Adaptive Dynamic Adjustment Kalman Filter (ADA-KF) for Robust Clock Synchronization in High-Mobility Wireless Environments

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Abstract

High-precision time synchronization is essential for reliable communication in next-generation wireless systems such as 5G and the Internet of Things (IoT), particularly under high mobility and dynamic noise conditions. In this paper, we propose an Adaptive Dynamic Adjustment Kalman Filter (ADA-KF) to enhance both the accuracy and robustness of clock synchronization in such challenging environments. The proposed method incorporates a dual-residual sliding window mechanism combined with an Exponentially Weighted Moving Average (EWMA). ADA-KF uses residual variance, theoretically grounded in Maximum Likelihood Estimation (MLE), to adaptively update process and observation noise covariances. In 5G scenarios, precise synchronization between the base station (gNB) and user equipment (UE) is essential. However, traditional methods relying on fixed noise assumptions often struggle to perform effectively in rapidly changing wireless conditions. By adaptively updating the noise model in real time, ADA-KF greatly enhances filtering performance in non-stationary environments. Simulation results demonstrate that ADA-KF achieves faster convergence and higher estimation accuracy than existing methods under low SNR and high mobility conditions. These results indicate strong potential for its application in future communication systems.

Keywords

Clock Synchronization, Adaptive Kalman Filter, Residual Variance Estimation, High-Mobility Wireless Networks

1. Introduction

With the rapid evolution of wireless communication technology, particularly the widespread deployment of the Internet of Things (IoT) and 5G networks, achieving high-precision time synchronization between base station (gNB) and user equipment (UE) has become a critical foundation for ensuring ultra-low latency and highly reliable communication. This requirement is especially prominent in application scenarios that demand high timing accuracy, such as industrial automation and vehicle-to-everything (V2X) systems. As illustrated in Figure 1, these time-sensitive applications are subject to dynamic conditions such as mobility and channel variability. However, real-world application scenarios present numerous challenges: the high mobility of terminal devices leads to frequent changes in their relative positions with respect to base station; environmental temperature fluctuations may cause clock source drift; and the uncertainty of wireless channels. These complex factors collectively result in significant time-varying characteristics of clock offset and clock skew. This severely limits the robustness and accuracy of clock synchronization systems.

Traditional clock synchronization methods typically rely on static noise assumptions, which result in significant performance degradation in highly dynamic and interfered environments, and failing to meet the dual requirements of synchronization accuracy and robustness demanded by next-generation communication systems. As shown in Figure 2, the 5G two-way time synchronization model achieves basic synchronization by exchanging timestamps between gNB and UE over the uplink and downlink. Although this model achieves high synchronization accuracy and strong interference resistance under ideal conditions, its performance degrades in complex environments. The fixed parameter estimation

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methods it relies on cannot adapt to dynamic noise characteristics, which are exacerbated by high-speed terminal movement and oscillator imperfections. To overcome these limitations, previous studies have attempted to introduce state estimation methods such as Kalman Filter (KF) for modeling and tracking [1, 2, 3]. However, most current methods still rely on fixed noise statistical models and lack adaptability to dynamic heterogeneous network environments [4, 5, 6, 7], necessitating more flexible and efficient solutions.

