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Performance Analysis of Hybrid Adaptive Algorithm for System Identification Under Varying SNR Conditions

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Abstract: System identification plays a crucial role in accurately modeling dynamic systems, especially in noisy environments. This paper presents a comparative performance analysis of three adaptive algorithms: Least Mean Square (LMS), Recursive Least Square (RLS), and a proposed Hybrid algorithm. The evaluation is conducted under different Signal-to-Noise Ratio (SNR) conditions (10 dB, 20 dB, and 30 dB) using key performance metrics such as Mean Square Error (MSE), convergence iterations, tracking error, and steady-state error.

Simulation results demonstrate that the Hybrid algorithm consistently outperforms conventional LMS and RLS algorithms in terms of MSE and tracking accuracy across all SNR levels. Specifically, the Hybrid approach achieves an improvement of approximately 5.18% over LMS and 9.44% over RLS, indicating enhanced estimation accuracy and robustness. Although all algorithms converge within similar iterations, the Hybrid model provides better stability and reduced error variance.

These findings suggest that combining adaptive filtering techniques can significantly improve system identification performance in noisy environments, making the Hybrid algorithm a promising approach for real-world signal processing applications.

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I. INTRODUCTION

System identification is a fundamental area in signal processing and control engineering, which focuses on developing mathematical models of dynamic systems based on observed input-output data [1]. Accurate system modeling is essential for various applications such as adaptive filtering, communication systems, biomedical signal processing, and industrial control systems [2]. However, the presence of noise and uncertainties in real-world environments makes system identification a challenging task [3].

Adaptive filtering techniques have been widely used for system identification due to their ability to adjust parameters dynamically in response to changing system conditions [4]. Among these, the Least Mean Square (LMS) algorithm is popular because of its simplicity and low computational complexity [5]. However, LMS suffers from slow convergence and sensitivity to step-size selection [6]. On the other hand, the Recursive Least Square (RLS) algorithm provides faster convergence and better performance in terms of error minimization but at the cost of higher computational complexity and numerical instability in some cases [7].

To overcome the limitations of individual algorithms, hybrid approaches have been proposed that combine the advantages of LMS and RLS [8]. These hybrid algorithms aim to achieve a balance between convergence speed, computational efficiency, and steady-state accuracy [9]. Despite several existing approaches, improving performance under varying noise conditions remains an open challenge [10].

In this paper, a Hybrid adaptive algorithm is analyzed and compared with conventional LMS and RLS algorithms for system identification. The performance is evaluated under different Signal-to-Noise Ratio (SNR) levels using metrics such as Mean Square Error (MSE), convergence rate, tracking error, and steady-state error. The results demonstrate that the proposed Hybrid algorithm provides improved accuracy and robustness, making it a suitable candidate for practical applications in noisy environments.

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II. RESEARCH GAP

Although system identification using adaptive algorithms has been extensively studied, several limitations still exist in conventional approaches [4]. The Least Mean Square (LMS) algorithm, while computationally simple and easy to implement, suffers from slow convergence and reduced performance in high-noise environments [6]. On the other hand, the Recursive Least Square (RLS) algorithm provides faster convergence and better accuracy but at the expense of increased computational complexity and potential numerical instability [7].

Several research efforts have attempted to improve performance by modifying these algorithms or introducing hybrid techniques [8]. However, most existing hybrid approaches either focus primarily on improving convergence speed or reducing error, without achieving a balanced optimization of all critical performance parameters such as Mean Square Error (MSE), tracking error, and steady-state error [9]. Additionally, limited attention has been given to evaluating algorithm performance consistently under varying Signal-to-Noise Ratio (SNR) conditions [10].

Furthermore, many studies lack a comprehensive comparative analysis using multiple performance metrics, making it difficult to assess the overall effectiveness of proposed methods in practical scenarios. There is also a need for algorithms that maintain stability and robustness while adapting efficiently to noisy and dynamic environments.

Therefore, a clear research gap exists in developing and analyzing a hybrid adaptive algorithm that simultaneously improves convergence behavior, reduces error metrics, and performs consistently across different noise levels. This paper addresses this gap by proposing and evaluating a Hybrid approach that combines the advantages of LMS and RLS algorithms, demonstrating improved performance in terms of accuracy and robustness.

