ANGLIA RUSKIN UNIVERSITY

FACULTY OF ENGINEERING AND BUILT ENVIRONMENT

MSC. ELECTRONIC/ELECTRICAL ENGINEERING

SENSING AND SENSORS FUSION

(MOD009177)

Sensor Fusion for Close-Range Obstacle Distance Estimation Using LiDAR, Sonar and IR

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Abstract

This project evaluated low-cost LiDAR, ultrasonic sonar and an IR sensor for close-range obstacle distance sensing and implemented calibration, fusion and Kalman filtering to improve reliability. Tests were performed at 5 cm, 15 cm and 30 cm on three surfaces (white cardboard, black cloth and metal), with 100 samples per condition analysed against ground truth using bias, variance and RMSE. Sonar was the most consistent sensor (mean RMSE 0.93 cm). LiDAR was surface dependent (mean RMSE 2.31 cm raw) and produced large outliers on reflective metal (max about 63 cm at the 30 cm test). A multipoint calibration minimised average LiDAR RMSE to 2.23 cm. LiDAR and sonar were fused using inverse-variance weighting and smoothed with a 1-D Kalman filter with adaptive measurement noise that was tested at 15 cm, diminishing the effect of spikes and dropouts. The final estimate supported an RGB light indicator suitable for real-time obstacle awareness.

Aims and Objectives

Aim:

To design and evaluate a strong close-range estimate of distance for obstacle detection using multiple sensors and simple computation of embedded system.

Objectives:

- Measure and compare LiDAR, sonar and IR outputs across different surfaces and distances.
- Apply multipoint calibration to minimise systematic error and quantify improvement using RMSE and variance.
- Fuse LiDAR and sonar using inverse-variance weighting to obtain a single distance estimate.
- Apply Kalman filtering (with adaptive sensor disturbance) to steady the fused estimate for real-time use.

Application Description

The target application is obstacle distance sensing for a small autonomous vehicle or mobile robot. The estimate must be stable: spiky readings can cause false braking, while missed detections are unsafe. No one sensor, in all conditions, is fully reliable: LiDAR can fail on incidence of dark objects or produce outliers on shiny targets, while sonar is generally stable but lower resolution. An IR proximity sensor can provide a near-object trigger. This work showed the estimate as an RGB proximity indicator driven by distance.

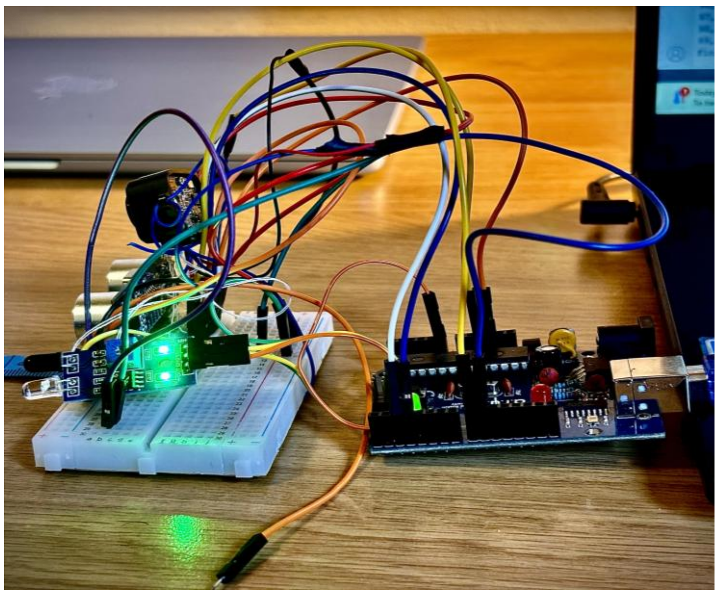


Figure 2: Hardware setup

Sensors and Models

Measurement principles

LiDAR (time-of-flight): d = (c*t)/2. Strength: high resolution. Weakness: sensitive to reflectivity and angle. Sonar (ultrasonic time-of-flight): d = (v*t)/2. Strength: stable detection at short-range. Weakness: dependence on environmental factors and low resolution. IR sensor is used mainly as a digital sensor because its measurement of distance was very unreliable over 5–30 cm in these experiments.

