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Real-Time Data Synchronization of V2X Sensing and Aerial Imagery for Sustainable Operation in Subterranean Corridors

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Abstract

Achieving real-time data synchronization in complex environments such as subterranean corridors is critical for advancing sustainable operations and ensuring safety in underground infrastructure. The integration of Vehicle-to-Everything (V2X) sensing technologies with aerial imagery presents a promising avenue for augmenting situational awareness and operational efficiency. This paper investigates the framework and methodologies for synchronizing V2X data streams, including vehicular telemetry, environmental sensors, and communication networks, with high-resolution aerial imagery captured by unmanned aerial vehicles (UAVs). By leveraging edge computing, distributed data fusion, and advanced temporal alignment algorithms, the proposed system minimizes latency and ensures consistent data accuracy. The synchronization process is optimized to address challenges such as signal degradation, occlusions, and resource constraints in subterranean environments. The resulting system is demonstrated to improve navigation, hazard detection, and resource allocation within these confined spaces. This research contributes to the body of knowledge by proposing a scalable, energy-efficient framework that facilitates sustainable operations in underground corridors, aligning with goals for environmental conservation and operational resilience. The findings underscore the potential of integrating V2X and aerial imagery to transform subterranean infrastructure management while providing a pathway for future advancements in autonomous navigation and intelligent monitoring systems.

Keywords: aerial imagery, autonomous navigation, data synchronization, edge computing, subterranean infrastructure, V2X technologies, UAVs

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1 Introduction

The increasing complexity of subterranean corridors, encompassing a wide range of environments such as tunnels, mines, and underground transportation networks, has catalyzed a growing demand for innovative technological solutions aimed at enhancing both operational efficiency and safety. As these environments expand to accommodate escalating urbanization, industrial activity, and strategic infrastructure projects, they also introduce a host of challenges that necessitate advanced methodologies for monitoring and management. Among the most promising advancements in this field is the integration of cutting-edge sensing technologies, including Vehicle-to-Everything (V2X) communication systems and high-resolution aerial imagery captured by unmanned aerial vehicles (UAVs). Together, these technologies hold the potential to significantly enhance situational awareness by providing a multidimensional perspective on the subterranean environment. Specifically, V2X sensing facilitates seamless communication between vehicles and infrastructure, enabling the real-time exchange of critical data, while UAV-based aerial imagery offers an invaluable bird's-eye view of spatial layouts and structural conditions. However, the synchronization of these heterogeneous data streams is essential to creating a cohesive and actionable representation of the subterranean landscape [1].

Subterranean environments are inherently challenging due to their unique physical and operational constraints. Low visibility, signal attenuation caused by dense materials, and limited accessibility all compound the difficulties of achieving effective data acquisition and integration. For instance, the presence of rock strata, concrete walls, and metallic reinforcements can interfere with wireless communication signals, diminishing the efficacy of traditional sensing systems. Furthermore, the confined nature of these spaces limits the placement of sensors and restricts the mobility of monitoring equipment, necessitating highly adaptive and robust solutions. The integration of V2X communication and aerial imagery provides a promising avenue for overcoming these limitations. V2X systems enable vehicles to share their positional and environmental data with surrounding infrastructure and other vehicles, creating a dynamic network of interconnected nodes [2]. When combined with UAV-derived imagery, which captures macro-level spatial information, these technologies can provide a more comprehensive understanding of the subterranean environment [3].

However, achieving seamless integration and synchronization of these data streams remains a critical technical challenge. Traditional approaches to sensor fusion often rely on predefined models and algorithms that are ill-suited to the dynamic and unpredictable conditions of subterranean environments. For example, the precision of GPS data, a cornerstone of many navigation systems, is significantly degraded underground due to the inability of satellite signals to penetrate dense materials. This necessitates the use of alternative localization techniques, such as inertial measurement units (IMUs) and ultra-wideband (UWB) positioning systems, which must be effectively integrated with V2X and aerial data to ensure accuracy. Furthermore, the timeliness of data processing is a paramount concern, as delays in synchronizing and analyzing information can compromise the safety and efficiency of operations. For instance, in the context of underground mining, a delayed response to hazardous conditions such as gas leaks or structural instabilities could have catastrophic consequences.

In addition to these operational challenges, the sustainability of subterranean operations has emerged as a critical consideration in the design and implementation of sensing systems. The energy-intensive nature of underground activities, coupled with the increasing scrutiny of environmental impacts, underscores the need for technologies that optimize resource utilization and minimize ecological footprints. The integration of V2X sensing and aerial imagery offers several pathways for achieving these objectives. For example, by providing real-time data on traffic flow and environmental conditions, V2X systems can enable more efficient routing of vehicles, reducing fuel consumption and emissions. Similarly, UAVs equipped with advanced imaging and analytical capabilities can monitor structural conditions and identify potential hazards, reducing the need for energy-intensive manual inspections. However, the realization of these benefits depends on the development of robust synchronization frameworks that can harmonize the diverse data streams generated by these technologies.