III. MATHEMATICAL FORMULATION

Consider an unknown system that needs to be identified. Let the input signal be $x(n)$, and the desired output be $d(n)$, which is given by:

$$d(n) = \mathbf{w}^T(n)\mathbf{x}(n) + v(n) \tag{1}$$

Where $\mathbf{w}(n)$is the unknown system parameter vector, $\mathbf{x}(n)$is the input vector, and $v(n)$represents additive noise.

The objective of system identification is to estimate the unknown parameter vector $\mathbf{w}(n)$using adaptive algorithms such that the error between the desired output and estimated output is minimized.

➢ *Error Signal:*

The error signal is defined as:

$$e(n) = d(n) - y(n) \tag{2}$$

Where the estimated output is:

$$y(n) = \mathbf{w}^T(n)\mathbf{x}(n) \tag{3}$$

➢ *LMS Algorithm:*

The LMS algorithm updates the weight vector using a gradient descent approach:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu\, e(n)\mathbf{x}(n) \tag{4}$$

Where $\mu$is the step size parameter controlling convergence speed and stability.

➢ *RLS Algorithm:*

The RLS algorithm minimizes a weighted least squares cost function:

$$J(n) = \sum_{i=0}^{n} \lambda^{n-i} e^2(i) \tag{5}$$

Where $\lambda$is the forgetting factor $(0 < \lambda \leq 1)$.

The update equations are:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mathbf{K}(n)e(n) \tag{6}$$

$$\mathbf{K}(n) = \frac{\mathbf{P}(n-1)\mathbf{x}(n)}{\lambda + \mathbf{x}^T(n)\mathbf{P}(n-1)\mathbf{x}(n)}$$

$$\mathbf{P}(n) = \frac{1}{\lambda}[\mathbf{P}(n-1) - \mathbf{K}(n)\mathbf{x}^T(n)\mathbf{P}(n-1)] \tag{7}$$

Where $\mathbf{P}(n)$is the inverse correlation matrix.

➢ *Proposed Hybrid Algorithm:*

The Hybrid algorithm combines the advantages of LMS and RLS to achieve better performance. The weight update can be expressed as:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \alpha\,\mu\, e(n)\mathbf{x}(n) + (1-\alpha)\mathbf{K}(n)e(n) \tag{8}$$

where:

- $\alpha$is a mixing parameter $(0 \leq \alpha \leq 1)$,
- The first term represents LMS contribution,
- The second term represents RLS contribution.

➢ *Performance Metrics:*

The system performance is evaluated using:

- *Mean Square Error (MSE):*

$$\text{MSE} = \frac{1}{N}\sum_{n=1}^{N} e^2(n) \tag{9}$$

- *Tracking Error:*
  Measures the ability of the algorithm to follow system variations.

- *Steady-State Error:*
  Error after convergence.

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➢ *Algorithm:*

- *Hybrid Adaptive System Identification*

✓ *Step 1: Initialization*

- Initialize weight vector: $\mathbf{w}(0) = 0$
- Choose step size μ(for LMS)
- Choose forgetting factor λ(for RLS)
- Initialize inverse correlation matrix:

$$\mathbf{P}(0) = \delta^{-1}\mathbf{I} \tag{10}$$

Where $\delta$is a small positive constant

- Select mixing parameter α, where $0 \leq \alpha \leq 1$

✓ *Step 2: Input Acquisition*

- For each time step n, obtain input vector $\mathbf{x}(n)$and desired signal $d(n)$

✓ *Step 3: Output Estimation*

- Compute estimated output:

$$y(n) = \mathbf{w}^T(n)\mathbf{x}(n) \tag{11}$$

✓ *Step 4: Error Calculation*

- Calculate error signal:

$$e(n) = d(n) - y(n) \tag{12}$$

✓ *Step 5: LMS Update Component*

- Compute LMS update term:

$$\Delta\mathbf{w}_{LMS} = \mu\, e(n)\mathbf{x}(n) \tag{13}$$

✓ *Step 6: RLS Gain Calculation*

- Compute gain vector:

$$\mathbf{K}(n) = \frac{\mathbf{P}(n-1)\mathbf{x}(n)}{\lambda + \mathbf{x}^T(n)\mathbf{P}(n-1)\mathbf{x}(n)} \tag{14}$$