Sensor	Measurement principle	Key strengths	Key weaknesses / limitations
Sonar (Ultrasonic)	Time-of-flight of sound echo	Robust on many surface colours/reflectivity; good for short-range obstacle detection; low cost; simple interfacing	Lower resolution than LiDAR; wider beam → poorer spatial selectivity; affected by air temperature/humidity; can struggle with soft/angled surfaces (weak echoes)
LiDAR (ToF laser)	Time-of-flight of laser pulses	High resolution and accuracy; narrow beam → good spatial selectivity; fast response; good for mapping	Sensitive to target reflectivity (e.g., dark/IR-absorbing surfaces) and angle (specular reflection on metal); can show spikes/dropouts; typically higher cost/power; may be affected by dust/fog/rain
Infrared (IR proximity / reflective)	Reflected IR intensity / thresholding	Very cheap; fast; good as a close-object trigger; simple digital output possible	Strongly surface-dependent (colour/texture); nonlinear vs distance; limited effective range; sensitive to ambient light; unreliable for accurate analogue distance measurement without careful calibration

Figure 3 (placeholder): Sensor strengths/weaknesses summary. [Insert PPT image.]

Specified distance range

Sensor	Specified Range
Sonar	2cm – 400cm
LiDAR	2cm – 80cm
IR	2cm – 30cm

Error model and metrics

Model: z_k = x_true + b + n_k, where b is systematic error and n_k is random noise.

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{k=1}^{N}(z_k - x_{\mathrm{true}})^2} \qquad \mathrm{Var}(z) = \frac{1}{N-1}\sum_{k=1}^{N}(z_k - \bar{z})^2 \qquad \mathrm{Bias} = \bar{z} - x_{\mathrm{true}}, \qquad \bar{z} = \frac{1}{N}\sum_{k=1}^{N} z_k$$

Bias and variance explain different failure modes. For example, a sensor can be low-variance but still wrong (high bias), or low-bias but unreliable (high variance/outliers). This is why the workflow uses calibration to reduce bias and filtering/fusion to reduce variance and outlier impact.

Typical failure modes observed

LiDAR relies on optical return strength, so dark materials such as black cloth can absorb the emitted light, leading to weak returns and dropouts or sudden jumps. Highly reflective metal can cause specular reflections; if the surface angle directs the reflection away from the receiver, the reported distance can become unstable. Sonar is less sensitive to surface colour, but the ultrasonic beam is broad and can reflect from edges or nearby objects, and the speed of sound varies with temperature. These differences make sensor fusion valuable because weaknesses do not occur in the same way at the same time.

Data Collection and Calibration

Data was collected at 5 cm, 15 cm and 30 cm for white cardboard, black cloth and metal. Each condition was sampled 100 times per sensor, and the data were exported to CSV. The Arduino loop used an approximate 120 ms delay (around 8 Hz).

Implementation detail: sonar used d = (duration * 0.034) / 2.0 (cm). LiDAR was decoded from serial packets and accepted only if $0 < d < 300$ cm; otherwise, the last valid value was reused to avoid missing samples. This can retain stale values during dropouts, so fusion and filtering are required to prevent stale reading from dominating the output.