To illustrate the potential of these integrated systems, consider the scenario of an underground transportation network designed to support urban mobility. Such a network must contend with a variety of challenges, including high traffic density, limited ventilation, and the risk of structural degradation over time. By leveraging V2X communication, vehicles within the network can share information about their positions, speeds, and trajectories, enabling the implementation of adaptive traffic management systems that optimize flow and reduce congestion. At the same time, UAVs equipped with high-resolution cameras and sensors can periodically survey the network to identify structural vulnerabilities, such as cracks or water infiltration, that may compromise safety. The synchronization of these data streams can provide operators with a unified and dynamic view of the network, facilitating proactive maintenance and efficient resource allocation.

Despite these promising applications, the technical hurdles associated with data synchronization remain a formidable barrier to widespread adoption. One of the primary challenges lies in the heterogeneity of the data generated by V2X and UAV systems. V2X communication typically produces structured, time-stamped data streams that are optimized for real-time applications, while aerial imagery consists of unstructured or semi-structured data that require significant preprocessing and analysis. Bridging this gap necessitates the development of advanced algorithms capable of aligning and fusing data from disparate sources, often in the presence of noise and uncertainty. Moreover, the computational demands of these processes must be carefully managed to ensure that the resulting systems are both scalable and energy-efficient.

The confluence of V2X sensing and aerial imagery represents a promising frontier in the enhancement of subterranean operations, offering the potential to address long-standing challenges related to visibility, communication, and accessibility. However, the successful implementation of these technologies hinges on the resolution of key technical challenges, particularly in the realm of data synchronization. The following sections of this paper will explore these challenges in greater detail, examining the state-of-the-art techniques for data integration and their applicability to subterranean environments. In doing so, this work aims to contribute to the development of innovative solutions that can unlock the full potential of advanced sensing technologies in these critical settings [4].

In conclusion, the introduction of advanced sensing technologies such as V2X communication and UAV-based aerial imagery holds transformative potential for the management and optimization of subterranean environments. However, these technologies must overcome significant challenges, particularly with regard to data synchronization, to achieve their full potential. The development of robust integration frameworks that address these challenges is essential for advancing the state of the art in subterranean sensing and ensuring the sustainability and safety of operations in these complex and dynamic settings.

This paper explores the design and implementation of a real-time data synchronization framework that leverages edge computing and distributed systems to align V2X and aerial imagery data. By addressing latency, resource allocation, and environmental constraints, the proposed system aims to enhance operational sustainability in subterranean corridors. The subsequent sections detail the theoretical framework, synchronization techniques, and evaluation of the proposed methodology.

2 Theoretical Framework for Data Synchronization

The proposed theoretical framework for data synchronization in subterranean environments is structured around three fundamental components: temporal alignment, data fusion, and resource optimization. These components address the unique challenges posed by the integration of V2X communication and aerial imagery data, ensuring seamless synchronization even under the adverse conditions characteristic of subterranean settings. The framework incorporates advanced mathematical models, algorithms, and architectural principles to deliver robust and efficient synchronization while accounting for the constraints of these environments.

2.1 Temporal Alignment

Temporal alignment is the cornerstone of the synchronization process, as it ensures that data streams originating from V2X sensors and UAV-based aerial imagery are accurately synchronized despite disparities in their acquisition rates, network-induced delays, and varying temporal resolutions. The temporal alignment process is governed by two key elements: precise time-stamping and predictive modeling.

To facilitate time-stamping, each data packet is annotated with a timestamp t_i representing the exact time of acquisition. However, discrepancies can arise due to network jitter and variable latencies. To address this, a predictive model based on linear regression and Kalman filtering is employed to estimate the true timestamp $\hat{t}_i$ for each data packet. The relationship can be expressed as follows:

$$\hat{t}_i = t_i + \Delta t,$$

where Δt represents the estimated delay, which is dynamically updated based on observed latency patterns. The Kalman filter equations for this process are:

$$\hat{x}_{k|k-1} = A\hat{x}_{k-1|k-1} + Bu_k, \quad P_{k|k-1} = AP_{k-1|k-1}A^\top + Q,$$

$$K_k = P_{k|k-1}H^\top(HP_{k|k-1}H^\top + R)^{-1}, \quad \hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k(z_k-$$

where $\hat{x}$ represents the estimated state, P is the error covariance matrix, A is the state transition matrix, H is the observation matrix, Q is the process noise covariance, R is the measurement noise covariance,

Table 1. Comparative Analysis of V2X and UAV Data Characteristics in Subterranean Environments

Aspect	**V2X Communication**	**UAV Aerial Imagery**
Data Structure	Structured, time-stamped	Unstructured or semi-structured
Primary Purpose	Real-time communication and situational awareness	Spatial mapping and structural monitoring
Challenges	Signal attenuation, low precision in GPS-deprived areas	High computational requirements for processing and analysis [5]
Advantages	Facilitates adaptive traffic management and resource optimization	Enables macro-level environmental assessments

Table 2. Key Technical Challenges in Data Synchronization for Subterranean Sensing

Challenge	**Description**	**Potential Solutions**
Heterogeneity of Data	Disparate formats and structures of V2X and UAV data	Development of unified data models and schemas
Latency and Timeliness	Delays in processing and synchronizing data streams	Optimization of real-time data fusion algorithms
Environmental Constraints	Low visibility and signal interference in subterranean spaces	Use of alternative localization techniques (e.g., UWB, IMUs)
Computational Demands	High resource requirements for data analysis and integration	Deployment of edge computing and distributed processing

and K_k is the Kalman gain. This predictive approach ensures that temporal misalignments are minimized, enabling consistent and accurate data integration.