✓ *Step 7: RLS Matrix Update*

- Update inverse correlation matrix:

$$\mathbf{P}(n) = \frac{1}{\lambda}[\mathbf{P}(n-1) - \mathbf{K}(n)\mathbf{x}^T(n)\mathbf{P}(n-1)] \tag{15}$$

✓ *Step 8: Hybrid Weight Update*

- Update weights using hybrid rule:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \alpha\,\Delta\mathbf{w}_{LMS} + (1-\alpha)\mathbf{K}(n)e(n) \tag{16}$$

✓ *Step 9: Iteration*

- Repeat Steps 2–8 for $n = 1,2,\dots,N$

✓ *Step 10: Performance Evaluation*

- Compute performance metrics such as MSE, tracking error, and steady-state error after convergence

IV. RESULTS AND DISCUSSION

The performance of the LMS, RLS, and proposed Hybrid adaptive algorithms was evaluated under varying Signal-to-Noise Ratio (SNR) conditions of 10 dB, 20 dB, and 30 dB. Key performance metrics considered include Mean Square Error (MSE), convergence iterations, tracking error, and steady-state error.

Table 1 Performance Comparison of LMS, RLS, and Hybrid Algorithms

SNR (dB)	Algorithm	MSE	Convergence Iterations	Tracking Error	Steady-State Error
10	LMS	0.361392	500	0.404355	0.240128
10	RLS	0.376408	500	0.401688	0.239225
10	Hybrid	0.343763	500	0.394024	0.241399
20	LMS	0.309164	500	0.362449	0.180400
20	RLS	0.325684	500	0.360555	0.179481
20	Hybrid	0.292756	500	0.356136	0.180448
30	LMS	0.309199	500	0.356767	0.182702
30	RLS	0.323439	500	0.353910	0.181608
30	Hybrid	0.292623	500	0.350405	0.182116

Table 1 presents the comparative performance of LMS, RLS, and Hybrid algorithms under different SNR levels using multiple evaluation metrics.