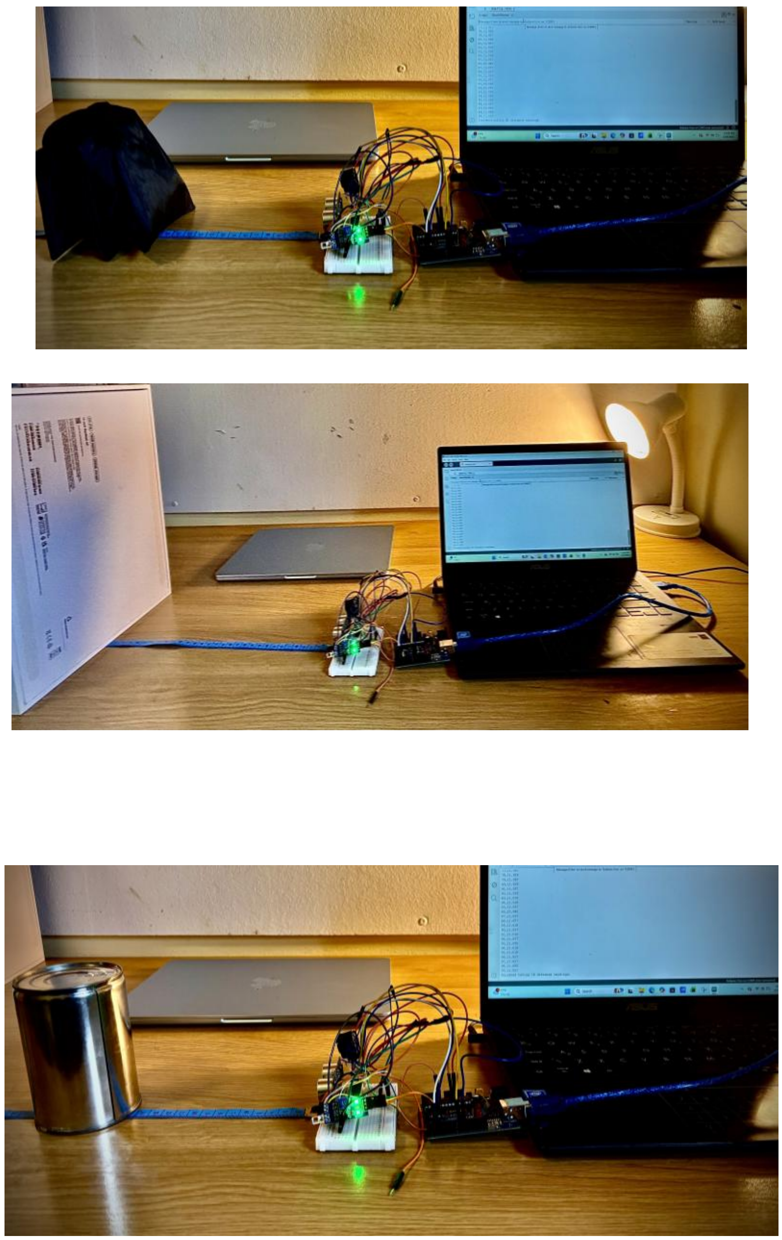
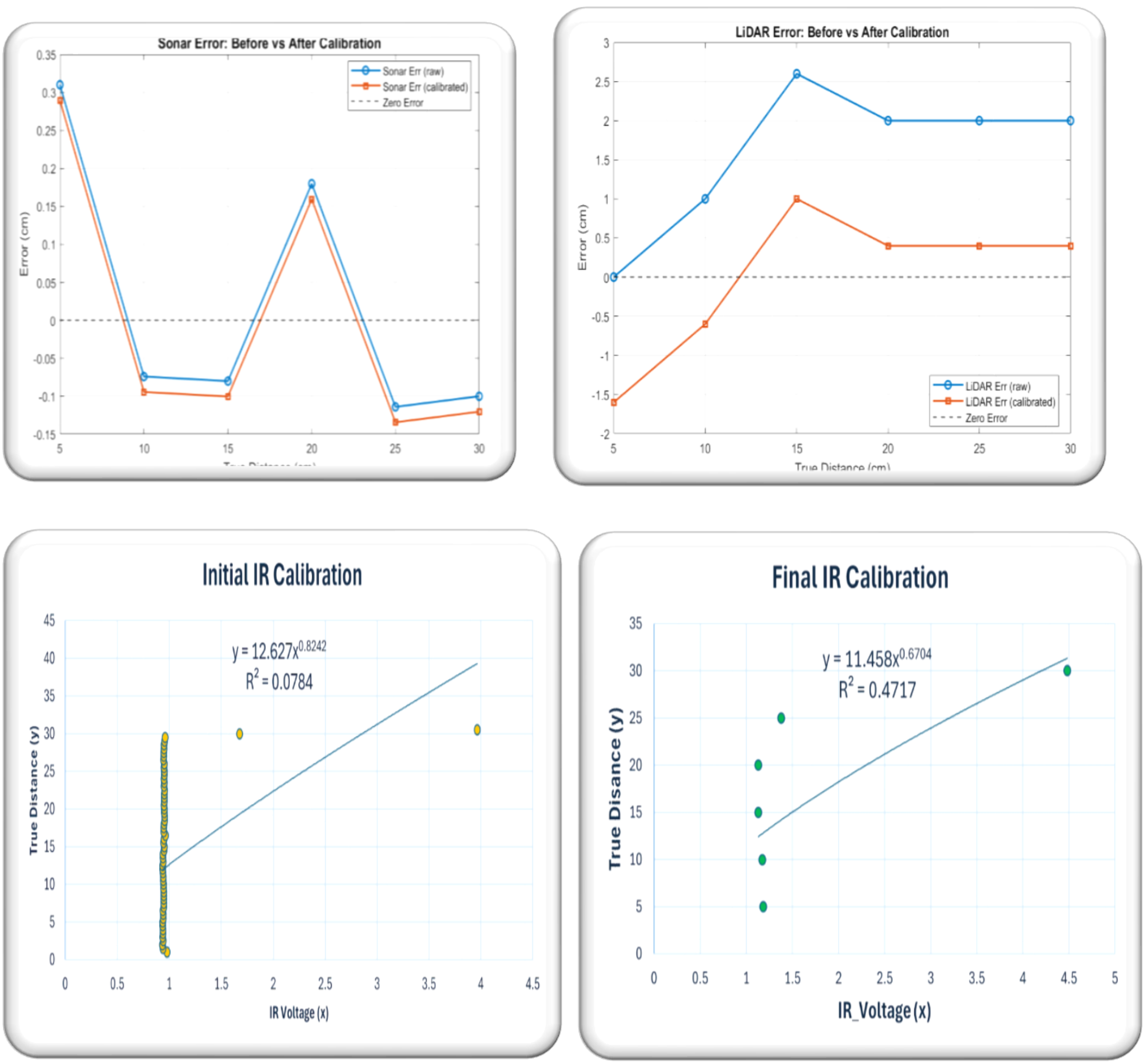


Figure 5: Test procedure and surfaces.