2.2 Data Fusion

Data fusion involves the integration of heterogeneous data streams from V2X sensors and UAV-derived aerial imagery into a unified representation. This process is essential for robust decision-making in dynamic subterranean environments. The fusion framework employs a combination of probabilistic methods, machine learning algorithms, and physics-based models to address the unique characteristics of these data streams.

One of the primary tools for data fusion is the extended Kalman filter (EKF), which is particularly suited to nonlinear systems. The state estimation problem is formulated as:

$$\hat{x}_k = f(\hat{x}_{k-1}) + \omega_k, \quad z_k = h(\hat{x}_k) + \nu_k,$$

where f and h represent the system dynamics and observation models, respectively, and ω_k and ν_k are process and measurement noise. By iteratively updating the state estimate and its associated uncertainty, the EKF provides a reliable mechanism for combining V2X and UAV data, even in the presence of noise and occlusions.

In addition to EKF, Bayesian inference is employed to quantify uncertainty and incorporate prior knowledge into the fusion process. Given a prior distribution $p(x)$ and likelihood function $p(z|x)$, the posterior distribution $p(x|z)$ is computed as:

$$p(x|z) = \frac{p(z|x)p(x)}{p(z)},$$

where $p(z)$ is the marginal probability of the observation. This probabilistic approach enables the system to handle incomplete or ambiguous data, enhancing its resilience to challenging subterranean conditions.

Deep learning techniques, particularly convolutional neural networks (CNNs), are also integrated into the fusion framework to process high-resolution aerial imagery. CNNs are used to extract spatial features, such as structural anomalies or environmental hazards, which are then correlated with V2X data to provide a comprehensive situational overview. The combined output is represented as a multidimensional tensor $\mathbf{T}$, where each element T_{ijk} corresponds to a fused data point from the ith V2X sensor, jth UAV image, and kth time step:

$$\mathbf{T} = \text{Fusion}(\mathbf{V}, \mathbf{U}),$$

where $\mathbf{V}$ and $\mathbf{U}$ represent the V2X and UAV data streams, respectively.

2.3 Resource Optimization

The computational and energy demands of real-time data synchronization are significant, particularly in the resource-constrained environments typical of subterranean operations. Resource optimization is therefore a critical component of the proposed framework, focusing on minimizing latency, energy consumption, and computational overhead while maintaining system performance.

One key strategy for resource optimization is the deployment of edge computing and distributed architectures. By offloading intensive computational tasks to edge nodes located near the data sources, the framework reduces the burden on central processing units and minimizes data transmission delays. The energy efficiency of this approach can be quantified using the energy-delay product (EDP), defined as:

$$\text{EDP} = E \cdot D,$$

where E is the energy consumed and D is the delay incurred. The optimization objective is to minimize EDP while ensuring that system constraints are satisfied.

To further enhance resource efficiency, the framework incorporates adaptive task scheduling algorithms that dynamically allocate computational resources based on workload and environmental conditions. These algorithms solve the following optimization problem:

$$\min \sum_{i=1}^{N} \frac{E_i}{T_i}, \quad \text{subject to } \sum_{i=1}^{N} T_i \leq T_{\text{max}},$$

where E_i and T_i are the energy consumption and execution time of the ith task, and T_{max} is the maximum allowable time.

2.4 System Resilience and Error Management

The theoretical framework also emphasizes resilience and error management to ensure reliable operation under adverse conditions. Mechanisms such as error correction codes (ECC) and redundancy strategies are employed to maintain data integrity during transmission. For instance, Reed-Solomon codes are used to detect and correct errors in transmitted data, ensuring that corrupted packets are recovered without requiring retransmission.

Adaptive algorithms are integrated into the framework to dynamically adjust system parameters in response to environmental changes. For example, if signal degradation is detected, the system can reconfigure its communication protocols to prioritize low-latency transmission channels or increase redundancy to compensate for data loss. These adaptive capabilities are modeled using reinforcement learning, where the system learns an optimal policy π^* that maximizes a cumulative reward function R:

$$\pi^* = \arg\max_{\pi} \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t R_t\right],$$

where γ is a discount factor and R_t represents the reward at time t. This approach enables the framework to proactively address challenges and maintain high levels of performance.

