
HYBRID TOA–RSS LOCALIZATION BASED ON SOCP WITH HUBER LOSS OPTIMIZATION

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ABSTRACT

Accurate wireless localisation in Non-Line-of-Sight (NLOS) environments remains challenging because multipath propagation, signal blockage, and environmental obstructions introduce severe measurement errors. Conventional Least Squares (LS) estimators are particularly vulnerable to NLOS-induced outliers because their quadratic loss function assigns disproportionately large weights to large residuals. This study proposes a robust hybrid Time of Arrival-Received Signal Strength (TOA-RSS) localisation framework that combines Second-Order Cone Programming (SOCP) with the Huber loss function to mitigate the influence of NLOS-corrupted measurements. The nonconvex Euclidean-distance localisation problem is transformed into a convex SOCP formulation through epigraph reformulation, while the piecewise-convex Huber penalty limits the contribution of large residuals. Monte Carlo simulations covering a comprehensive range of LOS/NLOS anchor configurations demonstrate the effectiveness of the proposed estimator. Under the most severe scenario, involving 0 LOS and 10 NLOS anchors, SOCP+Huber reduced position RMSE by up to 43.4% compared with conventional LS and 23.1% compared with non-robust SOCP. Cumulative distribution analysis further showed that 75–78% of localisation estimates were within 5 m of the true position, compared with approximately 70% for LS. The improvement was most pronounced under severe NLOS conditions, while performance remained competitive under LOS-dominant scenarios, confirming effective outlier suppression. The robustness was achieved with a modest computational increase, from $O(n^{3.5})$ for the standard SOCP to $O(n^{4.5})$, remaining substantially lower than the $O(n^6)$ complexity associated with semidefinite-programming alternatives.

Keywords: wireless localisation; TOA/RSS; NLOS mitigation; second-order cone programming; and Huber loss

I. INTRODUCTION

Accurate position estimation is a core requirement in modern wireless systems, spanning 5G infrastructure, IoT sensor networks, indoor navigation, autonomous robotics, and smart building management (Pan et al., 2022; Olejniczak et al., 2024; Pei et al., 2024). As these applications increase, the demand for reliable localisation in challenging real-world environments has intensified (Maduranga et al., 2023). Among widely used positioning techniques, time of arrival (TOA) estimates range by measuring signal propagation delay, achieving centimetre- to decimetre-level accuracy under ideal conditions (Kaune et al., 2011; Shui et al., 2025). Received signal strength (RSS) is used to estimate distance from received signal power via a path-loss model (Yaro et al., 2024; Li et al., 2023). Exploiting the complementary characteristics of both through sensor fusion has been recognised as a promising direction (Wang et al., 2022; Mukhopadhyay et al., 2022).

In dense or indoor environments, multipath propagation introduces a systematic positive bias into TOA estimates because the received signal may travel along indirect paths that are longer than the direct LOS path. For RSS measurements, NLOS propagation produces additional attenuation and shadowing that are not completely represented by the nominal path-loss model, resulting in significant ranging errors. Unlike zero-mean measurement noise, NLOS-induced errors contain a systematic bias component and therefore cannot generally be eliminated simply by averaging repeated measurements. Consequently, even a limited number of NLOS-corrupted links can introduce substantial position offsets in conventional least-squares localisation because large biased residuals can exert a

disproportionate influence on the estimated position (Wang et al., 2014; Wang et al., 2023; Charles et al., 2026).

Most hybrid TOA-RSS frameworks rely on a squared-error (L2) loss, which is optimal under Gaussian noise but highly sensitive to heavy-tailed outliers in severe NLOS conditions because large residuals are amplified quadratically (Huber, 1964). The Huber loss (Huber, 1964) addresses this by applying quadratic penalisation for small residuals and linear penalisation beyond a threshold δ , thereby limiting outlier influence. When embedded in a second-order cone programming (SOCP) framework, it preserves the convex optimisation structure and avoids dependence on initialisation heuristics (Kumar et al., 2015; Xiong et al., 2021), while δ provides a tunable robustness–efficiency trade-off (Mohanty et al., 2023). The combination of SOCP-based hybrid TOA–RSS localisation with Huber loss has received limited attention, motivating this work.

The remainder of this paper is organised as follows. Section II reviews related work. Section III presents the system model, the TOA and RSS measurement equations under NLOS conditions, and the proposed SOCP formulation with the Huber loss function. Section IV describes the simulation setup and presents the numerical results. Section V concludes the paper.