Multipoint calibration

Calibration used reference points (5/15/30 cm). A simple model is z_cal = a*z_raw + c. Calibration helped some cases (e.g., LiDAR at 5 cm on black cloth) but degraded others (e.g., LiDAR at 15 cm on white), showing that a single correction does not fully capture surface effects. In practice, calibration should be validated with additional check points and, if needed, fitted separately per sensor and surface class.



Figures 6a, b, c, d: raw vs calibrated plot

Fusion and Estimation Method

Inverse-variance fusion

With sonar z_s, LiDAR z_l, and variances σ_s^2, σ_l^2: $w_s = \frac{1}{\sigma_s^2}$, $w_l = \frac{1}{\sigma_l^2}$, $z_{\text{fused}} = \frac{w_s z_s + w_l z_l}{w_s + w_l}$. Fusion prioritises the sensor with lower variance. Calibration is still required to reduce bias.

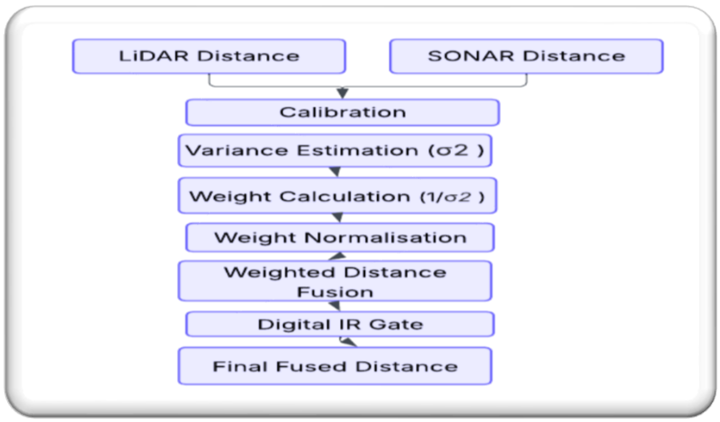


Figure 7: Fusion block diagram.

Kalman filter with adaptive measurement noise

Prediction: $x^- = x, \qquad P^- = P + Q, \qquad (Q = 0.1)$

Update: $K = \frac{P^-}{P^- + R} \qquad x = x^- + K\left(z - x^-\right) \qquad P = (1 - K)\,P^-$

Updates were applied sequentially (sonar then LiDAR) each cycle.

Measurement noise was adapted per sensor $R \leftarrow \beta R + (1-\beta)\,(z-x)^2$ with $\beta = 0.90$ and 0.1 <= R <= 50 (initial $R_{\text{sonar},0} = 9.0, \qquad R_{\text{lidar},0} = 4.0$). When a sensor becomes inconsistent, its innovation grows, R increases, and the Kalman gain drops, so the estimate follows that sensor less.

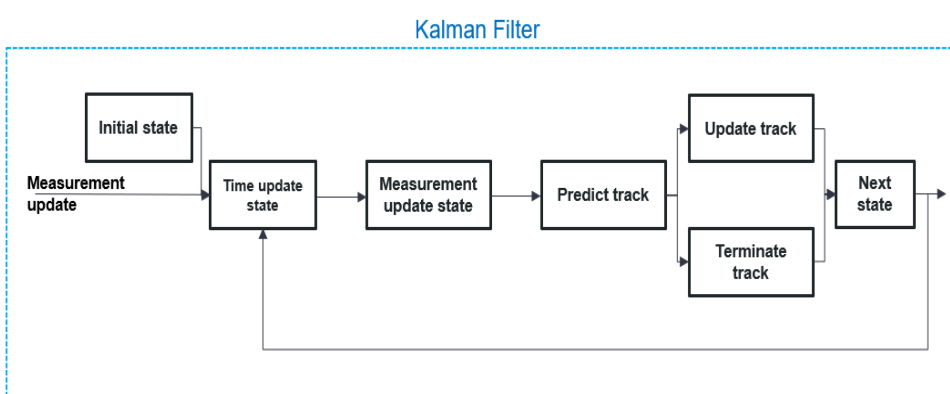


Figure 8: Kalman filter flow

Safety logic (IR trigger)

In the integrated system, IR was used as a near-object trigger so the estimator can behave conservatively when an obstacle is very close. This reduces the risk that a long-range outlier masks a close obstacle. For the Kalman evaluation plots, the Kalman estimate is treated as the primary fused output. It can be seen from these graphs that IR is highly unreliable for measuring analogue distance.