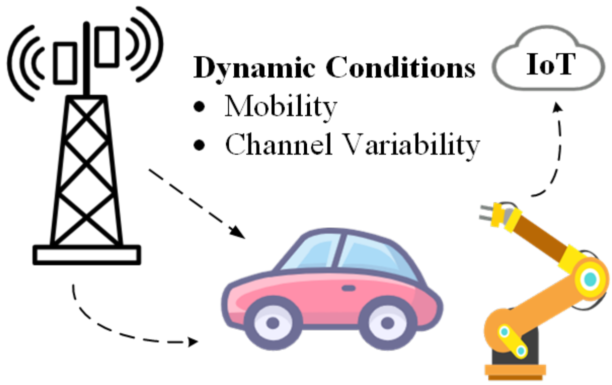


Figure 1: **O**verview of Time-Sensitive Applications in 5G Systems

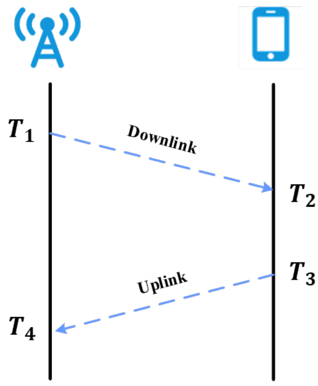


Figure 2: 5G Two-Way Time Synchronization Model

2. Related Work

In the field of time synchronization, early research primarily focused on the IEEE 1588 Precision Time Protocol (PTP) and the Network Time Protocol (NTP). The pioneering work of Mills [8] laid the foundation for internet time synchronization. Although these protocols perform well in wired networks, they struggle to achieve nanosecond-level precision in wireless scenarios due to variable delays, multipath effects, and dynamic channel conditions. As a result, researchers have increasingly adopted state-space models to tackle clock synchronization, with a focus on the estimation and correction of clock offset and clock skew. Among these, KF and its variants have received significant attention. Mehra et al. [9] proposed an innovative method for variance identification and iterative optimal gain adjustment, enabling optimal gain updates under unknown noise covariances. However, this method relies heavily on sufficient steady-state observational data, making it difficult to adapt to highly dynamic or short-term synchronization tasks. Moreover, its strong prior assumptions about the structure of process noise limit its flexibility in practical applications. To enhance filter robustness in dynamic environments, Zheng et al. [10] introduced a Robust Adaptive Unscented Kalman Filter, which addresses the challenges of unknown or varying process and observation noise covariances in nonlinear systems. This method incorporates a fault detection mechanism that dynamically updates covariance matrices based on innovations and residuals, improving estimation accuracy while reducing computational burden. However, due to its reliance on threshold-triggered abrupt adjustments, it struggles to maintain stable estimates in scenarios with frequent small-scale noise fluctuations. Huang et al. [11] proposed a Sliding Window Variational Adaptive Kalman Filter (SWVAKF), which jointly estimates state and noise covariance within a sliding window using Bayesian inference. It demonstrates strong performance under slowly varying noise conditions. However, its reliance on complex inverse-Wishart priors and backward smoothers results in high computational cost and suboptimal real-time performance in rapidly changing noise environments. In addition, Zuo et al. [12] proposed a joint estimation algorithm based on correlation detection and implicit synchronization (CDIS-JE) that allows clock offset estimation at the physical layer without increasing communication overhead. However, this method relies on a fixed topology and ideal reference nodes, limiting its adaptability.

In the context of 5G applications, Werner et al. [13] proposed an Extended Kalman Filter method based on DoA/ToA fusion for joint estimation of node position and clock offset. However, its noise model is fixed and lacks online adaptability, limiting its effectiveness in dynamic environments. Goodarzi et al. [14] combined BP and BRF to propose a hybrid Bayesian synchronization algorithm that balances global accuracy and edge synchronization efficiency. However, its strategy relies on a structured network and fixed noise model, making it difficult to adapt to rapidly changing wireless environments. Hu et al. [15] combined 5G NR multipath measurements with UWB systems and proposed an iterative maximum likelihood algorithm that improves positioning accuracy in GNSS-denied environments. Although the method effectively addresses positioning in 5G systems, it relies on a fixed error model and lacks adaptive covariance mechanisms, and its high dependence on 5G infrastructure limits its applicability in heterogeneous networks.