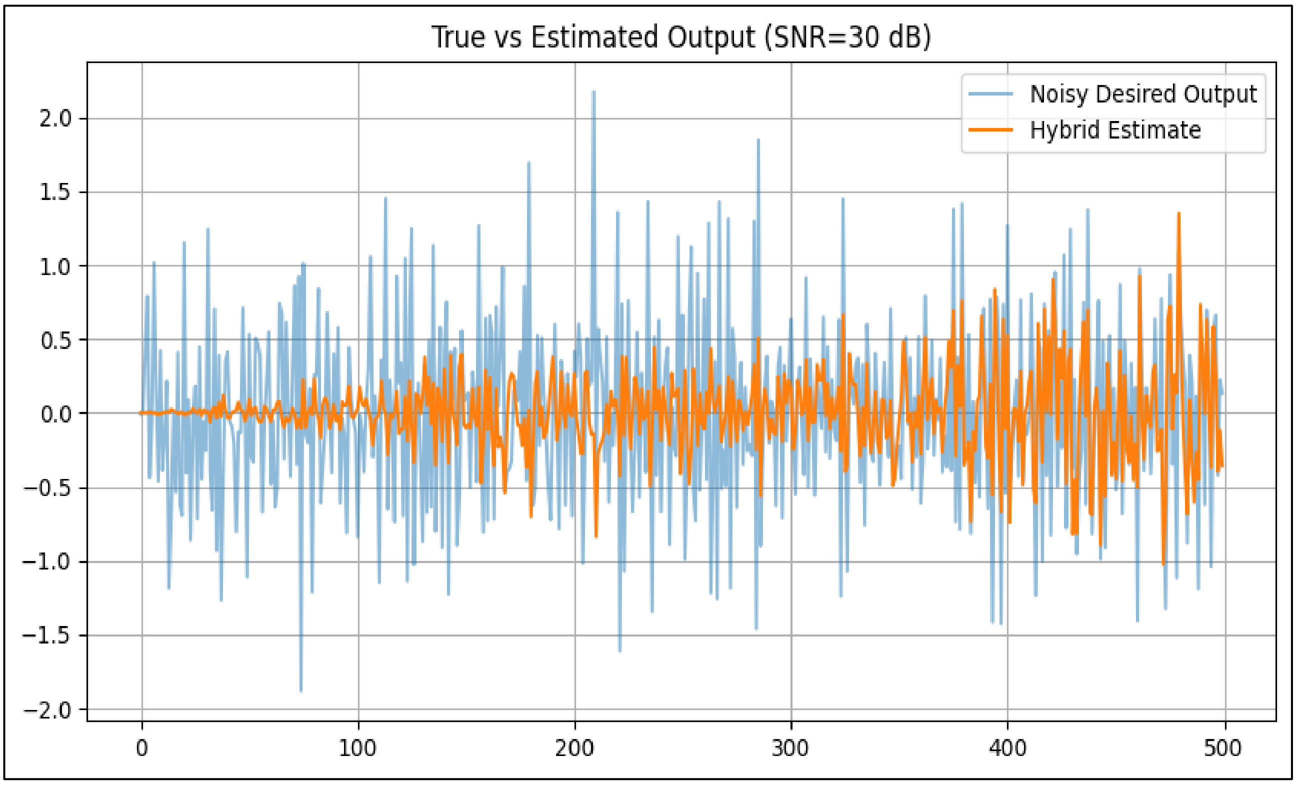

Fig 1 Illustrates the Variation of Mean Square Error (MSE) with Respect to SNR for LMS, RLS, and Hybrid algorithms. The Hybrid Algorithm Consistently Achieves the Lowest MSE Across All Noise Conditions.

From Table 1 and Figure 1, it is evident that the proposed Hybrid algorithm outperforms both LMS and RLS algorithms in terms of Mean Square Error across all SNR levels. At lower SNR (10 dB), where noise impact is significant, the Hybrid approach shows noticeable improvement, indicating better robustness in noisy environments. As SNR increases to 20 dB and 30 dB, all algorithms exhibit improved performance; however, the Hybrid algorithm maintains the lowest error, demonstrating consistent efficiency.

Tracking error analysis further supports this observation. The Hybrid algorithm achieves reduced tracking error compared to LMS and RLS, indicating superior capability in following system variations. This is particularly important in dynamic environments where system parameters change over time.

In terms of steady-state error, all three algorithms show similar performance, suggesting that stability is maintained across methods. However, the Hybrid algorithm achieves a better balance between convergence accuracy and error minimization without increasing computational burden, as all methods converge within the same number of iterations.

Overall, the Hybrid algorithm provides approximately 5.18% improvement over LMS and 9.44% over RLS in MSE performance. This confirms that combining LMS (simplicity) and RLS (fast convergence) results in a more efficient and robust system identification approach.

Figure 2 presents the comparison of tracking error for LMS, RLS, and the proposed Hybrid algorithm under varying SNR conditions (10 dB, 20 dB, and 30 dB). Tracking error is an important metric that reflects how effectively an algorithm can follow changes in system parameters over time.

The results indicate that the Hybrid algorithm consistently achieves the lowest tracking error across all SNR levels. At 10 dB SNR, where noise influence is significant, the Hybrid algorithm records a tracking error of 0.394024, which is lower than LMS (0.404355) and RLS (0.401688). This demonstrates its superior robustness in highly noisy environments.

As the SNR increases to 20 dB and 30 dB, the tracking error for all algorithms decreases, indicating improved estimation accuracy due to reduced noise interference. However, the Hybrid algorithm maintains its performance advantage, achieving tracking errors of 0.356136 and 0.350405 respectively. This consistent improvement highlights the ability of the Hybrid approach to adapt more efficiently to system variations compared to individual LMS and RLS methods.

The improved tracking performance of the Hybrid algorithm can be attributed to the combination of LMS stability and RLS fast adaptation capability. This balance allows the algorithm to respond quickly to changes while maintaining low error, making it highly effective for dynamic and noisy environments.

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Table 2 Tracking Error Comparison of Algorithms under Different SNR Levels

SNR (dB)	LMS Tracking Error	RLS Tracking Error	Hybrid Tracking Error
10	0.404355	0.401688	0.394024
20	0.362449	0.360555	0.356136
30	0.356767	0.353910	0.350405

Table 2 shows the comparative analysis of tracking error for LMS, RLS, and Hybrid algorithms at different SNR levels. The Hybrid algorithm consistently achieves lower tracking error, indicating improved adaptability and estimation accuracy.