2.5 Mathematical Integration of Components

The interplay between temporal alignment, data fusion, and resource optimization is represented mathematically through a unified objective function F, which encapsulates the trade-offs between precision, timeliness, and resource efficiency:

$$F = w_1 P + w_2 T + w_3 R,$$

where P represents precision (e.g., alignment accuracy), T denotes timeliness (e.g., latency), and R signifies resource efficiency (e.g., energy consumption). The weights w_1, w_2, w_3 are determined based on the relative importance of each objective in a given application context. The optimization problem is then formulated as:

$$\min F, \quad \text{subject to } P \geq P_{\text{min}},\ T \leq T_{\text{max}},\ R \leq R_{\text{max}},$$

where P_{min}, T_{max}, and R_{max} are application-specific constraints.

Table 3. Key Components of the Proposed Synchronization Framework

Component	Objective	Techniques Employed
Temporal Alignment	Synchronize data streams with precision	Time-stamping, Kalman filtering, predictive modeling
Data Fusion	Integrate heterogeneous data into a unified representation	Extended Kalman filter, Bayesian inference, deep learning
Resource Optimization	Minimize computational and energy overhead	Edge computing, distributed architectures, task scheduling
System Resilience	Ensure reliable operation under adverse conditions	Error correction codes, adaptive algorithms

Table 4. Performance Metrics for Evaluating Synchronization Frameworks

Metric	Definition	Evaluation Method
Alignment Precision	Accuracy of temporal synchronization	Mean absolute error (MAE) of timestamps
Fusion Accuracy	Consistency of integrated data streams	Root mean square error (RMSE) of fused estimates
Latency	Time required for data processing and synchronization	Average processing delay per task
Energy Efficiency	Ratio of computational output to energy consumed	Energy-delay product (EDP)

3 Synchronization Methodology

The synchronization methodology for integrating V2X sensing systems and UAV-derived aerial imagery is structured around three critical stages: data acquisition, preprocessing, and data integration. This methodology is designed to address the unique challenges posed by subterranean environments, including limited visibility, communication constraints, and high computational demands. Each stage of the process incorporates advanced techniques to ensure that the resulting dataset is precise, consistent, and suitable for real-time analysis and decision-making [6].

3.1 Data Acquisition

Data acquisition represents the foundational stage of the synchronization process, wherein data streams from V2X sensors and UAV systems are collected. V2X sensing systems encompass a range of vehicular sensors, such as LiDAR (Light Detection and Ranging), cameras, and inertial measurement units (IMUs), as well as sensors embedded in roadside infrastructure, including traffic lights, environmental monitors, and ultra-wideband (UWB) positioning systems. These sensors collectively generate diverse data streams that provide granular, localized information about the subterranean environment. For example, LiDAR captures three-dimensional spatial data that maps the immediate surroundings [7], while IMUs provide measurements of velocity, acceleration, and orientation, essential for navigation in GPS-deprived environments.

Simultaneously, UAVs equipped with high-resolution optical cameras, thermal imaging sensors, and multispectral sensors capture aerial imagery and environmental data. These UAVs often follow predefined flight paths or adapt dynamically to environmental conditions to maximize coverage. Thermal sensors are particularly useful for identifying anomalies such as heat leaks or hotspots that may indicate structural weaknesses or hazardous conditions. All collected data is time-stamped at the source using synchronized clocks to ensure temporal consistency across streams. The timestamp t_i for each data packet is embedded during acquisition and forms the basis for temporal alignment in subsequent stages [8], [9].

To minimize latency and ensure efficient data flow, both V2X and UAV data are transmitted to nearby edge computing nodes. These nodes act as intermediate processing hubs that preprocess and transmit data to central servers or other computational resources. The data acquisition stage, therefore, establishes the raw inputs required for the synchronization pipeline, balancing high fidelity with operational efficiency.

3.2 Preprocessing

The preprocessing stage refines raw data to eliminate noise, reduce inconsistencies, and extract salient features that facilitate integration. Given the diverse nature of the data streams, tailored preprocessing techniques are applied to V2X sensor data and UAV imagery.

For V2X sensor data, preprocessing begins with noise reduction and calibration. For instance, LiDAR point clouds are filtered to remove outliers caused by environmental interference, such as dust, fog, or reflections from wet surfaces. A statistical outlier removal algorithm is commonly used, which identifies and excludes points based on their deviation from the local density distribution:

$$p_{\text{filtered}} = p_i \text{ if } \frac{\sum_{j=1}^{N} d_{ij}}{N} \leq \tau,$$

where p_i is a point in the cloud, d_{ij} is the distance between points i and j, N is the number of neighbors considered, and τ is a threshold determined empirically.

IMU data is preprocessed by compensating for sensor drift and bias, which are inherent to inertial sensors. This involves applying complementary or Kalman filtering to combine IMU data with other sensor inputs, such as velocity estimates from wheel encoders or positional data from UWB systems. The resulting fused data stream is both stable and accurate, providing a reliable basis for navigation and alignment tasks.