To address the above issues, we propose a novel clock synchronization algorithm called ADA-KF (Adaptive Dynamic Adjustment Kalman Filter). This method is based on a dual-residual mechanism that continuously records both measurement and prediction residuals using a sliding window. It employs the Maximum Likelihood Estimation (MLE) principle to obtain unbiased estimates of residual variances. Additionally, an Exponentially Weighted Moving Average (EWMA) strategy and an adaptive smoothing factor are introduced to dynamically update the covariance matrices, enabling online modeling of non-stationary noise and adaptive adjustment of the filter structure. While maintaining the convergence properties of the classical KF, the proposed algorithm significantly enhances synchronization accuracy and robustness in dynamic environments. The main contributions are as follows:

- An Adaptive Dynamic Adjustment Kalman Filter algorithm (ADA-KF) for clock synchronization is proposed, which can dynamically update the noise covariance based on residual statistics.
- A dual residual sliding window mechanism is constructed to dynamically model non-stationary noise, effectively improving the filter's robustness and convergence speed under complex conditions.
- The introduction of MLE principle and EWMA smoothing strategy enables dynamic and stable updates of the covariance.
- System-level simulations demonstrate that ADA-KF outperforms existing methods under challenging conditions such as high mobility and low signal-to-noise ratio (SNR).

3. Proposed Approach

3.1. System Model

We adopt a standard second-order clock model to represent the local clock behavior of each node. The state vector is defined as:

$$\mathbf{x}_k = \begin{bmatrix} \theta_k \\ \phi_k \end{bmatrix} \tag{1}$$

where θ_k denotes the clock offset and ϕ_k represents the clock skew.
The state transition model is given by:

$$\mathbf{x}_k = \mathbf{A}\mathbf{x}_{k-1} + \mathbf{w}_{k-1} \tag{2}$$

where the transition matrix is:

$$\mathbf{A} = \begin{bmatrix} 1 & \Delta t_k \\ 0 & 1 \end{bmatrix} \tag{3}$$

where Δt_k denotes the sampling interval. The process noise $\mathbf{w}_{k-1}$ is modeled as a zero-mean Gaussian random variable with time-varying covariance $\mathbf{Q}_k$:

$$\mathbf{w}_{k-1} \sim \mathcal{N}(\mathbf{0}, \mathbf{Q}_k) \tag{4}$$

The observation model is:

$$\mathbf{z}_k = \mathbf{H}\mathbf{x}_k + \mathbf{v}_k \tag{5}$$

where $\mathbf{H} = [1, 0]$. The observation noise $\mathbf{v}_k$ is also modeled as a zero-mean Gaussian noise with time-varying covariance $\mathbf{R}_k$:

$$\mathbf{v}_k \sim \mathcal{N}(\mathbf{0}, \mathbf{R}_k) \tag{6}$$

Traditional methods typically assume $\mathbf{Q}_k$ and $\mathbf{R}_k$ to be fixed, which limits performance in highly dynamic environments. To address this, we propose an online adaptive estimation strategy that uses a sliding window of historical residuals to estimate noise covariances. Following the MLE principle, the sample variances of these residuals provide unbiased estimates for $\mathbf{Q}_k$ and $\mathbf{R}_k$, thereby improving the filter's adaptability under non-stationary noise.

3.2. Dual-Residual Sliding Window Mechanism

After each filtering step, two types of residuals are recorded:

- **Measurement residual:**

$$\mathbf{r}_k^y = \mathbf{z}_k - \mathbf{H}\hat{\mathbf{x}}_{k|k-1} \tag{7}$$

- **Prediction residual:**

$$\mathbf{r}_k^x = \hat{\mathbf{x}}_{k|k} - \mathbf{A}\hat{\mathbf{x}}_{k-1|k-1} \tag{8}$$

For each component, we have:

$$r_k^{(\theta)} = \hat{\theta}_k - \left(\hat{\theta}_{k-1} + \hat{\phi}_{k-1}\Delta t_k\right), \quad r_k^{(\phi)} = \hat{\phi}_k - \hat{\phi}_{k-1} \tag{9}$$

Each residual sequence is stored in a sliding window of length L:

- **Measurement residual buffer:**

$$\mathcal{R}_y = \{\mathbf{r}_{k-L+1}^y, \ldots, \mathbf{r}_k^y\} \tag{10}$$

- **Prediction residual buffer:**

$$\mathcal{R}_x = \{\mathbf{r}_{k-L+1}^x, \ldots, \mathbf{r}_k^x\} \tag{11}$$

The sample variances of these buffers are then used to estimate the noise covariances:

$$\hat{\mathbf{R}}_k = \mathrm{Var}(R_y), \quad \hat{\mathbf{Q}}_k = \mathrm{Var}(R_x) \tag{12}$$