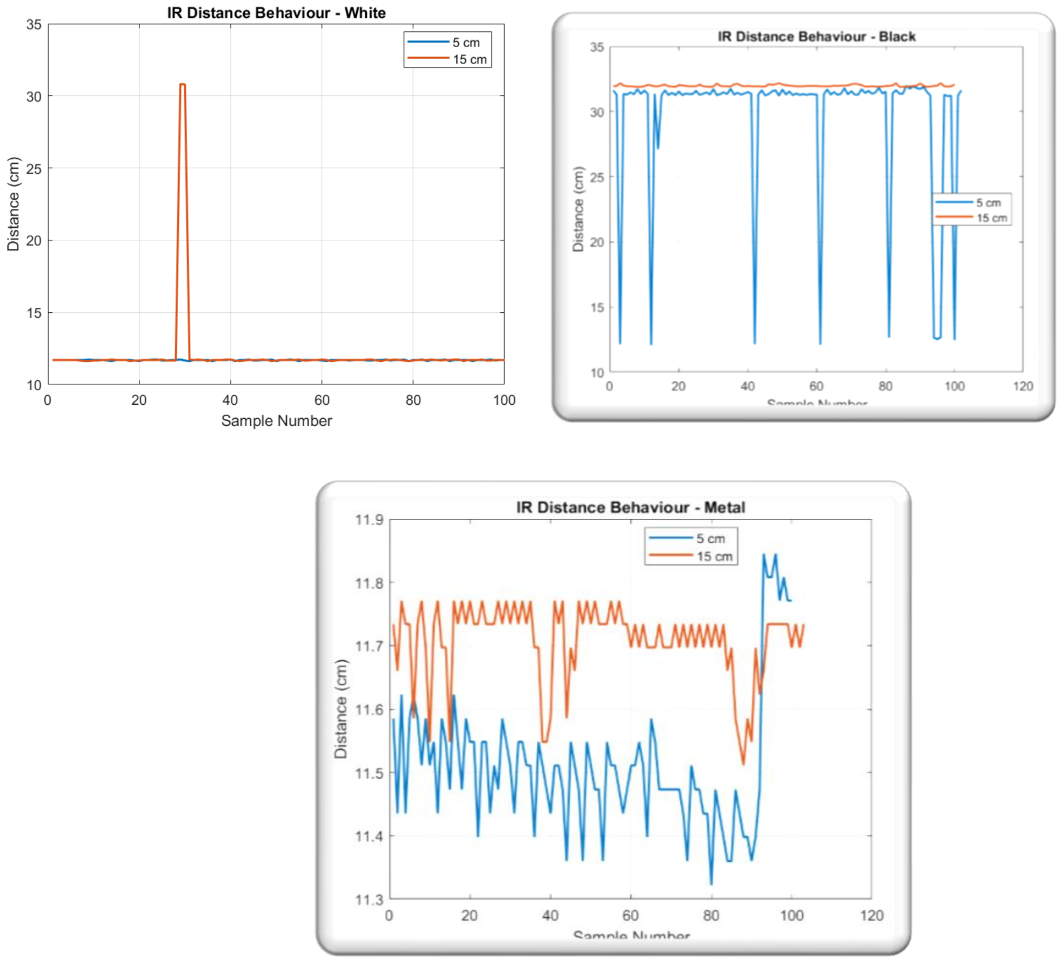


Figure 9: IR plot sample-series plots

Results and Analysis

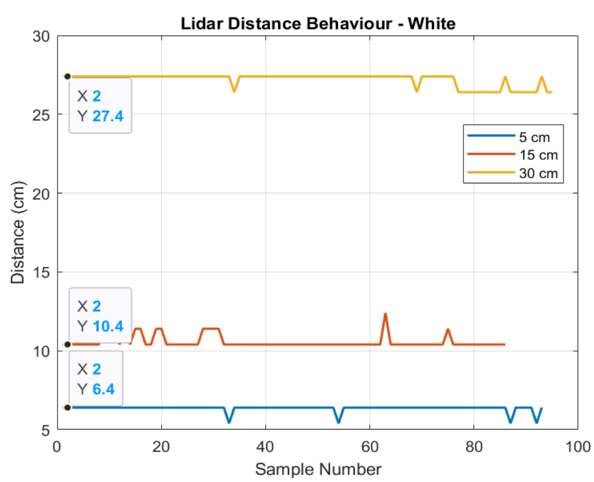
Single-sensor performance

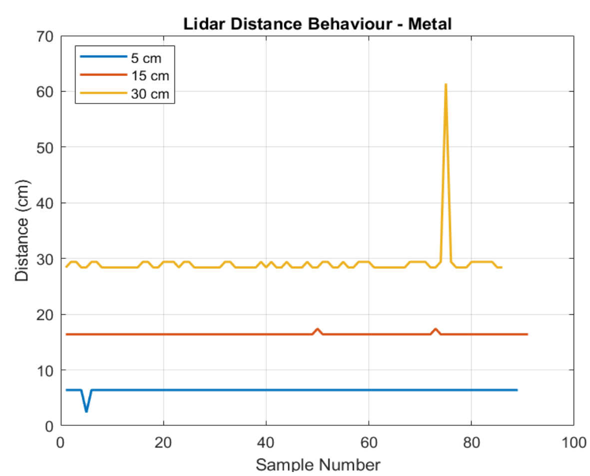
Across the nine conditions, sonar achieved mean RMSE 0.93 cm raw (0.92 cm calibrated). LiDAR achieved mean RMSE 2.31 cm raw (2.23 cm calibrated) and was more affected by surface reflectivity. Metal at 30 cm reached a maximum reading of about 63 cm, motivating robust fusion and filtering.