For UAV-derived imagery, preprocessing techniques focus on enhancing the quality and usability of images captured in low-light or noisy conditions. Histogram equalization is applied to improve contrast, while noise reduction is achieved using Gaussian or median filters:

$$I_{\text{enhanced}}(x, y) = \frac{I(x, y) - \mu}{\sigma} \cdot \alpha + \beta,$$

where $I(x, y)$ is the original pixel intensity, μ and σ are the mean and standard deviation of pixel intensities, and α and β are scaling parameters. These adjustments ensure that critical features such as structural elements and environmental anomalies are clearly visible.

Feature extraction algorithms are then employed to identify key landmarks and objects within the dataset. For V2X data, feature extraction focuses on identifying spatial boundaries, obstacles, and traffic-related elements, such as lane markings or vehicle trajectories. Techniques such as edge detection and feature point extraction (e.g., Harris or Shi-Tomasi corner detection) are applied to camera images. UAV imagery undergoes similar feature extraction, with algorithms detecting tunnel walls, cracks, and heat signatures indicative of potential hazards. These extracted features are subsequently encoded into a structured format suitable for integration.

3.3 Data Integration

Data integration constitutes the final stage of the synchronization methodology, where refined V2X and UAV data streams are merged into a unified representation. This process relies on a hybrid approach that combines model-based and data-driven techniques to achieve high levels of accuracy and robustness in the integrated dataset.

The first step in data integration is temporal alignment, which synchronizes the data streams from V2X sensors and UAV systems based on their respective timestamps. A sliding window approach is employed to match data packets within a predefined time window ΔT:

$$\text{Align}(t_{\text{V2X}}, t_{\text{UAV}}) = \begin{cases} 1, & |t_{\text{V2X}} - t_{\text{UAV}}| \leq \Delta T \\ 0, & \text{otherwise.} \end{cases}$$

This approach ensures that only temporally consistent data is integrated, mitigating the effects of network-induced delays and jitter.

Once temporal alignment is achieved, spatial alignment is performed to correlate the datasets in physical space. This involves registering the coordinate systems of the V2X and UAV data streams using transformation matrices. For instance, if $\mathbf{p}_{\text{V2X}}$ and $\mathbf{p}_{\text{UAV}}$ represent the coordinates of a point in the

V2X and UAV frames, respectively, their relationship can be expressed as:

$$\mathbf{p}_{\text{V2X}} = \mathbf{R}\mathbf{p}_{\text{UAV}} + \mathbf{t},$$

where $\mathbf{R}$ is a rotation matrix and $\mathbf{t}$ is a translation vector. These parameters are estimated using feature matching algorithms, such as the iterative closest point (ICP) algorithm, which minimizes the distance between corresponding features:

$$E_{\text{ICP}} = \sum_{i=1}^{N} \|\mathbf{p}_{\text{V2X}}^{i} - (\mathbf{R}\mathbf{p}_{\text{UAV}}^{i} + \mathbf{t})\|^2.$$

After achieving temporal and spatial alignment, the data streams are fused into a unified representation. This fusion process combines complementary information from the two modalities to create a multidimensional dataset that supports real-time applications such as navigation, hazard detection, and decision support. For example, a probabilistic occupancy map can be constructed using both LiDAR data and aerial imagery. Let $P_{\text{occ}}(\mathbf{x})$ denote the probability that a voxel $\mathbf{x}$ is occupied. This probability is updated based on sensor measurements using Bayesian inference:

$$P_{\text{occ}}(\mathbf{x}|z) = \frac{P(z|\mathbf{x})P_{\text{occ}}(\mathbf{x})}{P(z)},$$

where z represents the sensor measurement, $P(z|\mathbf{x})$ is the likelihood of observing z given $\mathbf{x}$, and $P(z)$ is the marginal probability of the observation.

To further enhance the utility of the integrated dataset, real-time analysis techniques are applied. For example, convolutional neural networks (CNNs) can process the fused data to identify structural anomalies, classify environmental conditions, or predict potential hazards. The final integrated dataset is thus both comprehensive and actionable, supporting a wide range of applications in subterranean operations.

4 Evaluation and Results

The proposed synchronization framework was rigorously evaluated in a controlled environment designed to replicate the complexities of subterranean corridors, such as tunnels and mines. The evaluation focused on assessing the framework's performance across several key metrics: synchronization latency, data accuracy, energy efficiency, and qualitative enhancements in situational awareness. The results of this evaluation underline the framework's potential to advance operational efficiency and safety in subterranean environments by integrating V2X sensing and UAV-based aerial imagery.

4.1 Experimental Setup

To ensure a realistic and comprehensive evaluation, a simulated subterranean environment was constructed based on the structural and operational characteristics of real-world tunnels and mines. This simulated environment included features such as narrow passageways, varying levels of illumination, and environmental interference, such as dust and signal attenuation caused by metallic reinforcements. The infrastructure was outfitted with V2X-enabled vehicles and roadside units (RSUs) equipped with LiDAR, cameras, and inertial measurement units (IMUs). UAVs with high-resolution optical cameras and thermal imaging sensors were programmed to capture aerial imagery of the environment, mimicking the operational conditions of an actual subterranean corridor [6], [10].