In practical clock synchronization systems, clock offset and clock skew are distinct error sources. Clock offset reflects a fixed initial deviation, while clock skew accumulates over time. For model simplification and filter stability, we assume a proportional relationship between the two process noise terms:

$$Q_k^{(\theta)} = \eta Q_k^{(\phi)}, \quad \eta \ll 1 \tag{13}$$

where η is a small scalar constant indicating that the offset noise is significantly smaller than the skew noise. Although this assumption is not physically derived, it is widely adopted in practice to simplify the state model, as skew variation typically dominates offset drift over short time intervals. This simplification improves KF convergence and robustness in dynamic environments.

3.3. MLE-Inspired Covariance Update

According to Mehra's covariance matching theory[9], the MLE estimate of noise covariance is consistent under the following conditions:

$$\mathbb{E}[\mathbf{r}_k^y(\mathbf{r}_k^y)^\top] = \mathbf{R}_k, \quad \mathbb{E}[\mathbf{r}_k^x(\mathbf{r}_k^x)^\top] = \mathbf{Q}_k \tag{14}$$

Thus, we treat the sample covariance over the sliding windows as an unbiased estimator.

$$\hat{\mathbf{R}}_{\mathbf{k}}^{\mathrm{MLE}} = \frac{1}{L}\sum_{i=k-L+1}^{k}(r_i^y)^2 \tag{15}$$

$$\hat{\mathbf{Q}}_{\mathbf{k}}^{\mathrm{MLE}} = \frac{1}{L}\sum_{i=k-L+1}^{k}\begin{bmatrix} \eta\left(r_i^{(\phi)}\right)^2 & 0 \\ 0 & \left(r_i^{(\phi)}\right)^2 \end{bmatrix} \tag{16}$$

3.4. Adaptive Factor Update

To balance responsiveness and stability while mitigating abrupt fluctuations caused by sample variance jumps,we apply an EWMA mechanism with adaptive smoothing factors λ_R and λ_Q for dynamic update:

$$\mathbf{R}_k = (1 - \lambda_R)\mathbf{R}_{k-1} + \lambda_R \hat{\mathbf{R}}_k^{\mathrm{MLE}} \tag{17}$$

$$\mathbf{Q}_k = (1 - \lambda_Q)\mathbf{Q}_{k-1} + \lambda_Q \hat{\mathbf{Q}}_k^{\mathrm{MLE}} \tag{18}$$

3.5. Algorithm Summary

We summarize the complete filtering procedure in Algorithm 1.

Algorithm 1 ADA-KF: Adaptive Dynamic Adjustment Kalman Filter

Input: Observation z_k, previous state estimate $\hat{\mathbf{x}}_{k-1|k-1}$, covariance $\mathbf{P}_{k-1}$, residual buffers $\mathcal{R}_x$, $\mathcal{R}_y$, smoothing factors λ_Q, λ_R, window size L
Prediction:
  $\hat{\mathbf{x}}_{k|k-1} = \mathbf{A}_k \hat{\mathbf{x}}_{k-1|k-1}$
  $\mathbf{P}_{k|k-1} = \mathbf{A}_k \mathbf{P}_{k-1} \mathbf{A}_k^\top + \mathbf{Q}_{k-1}$
Measurement Update:
  Compute residual: $\mathbf{r}_k^y = z_k - \mathbf{H}\hat{\mathbf{x}}_{k|k-1}$
  Compute Kalman gain: $\mathbf{K}_k = \mathbf{P}_{k|k-1}\mathbf{H}^\top(\mathbf{H}\mathbf{P}_{k|k-1}\mathbf{H}^\top + R_k)^{-1}$
  Update state estimate: $\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + \mathbf{K}_k \mathbf{r}_k^y$
  Update covariance: $\mathbf{P}_k = (\mathbf{I} - \mathbf{K}_k\mathbf{H})\mathbf{P}_{k|k-1}$
Residual Update:
  Compute residual
  Append $\mathbf{r}_k^y$, $\mathbf{r}_k^x$ to $\mathcal{R}_y$, $\mathcal{R}_x$
if residual window is full **then**
  MLE-Inspired Covariance Update:
    Compute sample variance and update the noise covariance $\mathbf{R}_k$ and $\mathbf{Q}_k$ based on the unbiased MLE estimate.
  EWMA Adaptive Factor Update: Update $\mathbf{R}_k$ and $\mathbf{Q}_k$ with smoothing factors λ_R and λ_Q
end if