II. RELATED WORK

Early NLOS mitigation methods relied on statistical identification, classifying links as LOS or NLOS using features such as measurement variance, channel impulse response characteristics, or deviation-based statistics, then discarding or down-weighting NLOS links prior to position estimation (Olejniczak et al., 2024; Yang et al., 2023; Yaro et al., 2024). These methods perform well when LOS and NLOS distributions are clearly separable, but can deteriorate in indoor environments where the distributions overlap (Qin & Luo, 2024). A deeper limitation is that classification is decoupled from estimation, so classification errors cannot be corrected downstream.

Convex optimisation offers a more principled alternative. Semidefinite programming (SDP) incorporates robustness directly into the estimator via positive semidefinite matrix constraints (Ma et al., 2022; Shamsian & Behnia, 2025), but its computational complexity can make it impractical at large scale. SOCP provides a lower-complexity convex alternative while retaining strong modelling expressiveness (Kumar et al., 2015), and convex-relaxation approaches have demonstrated good empirical performance under NLOS conditions without requiring precise knowledge of the error distribution (Wang et al., 2014; Xiong et al., 2021).

Hybrid TOA-RSS fusion exploits the complementary physical characteristics of the two measurement mechanisms, propagation delay bias and shadow fading, to improve robustness. Recent work has leveraged this through semidefinite relaxation (Katwe et al., 2020), majorisation–minimisation without prior NLOS bias knowledge (Panwar et al., 2022), and Huber-based robust formulations with convex relaxation (Xiong et al., 2023).

Learning-based approaches have also shown strong results for NLOS identification, signal denoising, and intelligent localisation in 5G and massive-MIMO-related settings (Liu et al., 2022; Zhang et al., 2024; Li et al., 2020), but they generally require representative training data and can be sensitive to environmental changes. Model-based optimisation methods require no training data and provide interpretable optimisation structures, making them attractive where predictable behaviour is important (Mohanty et al., 2023).

The combination of SOCP-based hybrid TOA-RSS localisation with a Huber loss has received limited attention in the published literature. Most existing robust SOCP localisation work focuses on either TOA or RSS alone, and hybrid frameworks that consider both models have largely retained squared-error objectives.

III. SYSTEM MODEL

A. Measurement and Hybrid Observation Model

Consider a two-dimensional localization scenario with an unknown target position

$$\mathbf{x} = [x, y]^T$$

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and (N) anchors located at known positions

$$\mathbf{a}_i = [x_i, y_i]^T, \quad i = 1, 2, \dots, N \quad 2$$

The TOA-based distance measurement is given by

$$d_i^{\text{TOA}} = \|\mathbf{x} - \mathbf{a}_i\| + \epsilon_i^{\text{TOA}} \quad 3$$

where (ϵ_i^{TOA}) represents measurement noise and NLOS bias.

The RSS measurement follows the log-distance path loss model:

$$P_i = P_0 - 10n \log_{10}(\|\mathbf{x} - \mathbf{a}_i\|) + \epsilon_i^{\text{RSS}} \quad 4$$

where (P_0) is the reference power and (n) is the path loss exponent.

The RSS-based distance estimate is obtained as

$$d_i^{\text{RSS}} = 10^{\frac{P_0 - P_i}{10n}} \quad 5$$

To combine TOA and RSS measurements, a combined distance estimate ($\hat{d}_i$) is defined.

$$\hat{d}_i = d_i^{\text{TOA}} + d_i^{\text{RSS}} \quad 6$$

The residual error is expressed as

$$r_i = \|\mathbf{x} - \mathbf{a}_i\| - \hat{d}_i \quad 7$$

The localisation problem becomes an optimisation problem that minimises the residuals across all anchors. A conventional least-squares formulation based on the residual in (7) is given as:

$$\min_{\mathbf{x}} \sum_{i=1}^N (\|\mathbf{x} - \mathbf{a}_i\| - \hat{d}_i)^2 \quad 8$$

$$\min_{\mathbf{x}} \sum_{i=1}^N (r_i)^2 \quad 9$$

Minimisation using the traditional least-squares method can result in large localisation errors under NLOS conditions because large residuals are penalised quadratically. Hence, the Huber loss is introduced to reduce the influence of NLOS-induced outliers.

