between 80 to 120mm). However, increasing the distance reduced the accuracy and precision of these measurements. Figure 7 displays the results of varying the distance for different angles using the S/F mode. The measurements can be seen to deviate further from the true value when the ramp is further away. Regardless of this, at $d = 80mm$ the measured angles are still within $10°$ of the true value with errors typically overestimated. This is performance was still deemed to be sufficient under the context of this experiment.

As a final thought experiment, a simple program was developed based on the S/F results. This program allowed a moving robot to detected a gradient in its path and decided whether or not to traverse. An upper limit for traversal was set to $13°$, such that the robot will not attempt to traverse a ramp with a larger gradient than this. The robot performed ideally for inclines $20°$ and greater and inclines $10°$ and less. However, it failed at $15°$ as the robot would sometimes attempt to ascend.

V. Discussion and Conclusion

In summary, this experiment found that operating the sensor in single range mode compared to continuous, regardless of the presence of a filter, produced more precise and time efficient measurements. The additional presence of a filter increased the accuracy of results making the S/F mode the most precise method and one of the most efficient. The C/F mode was equally accurate and had the desirable quality of overestimating error, however calculations showed that the time cost of this mode made it too slow for efficient application of the filter. It was deemed, for everyday robots, that the filtered single range mode displayed best performance in determining the angle of ramp inclination prior to ascension. If this method was implemented for a higher costing robot, the safely aspect of overestimating error would be deemed of higher importance than the time efficiency requiring the investigate of further methods. The results show that increasing the distance between the robot and the ramp increases the error in calculated angle. This insight will assist decisions in the design of code for which distances the angle is calculated.

All of the results obtained demonstrated the sensors ability to determine the angle of an incline and thus supports the hypothesis:

"We hypothesise that the VL6180X proximity sensor (based on an angled sensor and a given distance) is capable of determining a sufficiently reliable angle of inclination for a robot to traverse. We further believe, that implementing a low-pass filter or utilising the continuous ranging mode of the sensor will improve the consistency of sensor readings and reduce the calculated angle of inclination error. Finally, we presuppose that the error in angle will increase linearly with the distance from the robot."

A. Future work considerations

Further investigation in this field could experiment with multiple sensors at different separations and incident angles, this would allow the calculation of angles while the robot was in motion. The autonomous algorithm written can detected inclines, but traversing onto the gradient also requires further refinement to consider the oscillations in the boom from a non-smooth driving motion. Finally, further work needs to be carried out on the design of the filter for its implementation to a moving robot. To investigate this, a metric should be used to make a balance between the error and time delay when using an filter. Related metrics is following equation.

$$Error(f_c, N) = \frac{\sum_{t=1}^{t_m}(D_f(f_c, N) - groundtruth)^2}{t_m - 1} \quad (8)$$

$$Error_b(f_c, N) = \alpha\frac{Error(f_c, N)}{max(Error)} + (1-\alpha)\frac{T_d(f_c, N)}{max(T_d)} \quad (9)$$

$D_f(f_c, N)$ is data after filter,t_m is time when we receive the last signal.α is the weight we allocate to the Error(In our experiment,α is 0.5),$T_d(f_c, N)$ is time delay under parameter f_c and N.

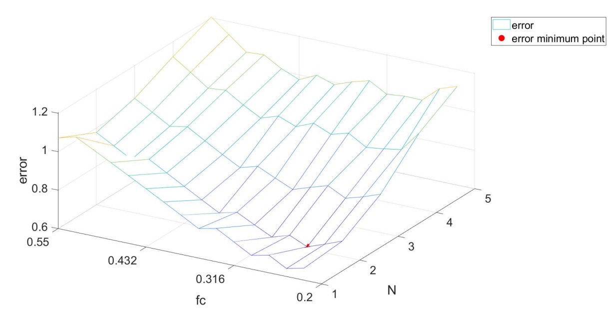

Fig. 8. A sketch to show the error balance between time delay and data error. Giving $N = 2, f_c = 0.25Hz, f_s = 5Hz$ as the optimal setting

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