4. Simulation Results

We conducted extensive simulations to evaluate the performance of the proposed ADA-KF under dynamic wireless synchronization scenarios, including high mobility and varying noise levels. To simulate different SNR conditions (ranging from −20 dB to 20 dB), zero-mean Gaussian noise was added to the system. All experiments were implemented in MATLAB with a fixed sampling interval. Each simulation was repeated 100 times, and the average results were reported.

ADA-KF is compared with three representative approaches: the KF with fixed process and observation noise covariances, the CDIS-JE algorithm, and the SWVAKF. In contrast to these methods, ADA-KF employs a dual-residual sliding window mechanism and adaptively updates noise covariances using sample variance estimates. To prevent abrupt changes in the estimated covariances, an EWMA is applied to smooth the updates. This process is theoretically supported by MLE consistency theory, which justifies the use of residual variances as unbiased estimators under suitable assumptions. This combined adaptive mechanism enables ADA-KF to respond more effectively and stably to dynamic and time-varying noise conditions.

Figure 3 illustrates the convergence behavior of the clock offset estimation under moderate noise conditions (SNR = 0 dB). A sliding window of 20 samples was applied to compute the root mean square

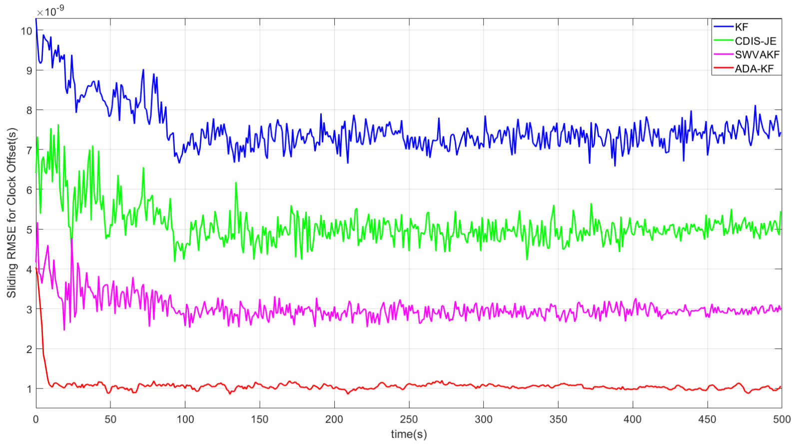


Figure 3: Sliding window RMSE of clock offset under 0 dB SNR

error (RMSE) of clock offset θ, enabling analysis of short-term fluctuations and convergence trends. Compared to the standard KF (blue line), CDIS-JE (green line), and SWVAKF (magenta line), ADA-KF achieves faster convergence and maintains a significantly lower steady-state RMSE. These results confirm the method's improved stability and enhanced noise suppression capability under moderate conditions.