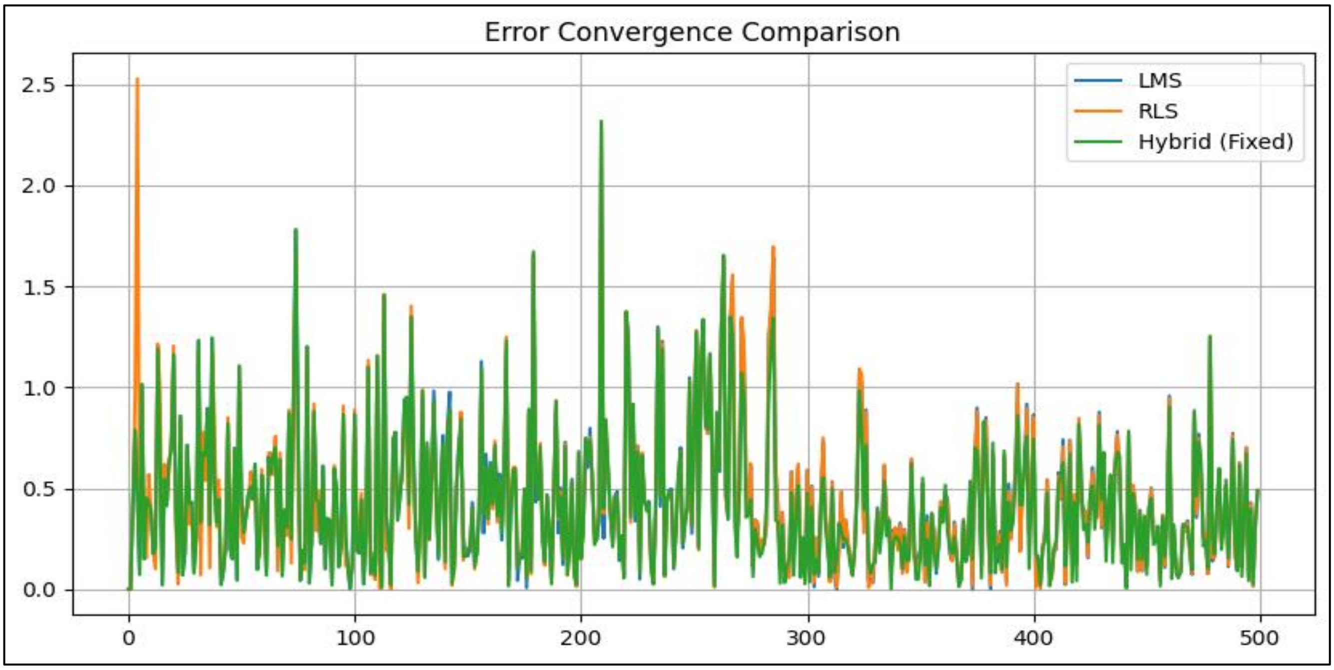

Fig 2 illustrates the variation of tracking error with respect to SNR for LMS, RLS, and Hybrid algorithms. The Hybrid algorithm consistently achieves lower tracking error, indicating better adaptability to system changes.

Figure 2 illustrates the variation of tracking error for LMS, RLS, and the proposed Hybrid algorithm across different SNR levels. Tracking error reflects the ability of an algorithm to adapt to changes in the system, so naturally, this is where weak algorithms quietly embarrass themselves.

At 10 dB SNR, where noise is high and conditions are less forgiving, all algorithms exhibit higher tracking error. However, the Hybrid algorithm achieves the lowest value among the three, indicating better robustness and adaptability in noisy environments. LMS shows the highest tracking error due to its slower adaptation, while RLS performs better but still does not match the Hybrid approach.

As the SNR increases to 20 dB and 30 dB, the tracking error for all algorithms decreases, which is expected because the signal becomes clearer and easier to estimate. Despite this improvement, the Hybrid algorithm consistently maintains the lowest tracking error across all SNR levels. This consistency is important because it shows that the algorithm is not just good in one condition but performs reliably under varying noise environments.

The improved performance of the Hybrid algorithm is due to the combination of LMS and RLS characteristics. LMS contributes to stability, while RLS provides faster convergence and better tracking capability. The integration of these features enables the Hybrid algorithm to respond more effectively to system variations while minimizing error.