B. Huber Loss Function

To mitigate the effect of NLOS-induced outliers, the Huber loss function is employed. The Huber loss is given as:

$$\phi(r_i) = \begin{cases} \frac{1}{2} r^2 & |r_i| \leq \delta \\ \delta |r_i| - \frac{1}{2} \delta^2 & |r_i| > \delta \end{cases} \quad 10$$

where δ is the predefined Huber threshold that determines the transition from quadratic to linear penalisation. Residuals with magnitude not exceeding δ are treated approximately as Gaussian perturbations, whereas larger residuals receive a linear penalty and therefore have bounded influence on the estimate (Huber, 1964).

The objective function becomes:

$$\begin{aligned} & \min_{\mathbf{x}} \sum_{i=1}^N \phi(r_i) \\ & \text{subject to:} \\ & r_i = \|\mathbf{x} - \mathbf{a}_i\| - \hat{d}_i \end{aligned} \quad 11$$

C. SOCP CONVEX RELAXATION

The original hybrid localisation problem is inherently nonlinear and non-convex because of the Euclidean norm in the distance expression. Hence, the problem is transformed into a convex SOCP formulation. This requires the introduction of auxiliary variables to enable convex reformulation. Introduce auxiliary variables such that:

$$t_i \geq \|\mathbf{x} - \mathbf{a}_i\| \quad 12$$

This converts the equality constraint into an inequality, which is essential for convex relaxation.

Thus, the residual becomes:

$$r_i = t_i - \hat{d}_i \quad 13$$

The constraint in (12) can be written in standard SOCP form:

$$\|\mathbf{x} - \mathbf{a}_i\| \leq t_i. \quad 14$$

Equation (14) is a second-order cone constraint and is therefore convex. Combining the robust objective and the cone constraints produces the complete SOCP–Huber relaxation. The resulting programme can be solved to global optimality with respect to the relaxed convex formulation transformations, the complete SOCP formulation becomes:

$$\min_{\mathbf{x}} \sum_{i=1}^N \phi(r_i)$$

subject to:

$$\|\mathbf{x} - \mathbf{a}_i\| \leq t_i, \quad i = 1, \dots, N,$$

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$$r_i = t_i - \hat{d}_i \quad 16$$

D. Performance Metric

Root mean square error (RMSE) is used as the principal accuracy metric because it measures the Euclidean position error accumulated over the Monte Carlo trials. Mathematically, RMSE is expressed as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (x_i - x_o)^2 + (y_i - y_o)^2}{N}} \quad 17$$

where:

N is the number of observations,

x_i, y_i are the estimated coordinates for the i th position, and

x_o, y_o are the actual coordinates of the true position.

IV. SIMULATION RESULTS AND DISCUSSION

This section presents the simulation setup and parameters, followed by the localisation performance results of the proposed scheme.

Table 1: Simulation Parameters

Parameter	Value / Range	Units
Simulation Area	100×100	m^2
Number of Anchors (N)	10	—
Number of Targets	1	—
TOA noise std. dev. (σ_{TOA})	0.5 – 3.0	m
RSS path-loss exponent (η)	2.0	—
Reference Distance (d_0)	1.0	m
Reference RSS (P_0)	−30	dBm
RSS shadow-fading std. (σ_{RSS})	4 – 8	dB
NLOS Bias (b_i)	0 – 5	m
NLOS Probability (P_{NLOS})	0 – 1	—
Huber Threshold (δ)	1.5σ	m / dB
Monte Carlo runs	500	—

The simulation considered a two-dimensional $100 \times 100 \text{ m}^2$ localisation region containing one target node and $N = 10$ anchors. Five propagation scenarios were investigated to evaluate estimator robustness as the environment transitions from severe NLOS to pure LOS conditions. These scenarios consisted of 0 LOS/10 NLOS, 3 LOS/7 NLOS, 5 LOS/5 NLOS, 7 LOS/3 NLOS, and 10 LOS/0 NLOS anchors, corresponding to realised NLOS fractions of 1.0, 0.7, 0.5, 0.3, and 0.0, respectively.

For each Monte Carlo trial, the prescribed number of NLOS anchors was selected from the available anchors, while all remaining links were treated as LOS. LOS measurements contained only the specified measurement noise, with the NLOS bias set to $b_i = 0$. For each designated NLOS link, an additional positive ranging bias within the interval $0 \leq b_i \leq 5m$ was introduced in addition to the nominal measurement noise. Thus, the number of corrupted links was explicitly controlled for each scenario rather than being determined solely from a Bernoulli NLOS probability. This procedure ensured that all five LOS/NLOS configurations contained exactly the required number of corrupted measurements.