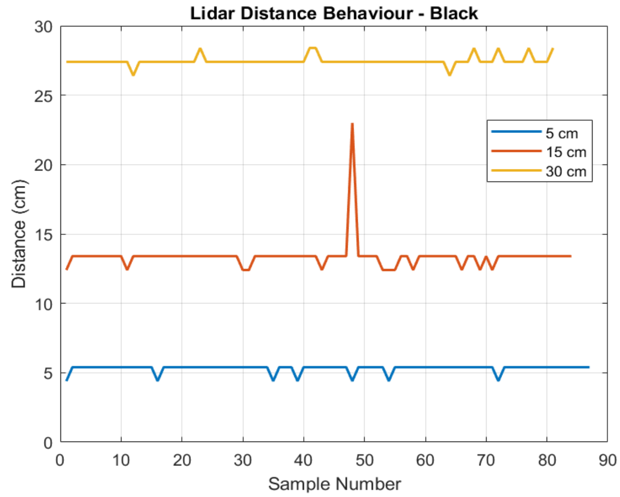
Table 1: RMSE (cm) by surface and distance (raw vs calibrated).

Surface	Distance	Sonar raw	Sonar cal	LiDAR raw	LiDAR cal
White	5 cm	0.67	0.65	2.96	1.37
White	15 cm	0.33	0.32	2.86	4.44
White	30 cm	0.46	0.48	1.26	2.83
Black	5 cm	1.23	1.21	1.94	0.42
Black	15 cm	1.62	1.60	1.11	1.97
Black	30 cm	2.05	2.03	0.99	2.56
Metal	5 cm	0.11	0.09	2.98	1.42
Metal	15 cm	0.28	0.26	3.03	1.43
Metal	30 cm	1.63	1.61	3.61	3.62