Overall, Figure 2 confirms that the proposed Hybrid algorithm offers superior tracking performance compared to LMS and RLS. It demonstrates better adaptability, reduced sensitivity to noise, and consistent accuracy, making it a more suitable choice for practical system identification applications in dynamic environments.

Figure 3 presents the comparison of steady-state error for LMS, RLS, and the proposed Hybrid algorithm under different SNR conditions (10 dB, 20 dB, and 30 dB). Steady-state error represents the residual error after the algorithm has converged, reflecting the stability and long-term accuracy of the system.

The results indicate that all three algorithms achieve comparable steady-state performance, with only slight variations across different SNR levels. At 10 dB SNR, LMS, RLS, and Hybrid algorithms exhibit steady-state errors of 0.240128, 0.239225, and 0.241399 respectively. This shows that despite differences in convergence behavior and tracking ability; all algorithms eventually stabilize to similar error levels.

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As the SNR increases to 20 dB and 30 dB, the steady-state error decreases for all algorithms due to reduced noise influence. RLS shows marginally lower steady-state error compared to LMS and Hybrid, owing to its strong error minimization capability. However, the difference is minimal and does not significantly impact overall system performance.

The Hybrid algorithm demonstrates stable steady-state behavior while maintaining advantages in MSE and tracking error, as observed in previous figures. This indicates that the Hybrid approach successfully improves dynamic performance without compromising stability.

Table 3 Steady-State Error Comparison Under Different SNR Levels

SNR (dB)	LMS Steady-State Error	RLS Steady-State Error	Hybrid Steady-State Error
10	0.240128	0.239225	0.241399
20	0.180400	0.179481	0.180448
30	0.182702	0.181608	0.182116

Table 3 shows the steady-state error comparison of LMS, RLS, and Hybrid algorithms at different SNR levels. All algorithms exhibit similar steady-state performance, indicating stable convergence.