A total of 500 independent Monte Carlo trials was performed for each configuration. Within an individual trial, identical measurement realisations, anchor geometry and LOS/NLOS assignments were supplied to the LS, SOCP and SOCP–Huber estimators so that differences in localisation performance resulted from the estimation method rather than from different measurement conditions. The resulting position errors were subsequently used to calculate RMSE and the empirical cumulative distribution function.

Results and Discussion

The results presented in Figures 1 and 2 demonstrate the localisation performance and robustness of Least Squares (LS), SOCP, and the proposed SOCP–Huber method under varying LOS/NLOS conditions.

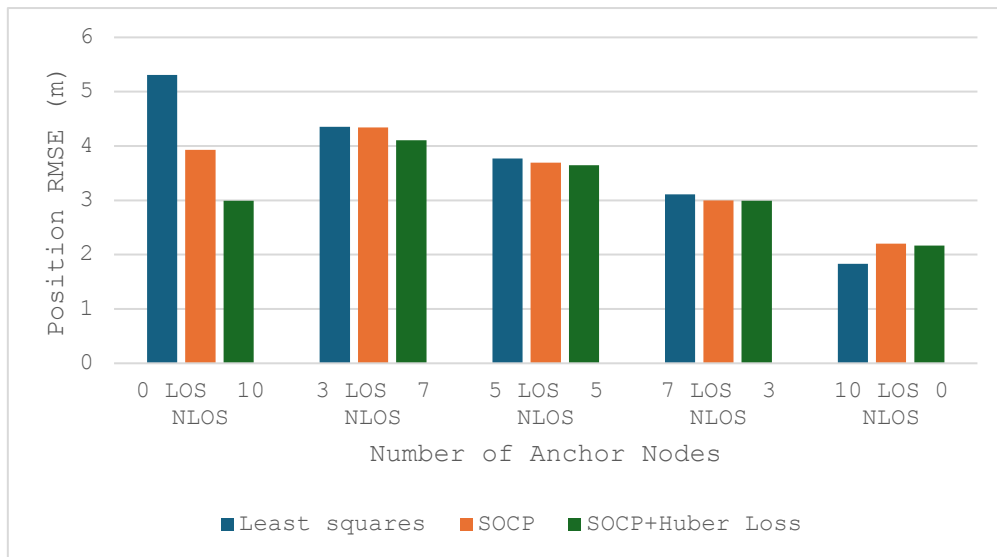


Figure 1: Position RMSE comparison of Least Squares, SOCP, and SOCP–Huber methods.

From the RMSE analysis in Figure 1, it is evident that localisation accuracy improves as the number of LOS anchors increases and the number of NLOS anchors decreases. Under the severe NLOS scenario of 0 LOS and 10 NLOS anchors, the Least Squares method recorded the highest localisation error of approximately 5.3 m, while SOCP achieved about 3.9 m and the proposed SOCP–Huber method attained the lowest RMSE of approximately 3.0 m. This corresponds to an improvement of nearly 43.4% over Least Squares and approximately 23.1% over conventional SOCP. The improvement is attributable to the behaviour of the Huber loss function, which suppresses the influence of large NLOS residuals that typically dominate quadratic-error minimisation approaches. As the propagation environment gradually transitions towards LOS-dominant conditions, the localisation errors of all methods decrease. For instance, under the 10 LOS and 0 NLOS configuration, the localisation RMSE reduced to approximately 1.8 m, 2.2 m, and 2.1 m for Least Squares, SOCP, and SOCP–Huber, respectively. This indicates that the advantage of robust optimisation becomes most significant in severe NLOS environments where measurement outliers are pronounced.