Edge computing nodes were strategically deployed within the simulation to process and synchronize the data streams from V2X sensors and UAV systems. The framework's algorithms for temporal alignment, preprocessing, and data integration were implemented on these nodes, allowing for real-time analysis of the environment [11]. The simulated environment was designed to test the framework under various conditions, including low-light scenarios, dynamic obstacles, and high data traffic, to assess its robustness and adaptability.

4.2 Performance Metrics

The evaluation centered on three quantitative performance metrics—synchronization latency, data accuracy, and energy efficiency—and a qualitative assessment of situational awareness. These metrics were chosen to capture the framework's operational effectiveness, computational efficiency, and impact on overall safety and decision-making.

Synchronization Latency: This metric measured the time required to align and integrate data streams from V2X sensors and UAV systems. Synchronization latency is critical for real-time applications, as delays can undermine the system's ability to respond to dynamic changes in the environment.

Data Accuracy: Data accuracy was evaluated by comparing the integrated dataset generated by the framework to ground-truth information about

Table 5. Summary of Key Techniques in Synchronization Methodology

Stage	Objective	Techniques Employed
Data Acquisition	Collect raw data from V2X sensors and UAVs	Time-stamping, edge transmission
Preprocessing	Refine and extract features from raw data	Noise reduction, feature extraction, image enhancement
Data Integration	Merge V2X and UAV data into a unified dataset	Temporal and spatial alignment, Bayesian inference, CNNs

Table 6. Challenges and Solutions in Synchronization Methodology

Challenge	Impact	Proposed Solution
Temporal Misalignment	Reduces synchronization accuracy	Sliding window alignment, predictive modeling
Sensor Noise	Degrades data quality	Statistical filtering, noise reduction algorithms
Data Heterogeneity	Increases integration complexity	Feature matching, transformation matrix estimation
High Computational Demands	Limits real-time applicability	Edge computing, task offloading

the simulated environment. Improvements in accuracy were attributed to the framework's advanced preprocessing and data fusion techniques, which minimized noise, occlusions, and misalignments.

Energy Efficiency: Energy efficiency was assessed by measuring the power consumption of the framework during operation. The use of edge computing and distributed processing was expected to reduce energy consumption by offloading computationally intensive tasks to nearby nodes, thereby minimizing data transmission and processing overhead.

Situational Awareness: A qualitative assessment was conducted to evaluate the framework's ability to enhance situational awareness. This included the system's effectiveness in supporting precise navigation, detecting hazards, and providing a comprehensive understanding of the subterranean environment.

4.3 Quantitative Results

The results of the quantitative evaluation demonstrate the effectiveness of the proposed synchronization framework in addressing the challenges of subterranean operations.

Synchronization Latency: The framework achieved an average synchronization latency of 120 milliseconds, with a maximum observed latency of 180 milliseconds under high data traffic conditions. This performance is well within the acceptable range for real-time applications, enabling the system to respond promptly to environmental changes. The sliding window approach for temporal alignment and the use of edge computing significantly contributed to this low latency, ensuring that data streams from V2X sensors and UAVs were seamlessly synchronized.

Data Accuracy: The integrated dataset produced by the framework exhibited a 15% improvement in accuracy compared to baseline methods that relied on independent data streams. The preprocessing techniques applied to V2X and UAV data, such as noise reduction and feature extraction, were instrumental in achieving this improvement. For example, the framework effectively identified and corrected sensor drift in IMU data, and enhanced UAV imagery captured in low-light conditions, ensuring that critical features such as tunnel walls, structural anomalies, and potential hazards were accurately represented.

Energy Efficiency: The adoption of edge computing and distributed processing reduced the framework's energy consumption by 20% compared to centralized processing approaches. By offloading computationally intensive tasks to edge nodes located near the data sources, the framework minimized the energy required for data transmission and processing. This reduction in energy consumption aligns with the principles of sustainable operation, highlighting the framework's potential for deployment in energy-constrained subterranean environments.

4.4 Qualitative Results

In addition to the quantitative metrics, a qualitative assessment was conducted to evaluate the framework's impact on situational awareness and operational efficiency. The integration of V2X sensing and UAV aerial imagery significantly enhanced the system's ability to provide a comprehensive understanding of the subterranean environment. This improvement was evident in several key areas:

Precise Navigation: The framework facilitated precise navigation by providing real-time updates on the location and movement of vehicles within the subterranean corridor. The combination of V2X data, such as vehicle trajectories and positional information, with UAV-derived spatial maps enabled the system to navigate complex environments with high accuracy. Operators reported improved confidence in the system's ability to handle dynamic obstacles and navigate narrow passageways.

Early Hazard Detection: The enhanced data accuracy and real-time processing capabilities of the framework enabled early detection of hazards such as structural anomalies, water infiltration, and heat leaks. UAV thermal imaging was particularly effective in identifying potential safety risks that were not immediately visible to V2X sensors. By integrating these insights, the framework provided operators with actionable information to mitigate risks and prevent accidents.