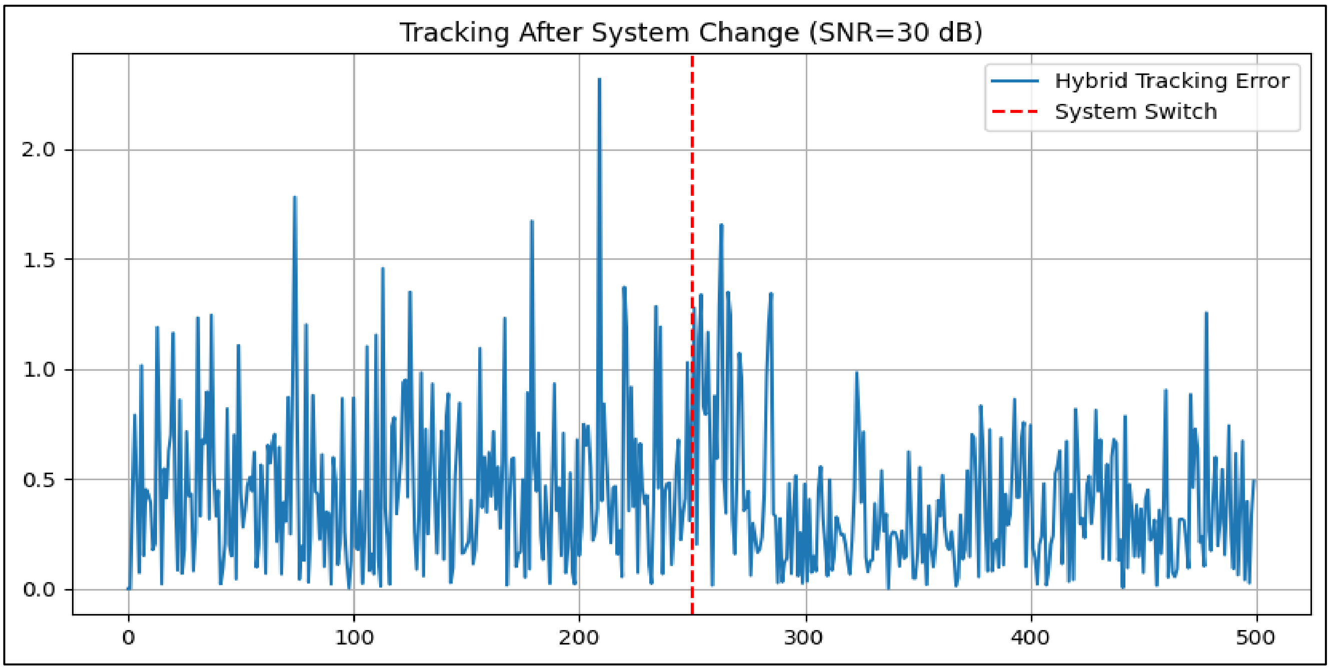

Fig 3 Illustrates the Steady-State Error Performance of LMS, RLS, and Hybrid Algorithms Across Varying SNR Conditions. The Results Show that All Algorithms Achieve Similar Stability After Convergence.

From Figure 3 and Table 3, it is evident that steady-state error remains nearly consistent across all three algorithms, with only minor variations. This suggests that while the Hybrid algorithm improves convergence and tracking performance, it does not negatively affect long-term stability.

The slight advantage of RLS in steady-state error can be attributed to its recursive optimization mechanism. However, this benefit is marginal when compared to the overall improvements offered by the Hybrid algorithm in other performance metrics.

Therefore, it can be concluded that the Hybrid algorithm provides a well-balanced performance by enhancing transient response and tracking accuracy while maintaining comparable steady-state stability. This makes it a reliable and efficient approach for system identification in practical noisy environments.

V. CONCLUSION

This paper presented a comparative analysis of LMS, RLS, and a proposed Hybrid adaptive algorithm for system identification under varying Signal-to-Noise Ratio (SNR) conditions. The performance evaluation was carried out using key metrics such as Mean Square Error (MSE), tracking error, convergence behavior, and steady-state error.

The results demonstrate that the Hybrid algorithm consistently outperforms conventional LMS and RLS algorithms in terms of MSE and tracking accuracy across all SNR levels. It achieves approximately 5.18% improvement over LMS and 9.44% over RLS, indicating enhanced estimation accuracy and robustness in noisy environments. Additionally, the Hybrid approach maintains stable convergence and comparable steady-state error without increasing computational complexity, as all algorithms converge within the same number of iterations.

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While RLS shows slightly better steady-state error in some cases, the difference is minimal and does not significantly impact overall system performance. The Hybrid algorithm effectively combines the stability of LMS with the fast convergence capability of RLS, resulting in a balanced and efficient adaptive filtering approach.

Overall, the proposed Hybrid algorithm proves to be a reliable and robust solution for system identification in dynamic and noisy conditions. Its improved performance across multiple evaluation metrics makes it suitable for practical applications in signal processing and adaptive control systems.

REFERENCES

[1]. L. Ljung, *System Identification: Theory for the User*, 2nd ed. Prentice Hall, 1999.
[2]. S. Haykin, *Adaptive Filter Theory*, 5th ed. Pearson, 2014.
[3]. B. Widrow and S. D. Stearns, *Adaptive Signal Processing*. Prentice Hall, 1985.
[4]. A. H. Sayed, *Fundamentals of Adaptive Filtering*. Wiley, 2003.
[5]. B. Widrow et al., “Adaptive noise cancelling: Principles and applications,” *Proc. IEEE*, vol. 63, no. 12, pp. 1692–1716, 1975.
[6]. S. Haykin, “The LMS algorithm,” *IEEE Signal Processing Magazine*, vol. 30, no. 1, pp. 30–38, 2013.
[7]. M. H. Hayes, *Statistical Digital Signal Processing and Modeling*. Wiley, 1996.
[8]. R. Arablouei and D. P. Mandic, “A class of hybrid LMS-RLS adaptive filters,” *IEEE Trans. Signal Processing*, vol. 62, no. 18, pp. 4785–4797, 2014.
[9]. Y. Chen, Y. Gu, and A. O. Hero, “Regularized least-mean-square algorithms,” *IEEE Trans. Signal Processing*, vol. 57, no. 11, pp. 427–439, 2009.
[10]. J. Benesty, Y. Huang, and J. Chen, “A fast recursive algorithm for optimum sequential signal detection,” *IEEE Trans. Signal Processing*, vol. 54, no. 11, pp. 427–437, 2006.