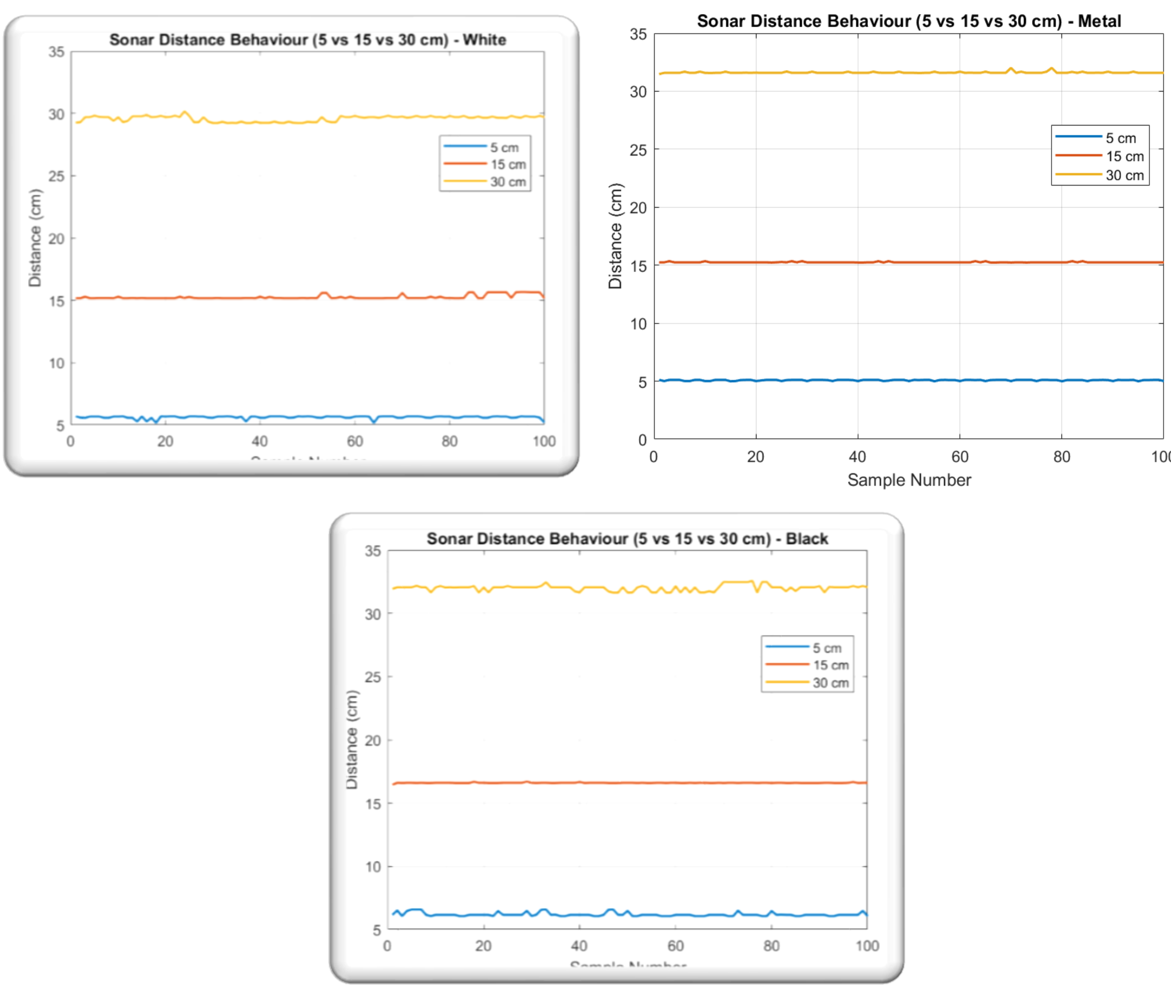
Table 1 also reflects bias and variance behaviour. Sonar on black cloth at 30 cm had a positive bias of about +2.04 cm but low variance (about 0.056 cm^2), meaning it was consistently a little high. LiDAR on metal at 30 cm had a much higher variance (about 12.60 cm^2) due to outliers, which is more disruptive for control than a steady bias.







Figures 10a, b, c: LiDAR sample-series plots.



Figures 11a, b, c: Sonar sample-series plots

Kalman-filtered fusion at 15 cm

Kalman fusion was evaluated at 15 cm on the three surfaces. Table 2 summarises RMSE and variance for sonar, LiDAR and the Kalman-fused output.

Table 2: 15 cm test (N=100): RMSE and variance.

Surface	Sonar RMSE	LiDAR RMSE	Kalman RMSE	Sonar var	LiDAR var	Kalman var
White	0.40	10.09	1.93	0.026	101.846	0.425
Black	0.46	3.61	0.88	0.090	12.975	0.176
Metal	1.38	1.68	1.38	1.254	0.240	1.254

Filtering reduced the impact of unstable LiDAR on white and black surfaces (e.g., white: LiDAR RMSE 10.09 cm vs Kalman 1.93 cm). The Kalman variance values are also much smaller than LiDAR variance in those cases, confirming a smoother output. On metal, LiDAR was already stable (variance 0.240 cm^2), so the gain from filtering was smaller.