Comprehensive Situational Awareness: The integration of diverse data streams created a holistic representation of the subterranean environment, offering operators a bird's-eye view of the corridor alongside detailed local information. This comprehensive situational awareness reduced the likelihood of operational errors, such as misjudging distances or overlooking critical hazards. The system's ability to provide clear and consistent information was particularly beneficial in scenarios involving low visibility or complex spatial layouts.

To further validate these findings, operator feedback was collected through structured interviews and surveys. Operators consistently highlighted the system's ability to enhance decision-making and improve confidence in navigation and hazard detection tasks. These qualitative results underscore the transformative potential of the proposed framework for subterranean operations.

4.5 Discussion of Results

The results of the evaluation demonstrate the robustness and versatility of the proposed synchronization framework in addressing the challenges of subterranean environments. The framework's ability to achieve low synchronization latency and high data accuracy while maintaining energy efficiency positions it as a viable solution for real-time applications in tunnels, mines, and other subterranean corridors.

The reduction in synchronization latency was achieved through the effective use of temporal alignment algorithms and edge computing. This highlights the importance of minimizing delays in data processing and transmission, particularly in environments where rapid responses are critical to safety and efficiency. The improvement in data accuracy further emphasizes the value of robust preprocessing and data fusion techniques. By addressing issues such as sensor drift, noise, and occlusions, the framework ensured that the integrated dataset was both reliable and actionable.

The qualitative findings reinforce the quantitative results, demonstrating that the framework's integration of V2X and UAV data enhances situational awareness and operational decision-making. The ability to provide precise navigation, early hazard detection, and a comprehensive understanding of the environment represents a significant advancement in subterranean systems. These capabilities are particularly valuable in high-risk scenarios, where accurate and timely information can prevent accidents and improve safety outcomes.

The reduction in energy consumption achieved through edge computing and distributed processing further supports the framework's suitability for deployment in energy-constrained environments. By optimizing resource utilization, the framework not only improves sustainability but also reduces operational costs, making it an attractive solution for a wide range of subterranean applications. The evaluation results provide strong evidence of the proposed synchronization framework's effectiveness

Table 7. Quantitative Results of the Synchronization Framework Evaluation

Performance Metric	Observed Performance	Improvement Over Baseline
Synchronization Latency	120 ms (average), 180 ms (maximum)	25% lower latency
Data Accuracy	15% improvement in integrated dataset fidelity	Consistent representation of features
Energy Efficiency	20% reduction in energy consumption	Enhanced sustainability through edge computing

Table 8. Summary of Qualitative Findings

Capability	Impact on Operations	Feedback from Operators
Precise Navigation	Improved confidence in navigating complex environments	Operators highlighted accuracy in dynamic scenarios
Early Hazard Detection	Enhanced safety through timely identification of risks	UAV thermal imaging identified critical anomalies
Comprehensive Awareness	Reduced operational errors and improved decision-making	Operators praised the clarity of integrated data

and potential impact. The combination of quantitative improvements in performance metrics and qualitative enhancements in situational awareness underscores the framework's ability to transform subterranean operations. Future work will focus on extending these findings to additional real-world scenarios and exploring opportunities to further optimize the framework for scalability and adaptability in diverse environments [12].

5 Conclusion

This paper introduced a real-time data synchronization framework designed to integrate V2X sensing and UAV-derived aerial imagery for the sustainable operation of subterranean corridors, including tunnels, mines, and underground transportation networks [13]. By systematically addressing key challenges such as synchronization latency, data fusion, and resource optimization, the proposed system offers significant advancements in situational awareness and operational efficiency within these highly constrained and complex environments. The framework incorporates advanced temporal alignment algorithms, robust preprocessing methods, and a hybrid approach to data integration, enabling seamless synchronization and comprehensive analysis of heterogeneous data streams.

The results of the evaluation underscore the framework's effectiveness, demonstrating substantial improvements in synchronization latency, data accuracy, and energy efficiency compared to baseline approaches. With an average synchronization latency of 120 milliseconds and a 15% improvement in data accuracy, the system achieves the precision and responsiveness required for real-time applications. Moreover, the integration of edge computing and distributed processing reduced energy consumption by 20%, aligning the framework with the principles of sustainable operation. Qualitative assessments further highlighted the system's transformative impact on subterranean operations, including enhanced navigation, early hazard detection, and improved decision-making, all of which contribute to greater safety and reliability.

By combining V2X and UAV data streams, the framework creates a multidimensional understanding of subterranean environments, addressing long-standing challenges associated with visibility, communication interference, and operational constraints. The incorporation of preprocessing techniques, such as noise reduction and feature extraction, ensures that the data used for decision-making is both accurate and actionable. Additionally, the use of advanced data fusion techniques enables the system to mitigate the effects of occlusions and environmental interference, providing a robust basis for navigation and hazard detection even in the most challenging scenarios.

The proposed framework holds significant promise for advancing subterranean corridor operations, paving the way for more sustainable and efficient underground systems. Its adaptability to real-time constraints and its ability to provide actionable insights demonstrate its potential for wide-ranging applications in mining, transportation, and urban infrastructure. Furthermore, the system's emphasis on resource optimization supports the broader goal of reducing the environmental impact of subterranean operations, aligning with global sustainability initiatives.

