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ACCURATE REAL-TIME TRACKING IN GEOLOGY: A DATA-DRIVEN APPROACH

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Annotation. Accurately tracking the position of machinery like tunnel borers or robots in underground environments is a major challenge. Standard GPS fails in these settings, and sensor systems like inertial navigation units accumulate large positioning errors over time. This paper presents a novel, data-driven solution to this problem. The core of our system is a powerful data processing framework that fuses these vast, real-time sensor datasets. Using a machine learning model, we correct the drift in the motion sensors, enabling highly accurate, real-time geological positioning.

Keywords: Real-Time Tracking, Geological Monitoring, Data-Driven System, Machine Learning, Big Data.

GEOLOGIYADA ANIQ REAL VAQT REJIMIDA KUZATISH: MA'LUMOTLARGA ASOSLANGAN YONDASHUV

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Annotatsiya. Yer osti muhitida tunnel qazuvchilar yoki robotlar kabi mashinalarning holatini aniq kuzatish katta qiyinchilik tug'diradi. Standart GPS bu muhitlarda ishlamay qoladi va inertsial navigatsiya qurilmalari kabi sensor tizimlari esa vaqt o'tishi bilan joylashish xatolarini to'playdi. Maqolada ushbu muammoga “Big Data”ga asoslangan yechim taqdim etiladi. Bizning tizimimizning yadrosi bu ulkan, real vaqtda sensor ma'lumotlar to'plamlarini birlashtirgan kuchli ma'lumotlarni qayta ishlash tizimidir. Mashinali o'qitish (Machine learning) modelidan foydalanib, biz harakat sensorlaridagi siljishni to'g'irlaymiz va bu juda aniq, real vaqtda geologik joylashishni aniqlash imkonini beradi.

Kalit so’zlar: Real vaqt rejimida kuzatish, geologik monitoring, ma'lumotlarga asoslangan tizim, mashinali oqitish, Big Data.

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1. Introduction

The development of high-precision monitoring systems for tracking moving objects within a geological context generates massive, multi-modal data streams from sensors like inertial measurement units (IMUs) and fiber-optic networks. The primary challenge is no longer data acquisition but the real-time processing and fusion of this Big Data to achieve accurate, drift-free positioning. This capability is critical for enhancing safety and operational efficiency in high-risk industries such as underground mining and tunnel construction, where traditional positioning systems are inadequate [1].

This paper presents an integrated solution combining a robust Big Data pipeline with a sophisticated mathematical model for sensor fusion. We focus on the specific problem of using a static fiber-optic sensor (FOS) network as a geological reference to correct the cumulative drift of a moving IMU, formulating the solution within a Kalman Filter framework augmented by machine learning. Our approach addresses the fundamental limitation of inertial navigation in GNSS-denied environments by creating a data-driven correction loop that learns and compensates for sensor drift in real-time.

2. Methods

Precise navigation without GPS remains a significant challenge. Traditional methods rely on Inertial Navigation Systems (INS), but their positional error grows cubically over time due to sensor drift, making them unsuitable for long-term use. While Zero-Velocity Updates (ZUPTs) can correct drift in foot-mounted systems, they are ineffective for continuously moving vehicles. Alternative solutions like Ultra-Wideband (UWB) require pre-installed infrastructure and offer limited range in complex geology. Fiber-Optic Sensing (FOS) is well-established for monitoring static structures like pipelines but has not been used for dynamic positioning of moving objects. This work's novelty lies in using a FOS network as a dynamic "geological reference frame" to continuously calibrate a moving INS. Furthermore, while Machine Learning (ML) models like LSTMs can model sensor errors, they often lack physical constraints. Our hybrid approach integrates an LSTM within a Kalman filter framework, combining data-driven adaptation with physical model stability [2].

The methodology integrates a distributed computing architecture with a state-space mathematical model.

The system employs a streamlined pipeline: Sensor Data → Apache Kafka (Ingestion) → Apache Spark (Processing) → Data Store. Kafka topics buffer high-velocity data streams from the IMU and FOS, providing resilience against back-pressure. Spark executes two primary jobs: a streaming job for real-time fusion and a batch job for model re-training and long-term trend analysis.

The fusion of IMU and FOS data is formulated as a Bayesian estimation problem. The state vector $\mathbf{x}_t$ represents the system's true condition at time t:

$$\mathbf{x}_t = [p_t, v_t, a_t, b_t]^T$$

The state transition is governed by:

$$\mathbf{x}_t = \mathbf{F}_t\mathbf{x}_{t-1} + \mathbf{B}_t\mathbf{u}_t + \mathbf{w}_t, \mathbf{w}_t \sim \mathcal{N}(0, \mathbf{Q}_t)$$

where $\mathbf{F}_t$ is derived from kinematic equations, and $\mathbf{w}_t$ is process noise. The IMU provides a direct but noisy measurement of acceleration and angular velocity, while the FOS network provides an indirect measurement of position by detecting strain $\mathbf{s}_t$ correlated with the object's proximity [3]. The measurement model is:

$$\mathbf{z}_t = \mathbf{H}\mathbf{x}_t + \mathbf{v}_t, \mathbf{v}_t \sim \mathcal{N}(0, \mathbf{R}_t)$$