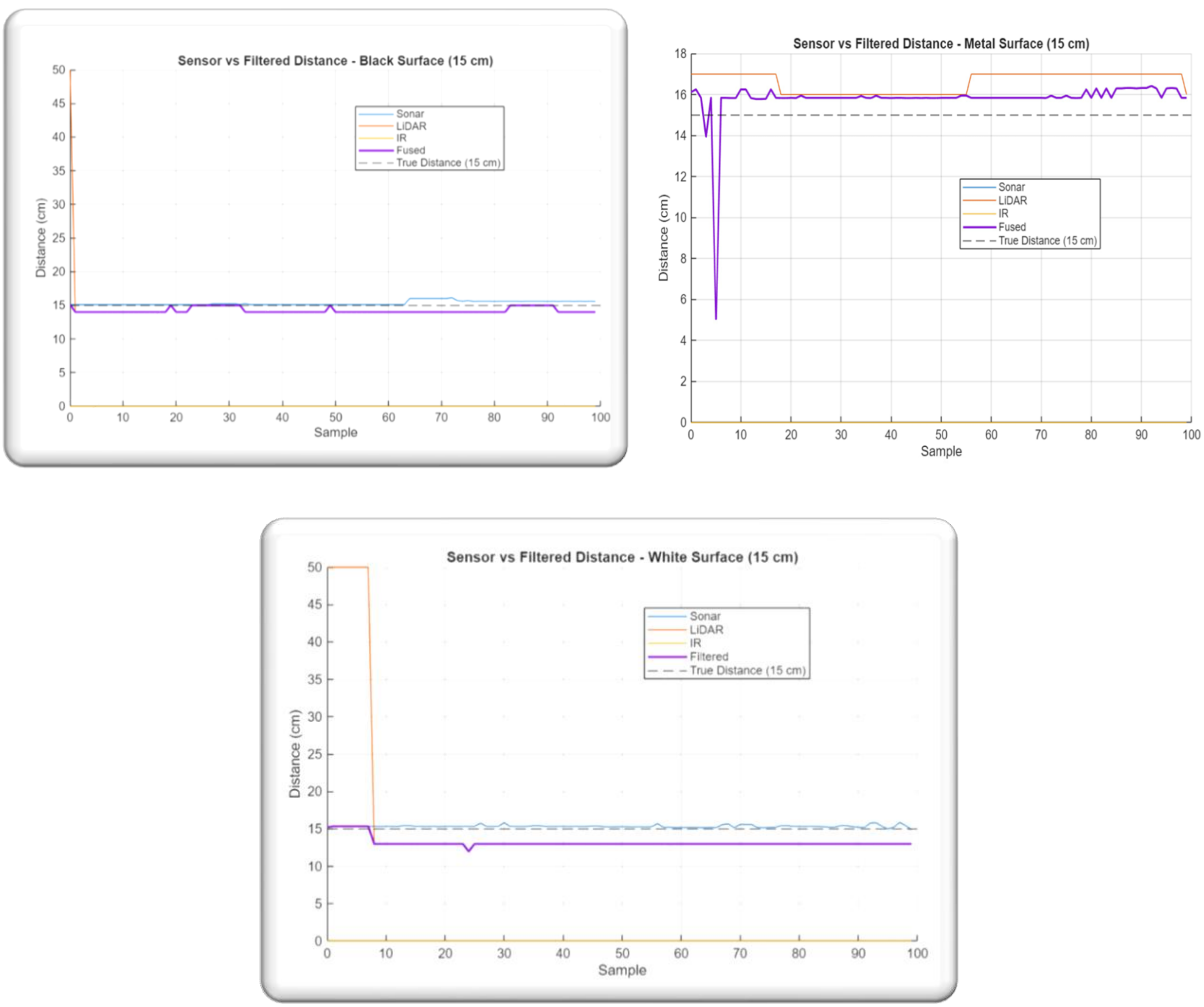


Figure 12: Kalman estimate vs sonar and LiDAR at 15 cm.

Practical implications

The adaptive R update automatically down-weights a sensor when it becomes inconsistent, so the output remains stable for control and indication. This is valuable in robotics where surface properties can change unexpectedly.

Critical Reflection

Strengths:

- Surface testing revealed realistic failure modes and justified fusion rather than single-sensor reliance.
- Kalman filtering provides a confidence mechanism suitable for microcontrollers.
- The design combines IR trigger (safety logic) with estimation, supporting practical deployment.
- RGB indicator demonstration connects analysis to a clear user-facing output.

Limitations:

- Kalman validation was performed at one distance only (15 cm).
- Calibration was not surface dependent; a single model cannot capture all materials and angles.
- Last-valid LiDAR fallback can propagate stale values during dropouts unless gated.

Future work:

- Extend Kalman tests to 5 cm and 30 cm and include moving-target tests.
- Use regression-based calibration and add gating to reject impossible jumps before fusion.
- Investigate alternative sensors or sensor placement to reduce specular effects on metal.

Conclusion

Multi-sensor estimation improved robustness for obstacle sensing. Sonar was consistently accurate and low-variance (mean RMSE 0.93 cm), while LiDAR was surface-dependent and produced outliers (mean RMSE 2.31 cm raw). Multipoint calibration provided minor average improvements but did not remove surface effects. Inverse-variance fusion and a 1-D adaptive Kalman filter produced a smoother estimate and reduced the impact of LiDAR outliers in the 15 cm tests. With broader validation and improved calibration/outlier handling, the approach is suitable for real-time robotics proximity sensing.

References

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