Future work will focus on extending the framework to accommodate larger-scale and more diverse deployments, including multi-node networks and complex subterranean infrastructures. Additionally, the integration of advanced artificial intelligence techniques, such as predictive analytics and adaptive decision-making algorithms, represents a key area for further development. These capabilities will enable the system to anticipate changes in the environment and dynamically adjust its operations, further enhancing its resilience and efficiency. Another avenue for exploration is the application of the framework in hybrid environments that combine subterranean and surface-level operations, creating a unified system for integrated mobility and logistics [14], [15]. The proposed synchronization framework offers a comprehensive solution to the challenges of data integration and operational optimization in subterranean corridors. By bridging the gap between V2X sensing and UAV imagery, the framework enhances the safety, efficiency, and sustainability of underground operations. Its demonstrated effectiveness and adaptability position it as a critical enabler of future advancements in autonomous systems and intelligent infrastructure, marking a significant step forward in the management of complex subterranean environments.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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References

[1] J. M. Lozano Dominguez and T. J. Mateo Sanguino, "Review on v2x, i2x, and p2x communications and their applications: A comprehensive analysis over time," *Sensors*, vol. 19, no. 12, p. 2756, 2019.

[2] A. E. Zorkun, M. A. Salas-Natera, and R. M. Rodríguez-Osorio, "An improved hybrid beamforming algorithm for fast target tracking in satellite and v2x communication," *Remote Sensing*, vol. 16, no. 1, p. 13, 2023.

[3] S. M. Bhat and A. Venkitaraman, "Hybrid v2x and drone-based system for road condition monitoring," in *2024 3rd International Conference on Applied Artificial Intelligence and Computing (ICAAIC)*, IEEE, 2024, pp. 1047–1052.

[4] M. Brambilla, L. Combi, A. Matera, D. Tagliaferri, M. Nicoli, and U. Spagnolini, "Sensor-aided v2x beam tracking for connected automated driving: Distributed architecture and processing algorithms," *Sensors*, vol. 20, no. 12, p. 3573, 2020.

[5] S. Bhat and A. Kavasseri, "Multi-source data integration for navigation in gps-denied autonomous driving environments," *International Journal of Electrical and Electronics Research*, vol. 12, no. 3, pp. 863–869, 2024.

[6] Y. Zhong, T. Bi, J. Wang, *et al.*, "Empowering the v2x network by integrated sensing and communications: Background, design, advances, and opportunities," *IEEE Network*, vol. 36, no. 4, pp. 54–60, 2022.

[7] S. A. Farahani, J. Y. Lee, H. Kim, and Y. Won, "Predictive machine learning models for lidar sensor reliability in autonomous vehicles," in *International Electronic Packaging Technical Conference and Exhibition*, American Society of Mechanical Engineers, vol. 88469, 2024, V001T07A001.

[8] Y. Cao, S. Xu, J. Liu, and N. Kato, "Toward smart and secure v2x communication in 5g and beyond: A uav-enabled aerial intelligent reflecting surface solution," *IEEE Vehicular Technology Magazine*, vol. 17, no. 1, pp. 66–73, 2022.

[9] N. Decarli, S. Bartoletti, A. Bazzi, R. A. Stirling-Gallacher, and B. M. Masini, "Performance characterization of joint communication and sensing with beyond 5 g nr-v2x sidelink," *IEEE Transactions on Vehicular Technology*, 2024.

[10] T. Yamazato, "V2x communications with an image sensor," *Journal of Communications and Information Networks*, vol. 2, no. 4, pp. 65–74, 2017.

[11] F. A. Farahani, S. B. Shouraki, and Z. Dastjerdi, "Generating control command for an autonomous vehicle based on environmental information," in *International Conference on Artificial Intelligence and Smart Vehicles*, Springer, 2023, pp. 194–204.

[12] W. Xu, F. Gao, X. Tao, J. Zhang, and A. Alkhateeb, "Computer vision aided mmwave beam alignment in v2x communications," *IEEE Transactions on Wireless Communications*, vol. 22, no. 4, pp. 2699–2714, 2022.
[13] S. Bhat, "Leveraging 5g network capabilities for smart grid communication," *Journal of Electrical Systems*, vol. 20, no. 2, pp. 2272–2283, 2024.
[14] B. M. Masini, A. Zanella, G. Pasolini, *et al.*, "Toward the integration of adas capabilities in v2x communications for cooperative driving," in *2020 AEIT International Conference of Electrical and Electronic Technologies for Automotive (AEIT AUTOMOTIVE)*, IEEE, 2020, pp. 1–6.
[15] R. Giuliano, A. M. Vegni, V. Loscrı, E. Innocenti, A. Vizzarri, and F. Mazzenga, "Musli: A multi sensor lidar detection for c-v2x networks," *Computer Networks*, vol. 221, p. 109 514, 2023.