Table 2: Key RMSE Values Reported in Figure 1

LOS/NLOS configuration	LS RMSE (m)	SOCP RMSE (m)	SOCP–Huber RMSE (m)
0 LOS / 10 NLOS	5.3	3.9	3.0
10 LOS / 0 NLOS	1.8	2.2	2.1

Under the pure-LOS configuration of 10 LOS and 0 NLOS anchors, LS achieved an RMSE of approximately 1.8 m, compared with 2.2 m for conventional SOCP and 2.1 m for SOCP–Huber. The slightly better performance of LS in this clean propagation regime can be explained by both statistical efficiency and the relaxation mechanism employed in the SOCP formulation. In the original localisation problem, the estimated geometric distance is constrained by the equality $d_i = \|x - a_i\|$, whereas the convex reformulation replaces this equality with the second-order cone constraint $\|x - a_i\|_2 \leq t_i$. Although this constraint is expected to approach equality when the relaxation is tight, small inconsistencies among the noisy TOA–RSS range measurements may result in $t_i > \|x - a_i\|$ for some anchors. In such cases, the auxiliary variable can partially absorb measurement perturbations without requiring an equivalent change in the target position, thereby introducing a small relaxation gap between the fitted range and the physical geometric distance. This additional degree of freedom may cause a modest localisation penalty relative to direct LS estimation when measurements are predominantly LOS and approximately Gaussian. In contrast, LS directly minimises the squared geometric-range residuals and is therefore statistically efficient under such conditions. The 0.4 m difference between LS and SOCP observed in the pure-LOS case is consequently attributable to the trade-off introduced by convex relaxation rather than to a failure of the SOCP estimator. As NLOS contamination increases, however, the robustness provided by the convex formulation and particularly the Huber penalty outweighs this small clean-data efficiency loss.

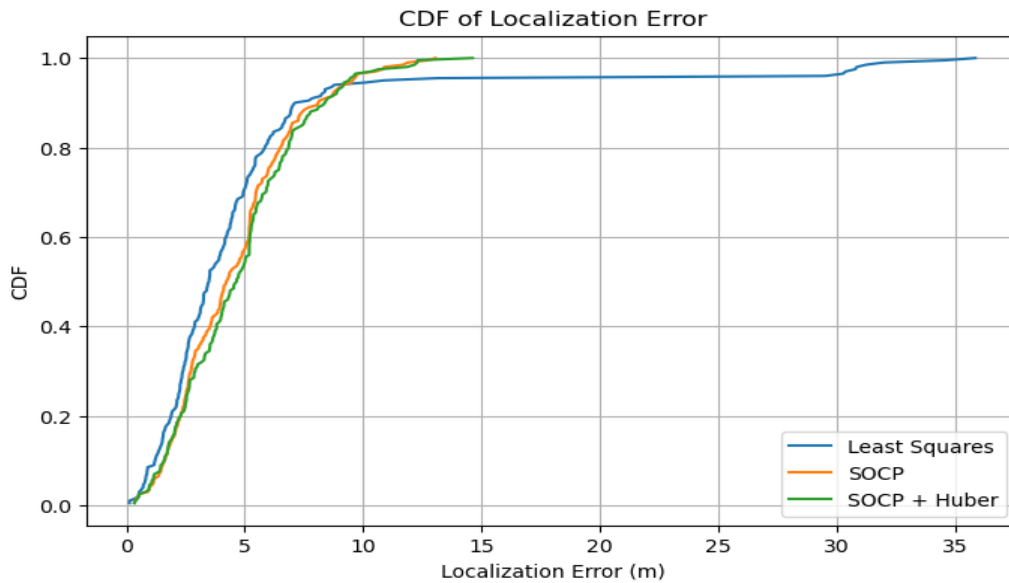


Figure 2: CDF of the localisation error.

The CDF results shown in Figure 2 further demonstrate the robustness and reliability of the proposed SOCP–Huber framework. The cumulative distribution curves represent the probability that the localisation error remains below a specified threshold. Both the conventional SOCP and SOCP–Huber methods exhibit more concentrated error distributions than Least Squares, particularly in terms of limiting large localisation errors. The LS method shows a pronounced long-tail behaviour, with errors extending to approximately 35–36 m. In contrast, the SOCP-based methods concentrate the majority of localisation errors below 10 m and reach their upper CDF plateau at approximately 12–15 m. At a localisation-error threshold of approximately 5 m, nearly 70% of LS estimates fall below this value, whereas the proposed SOCP–Huber method achieves approximately 75–78%. The steeper rise of the

SOCP–Huber curve in the low-to-moderate error region further indicates reduced error dispersion and improved localisation consistency. Overall, the CDF analysis confirms that incorporating the Huber loss into the SOCP framework improves robustness to NLOS-induced outliers and reduces the occurrence of large localisation errors.