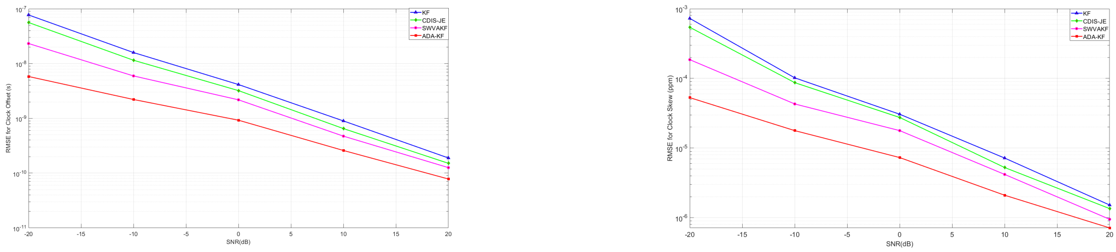
To further investigate performance under challenging environments, we simulated a high-mobility scenario with SNR = −10 dB and UE speed of 120 km/h. The convergence point is defined as the first time step when the RMSE of clock offset θ drops below 10e-8, measured in frame numbers. Table 1 presents the comparative performance of ADA-KF and other methods, including convergence frame and RMSE values for both clock offset θ and clock skew ϕ.

Table 1
Performance Comparison under High Mobility (SNR = −10 dB, Speed = 120 km/h)

Algorithm	**Convergence Frame**	**RMSE(θ) [s]**	**RMSE(ϕ) [ppm]**
KF	82	1.59e−8	1.02e−4
CDIS-JE	70	1.15e-8	8.7e−5
SWVAKF	58	5.95e-9	4.3e−5
ADA-KF	22	2.21e-9	1.78e−5

As shown in the table, ADA-KF achieves the fastest convergence (22 frames) and the lowest RMSE for both clock offset and clock skew, demonstrating its superior convergence speed and estimation accuracy in this challenging scenario. These improvements confirm the effectiveness of adaptive noise covariance adjustment in high-mobility and noisy environments.

To evaluate robustness under various noise conditions, we conducted experiments under varying SNR levels from −20 dB to 20 dB (−20, −10, 0, 10, 20 dB). Figures 4 (a) and (b) show the RMSE performance of clock offset θ and clock skew ϕ, respectively. Across all tested SNR levels, ADA-KF consistently outperforms other methods. The advantage of ADA-KF is especially pronounced under low-SNR conditions (−20 dB and −10 dB), where the fixed-parameter KF suffers severe degradation due to its inability to adapt process and measurement noise covariances to the actual noise environment. CDIS-JE benefits from its lightweight correlation-based design but shows limited resilience against channel noise, particularly in skew estimation, where the cumulative effect necessitates long-term tracking. SWVAKF adapts to noise statistics via variational Bayesian inference and achieves competitive accuracy, but its sliding-window structure leads to slower adaptation to abrupt noise changes compared to ADA-KF's dual-residual updating mechanism. As the SNR increases, all methods improve due to enhanced signal quality. However, ADA-KF consistently achieves lower RMSE. Notably, ADA-KF and SWVAKF demonstrate significantly better skew estimation than CDIS-JE and KF, confirming the importance of adaptive state-space modeling for robust clock synchronization in dynamic wireless environments.



(a) (b)

Figure 4: RMSE analysis under different conditions. (a) RMSE of clock offset (b) RMSE of clock skew

5. CONCLUSIONS

In this paper, we have proposed an innovative ADA-KF algorithm for clock synchronization in wireless networks, specifically designed to address the challenges arising from high mobility and dynamic noise environments. By incorporating a sliding window mechanism and leveraging sample variance estimates for covariance estimation, the ADA-KF algorithm adapts to time-varying noise. These estimates are theoretically supported by MLE consistency theory and are further stabilized using EWMA smoothing. As a result, ADA-KF achieves superior performance compared to other methods, providing faster convergence and better synchronization accuracy. The method exhibits significant improvements in both convergence speed and steady-state error, particularly in low SNR and high-speed environments. Future research can explore deploying ADA-KF in practical 5G/6G deployments and integrating it with deep learning models to further improve noise estimation accuracy and scalability.

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Declaration on Generative AI

The authors declare that OpenAI tool was used to assist in improving the language fluency of this paper. All content, ideas, and conclusions are those of the authors, and the AI tool did not contribute to the results or analysis.

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