A standard Kalman Filter would struggle with the non-linear relationship between strain $\mathbf{s}_t$ and position p_t. Therefore, we employ an LSTM network, $\mathcal{L}$, to learn this mapping and predict the critical bias and noise parameters:

$$[\hat{b}_t, \widehat{\mathbf{w}}_t] = \mathcal{L}(\mathbf{s}_{t-n:t}, \mathbf{z}_{t-n:t})$$

These predictions are then fed back into the Kalman Filter equations, leading to a more accurate prediction and update cycle:

$$\hat{\mathbf{x}}_{t|t-1} = \mathbf{F}_t \hat{\mathbf{x}}_{t-1|t-1} + \mathbf{B}_t \mathbf{u}_t + \widehat{\mathbf{w}}_t$$
$$\mathbf{P}_{t|t-1} = \mathbf{F}_t \mathbf{P}_{t-1|t-1} \mathbf{F}_t^T + \mathbf{Q}_t$$

This hybrid model leverages the sequential learning capability of the LSTM to model complex drift and the probabilistic framework of the Kalman Filter for optimal state estimation [2].

3. Results and Discussion

A simulation was conducted to evaluate the framework's performance. A moving object's trajectory was simulated within a 100m x 100m area instrumented with a virtual FOS grid. The IMU data was simulated with significant bias and Gaussian noise. The results, summarized in Table 1, show a dramatic improvement.

Table 1. Positioning Error (RMSE)

System Configuration	RMSE (m)
IMU Only (30s)	4.82
Proposed Fusion Framework	0.51

The key result is the 90% reduction in Root Mean Square Error (RMSE), defined as $\sqrt{\frac{1}{N}\sum_{i=1}^{N} (p_{true,i} - p_{estimated,i})^2}$. This demonstrates that the LSTM-enhanced Kalman Filter successfully used the FOS data to learn and correct the IMU's drift. The discussion centers on the synergy between the Big Data pipeline and the mathematical model; the pipeline ensures the continuous flow of data necessary for the LSTM's real-time inference, while the model provides the algorithmic intelligence that transforms this data into a high-precision output. The main limitation is the computational cost of the LSTM, which necessitates powerful GPUs within the Spark cluster for real-time operation [4].

The success of the LSTM in this context suggests that the drift patterns in IMUs are not entirely random but contain learnable signatures that are correlated with the geological strain field. This opens up new possibilities for using data-driven models to correct systemic errors in physical sensor systems [5]. The ability to maintain sub-meter accuracy in real-time could transform safety protocols in underground mining by providing reliable location data for personnel and equipment, potentially preventing accidents.

Raw sensor data requires significant cleaning and transformation. IMU data undergoes low-pass filtering to remove high-frequency noise, followed by static bias removal and gravity compensation. FOS data is processed to convert raw strain ε(x, t) into a usable form. This involves spatial filtering to isolate the strain "footprint" of the moving object and feature extraction to create a concise input vector for the ML model. The key features extracted are the Centroid Location (the mean position of the strain peak), Peak Amplitude (correlated with proximity), and Spatial Variance (the width of the peak). This curated feature set drastically reduces model complexity compared to using raw data [5].

The designed LSTM network is central to the drift correction. Its input is a sliding window of 50 time steps, containing preprocessed IMU data and the extracted FOS features. The architecture consists of two LSTM layers (128 and 64 units) with dropout for regularization, followed by a dense output layer that predicts the bias and non-linear noise components [b̂_t, ŵ_t] for the Kalman filter. The model was trained on a large, simulated dataset of over 100 hours of varied movement patterns. The training used Mean Squared Error (MSE) as the loss function and the Adam optimizer, allowing the network to learn the complex relationship between the FOS strain patterns and the IMU's inherent drift [6].

4. Conclusion

This research has demonstrated a data-driven framework for high-precision geological positioning in GPS-denied environments. The system fuses a static Fiber-Optic Sensor network with a moving inertial unit through a hybrid LSTM-enhanced Kalman filter, all supported by a robust Big Data pipeline. This approach directly tackles the fundamental issue of INS drift, achieving a 90% accuracy improvement in simulation [4]. This represents a significant advance for safety and automation in underground industries. While challenges regarding deployment cost and computational load remain, this work establishes a viable and powerful paradigm for the future of subsurface navigation.

5. Limitations and Future Work

The proposed system has limitations that guide future research. Its accuracy depends on a pre-deployed FOS network, making initial setup in new areas costly. Future work will investigate sparse or mobile FOS deployment. The computational load of the LSTM is high, necessitating the development of lighter, quantized models for embedded hardware. The current model was validated in a homogeneous medium; testing in complex, real-world geology with varying strata is essential. Finally, extending the system from single-object to multi-object tracking by deciphering overlapping strain patterns on the FOS network is a critical next step.

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