Table 3: Complexity Comparison of Localisation Methods

Method	Objective Function	Computational Complexity	Interpretation
Least Squares (LS)	Squared residual minimization	$\mathcal{O}(kn^2)$	Iterative least-squares solution
Semi-Definite Programming (SDP)	Semi-definite relaxation	$\mathcal{O}(n^6)$	Large PSD matrix operations
Second-Order Cone Programming (SOCP)	Cone-constrained minimization	$\mathcal{O}(n^{3.5})$	Interior-point SOCP scaling
SOCp + Huber Loss	Huber-penalized cone minimization	$\mathcal{O}(n^{4.5})$	Additional auxiliary/epigraph variables Huber

Note. n represents the effective optimisation problem size (which scales with the number of anchors and auxiliary variables), and k represents the number of iterations for iterative LS implementations. The stated complexities are approximate order-of-growth estimates for generic interior-point implementations. Actual computational cost depends on the cone structure, variable dimensions, sparsity, solver implementation and required solution accuracy.

Table 3 compares the computational complexity of LS, SDP, SOCP, and the proposed SOCP–Huber framework. The reported values should be interpreted as indicative order-of-growth estimates rather than exact execution times, since actual computational cost depends on solver implementation, sparsity, numerical tolerance, and hardware.

LS has the lowest computational burden, approximately $(\mathcal{O}(kn^2))$, but its squared-error objective makes it sensitive to large NLOS residuals. SDP provides a convex relaxation but incurs a much higher computational cost, commonly approximated as $(\mathcal{O}(n^6))$, because of its matrix-valued variables and positive-semidefinite constraints. SOCP offers a more efficient convex alternative. For a dense primal-dual interior-point implementation, the Newton/KKT solution cost is approximately $(\mathcal{O}(n^3))$, while the iteration bound contributes about $(\mathcal{O}(\sqrt{n} \log(1/\epsilon)))$, giving an indicative complexity of

$$\mathcal{O}\left(n^{3.5} \log\left(\frac{1}{\epsilon}\right)\right) \quad 18$$

(Nesterov & Nemirovskii, 1994; Boyd & Vandenberghe, 2004).

The proposed SOCP–Huber method introduces additional auxiliary and epigraph variables to implement the Huber loss. These increase the practical computational burden but scale approximately linearly with the number of anchors; therefore, they mainly increase the computational constant rather than necessarily changing the asymptotic exponent. Thus, SOCP–Huber retains a complexity of the same general order as SOCP, while providing improved robustness to NLOS-induced outliers. Overall, the proposed method offers a favourable compromise between localisation accuracy, robustness, and computational efficiency.

V. CONCLUSION

This paper presented a robust hybrid TOA-RSS localisation framework based on Second-Order Cone Programming integrated with the Huber loss function for effective mitigation of NLOS-induced measurement errors. By combining complementary TOA and RSS observations within a convex

optimisation framework, the proposed method reduces the influence of large biased residuals that adversely affect conventional least-squares estimation.

Simulation results demonstrated that the proposed SOCP-Huber method provides its greatest benefit under severe NLOS conditions, where it achieved lower localisation error and a more concentrated error distribution than both conventional LS and standard SOCP. Under pure-LOS conditions, LS retained a small accuracy advantage, which reflects both its statistical efficiency under approximately Gaussian measurement errors and the small relaxation gap introduced by the SOCP formulation. This behaviour confirms that the principal advantage of the proposed framework lies in robustness to contaminated measurements rather than in improving already clean LOS observations.

From a computational perspective, the enhanced robustness is obtained at the cost of a moderate increase in complexity relative to conventional SOCP because of the additional auxiliary variables and Huber-loss constraints. Nevertheless, the computational burden remains substantially lower than that associated with semidefinite-programming-based localisation methods. The proposed method therefore provides a practical compromise between localisation accuracy, robustness and computational cost. This trade-off is particularly relevant to real-time indoor positioning systems, where resilience to NLOS errors must be achieved without introducing the substantially higher processing requirements associated with more complex convex relaxations.

Overall, the results indicate that SOCP-Huber localisation is most suitable for propagation environments in which NLOS contamination is significant and computational resources are constrained. The framework therefore offers a promising basis for robust real-time indoor positioning in wireless sensor networks, industrial facilities and other multipath-dominated environments. Future work will investigate adaptive selection of the Huber threshold, residual-statistics-based regularisation, and experimental validation using measured TOA-RSS datasets.

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