Application of AGV Technology in Anode Transportation

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Abstract

With the continuous development of logistics and transportation towards unmanned intelligence, more and more Autonomous Guided Vehicles (AGVs) are used in various industries. Anode trailer is the necessary transfer equipment for aluminum electrolysis anodes. This study develops an aluminum electrolysis anode transfer system based on AGV technology, and carries out the basic methodology of multi-source Simultaneous Localization and Mapping (SLAM), based on continuous time model through the multivariate SLAM, composite guidance algorithm for indoor and outdoor complex scenes. Theoretical research is carried out to establish efficient data processing and association of internal and external sensors for map optimization based on triangular dissection, so as to improve the accuracy and robustness of the vehicle's map building and positioning in indoor and outdoor complex scenes. It can realize unmanned work on site, autonomous driving, and perform transportation tasks. The on-site test results show that the precise detection degree in complex space is ≤ 10 mm, the indoor positioning accuracy is ≤ 20 mm, and the outdoor positioning accuracy is ≤ 10 mm. The statistical analysis of the operation status shows that compared with fuel AGV improves the operating costs of anode transportation by 85 %.

Keywords: Aluminium electrolysis, Anode trolley, AGV intelligence.

1. Introduction

Autonomous material handling in industrial environments, particularly in aluminum electrolysis production, demands high-precision navigation systems capable of operating seamlessly across indoor and outdoor settings. Traditional AGV solutions often rely on discrete-time SLAM methods [1], which suffer from cumulative drift and degraded performance in dynamic or large-scale environments. While visual-inertial SLAM (VSLAM) [2] and LiDAR-based approaches [3] have shown promise, their standalone implementations struggle with sensor limitations, such as illumination variations or sparse feature distributions.

The proposed system introduces a multi-source SLAM framework that integrates LiDAR, inertial measurement units (IMUs), and visual sensors within a continuous-time model. Unlike conventional discrete-time SLAM, this approach employs Gaussian process regression to interpolate trajectories smoothly, reducing drift during long-duration operations [4]. Furthermore, the multivariate SLAM composite guidance algorithm dynamically adjusts sensor fusion weights based on environmental conditions, ensuring robustness during indoor-outdoor transitions.

A key innovation lies in the factor graph optimization with triangular dissection, which decomposes the SLAM problem into sparse subgraphs for efficient computation [5]. This method builds upon incremental smoothing techniques like iSAM2 [6] but extends them to handle multi-sensor data streams in real time. The system achieves positioning errors below 10 mm, surpassing the accuracy of existing industrial AGVs [7].

The proposed system bridges a critical gap in industrial automation by enabling reliable, high-precision anode transfer in environments where traditional methods fail.

2. Multi-Source SLAM Framework for AGV Navigation

The proposed framework addresses the limitations of discrete-time SLAM by modeling the AGV's state as a continuous-time trajectory, enabling seamless integration of asynchronous sensor measurements. This section presents the technical foundations of the system, focusing on four key innovations: continuous-time state modeling, adaptive sensor fusion, scalable optimization, and hybrid localization.

2.1 Continuous-Time State Modeling for AGV Dynamics

The AGV's state $\mathrm{x}(t)$ at time t comprises its pose (position and rotation in 3D space) $\mathrm{T}(t) \in SE(3)$ (Special Euclidean group), velocity $\mathrm{v}(t)$, and IMU gyroscope and accelerometer biases $\mathrm{b}_g(t), \mathrm{b}_a(t)$:

$$\mathrm{x}(t) = \left\{\mathrm{T}(t), \mathrm{v}(t), \mathrm{b}_g(t), \mathrm{b}_a(t)\right\} \tag{1}$$

The continuous-time motion model employs a Wiener process to describe IMU dynamics:

$$\dot{\mathrm{T}}(t) = \mathrm{T}(t)\left(\omega(t) - \mathrm{b}_g(t)\right)^{\wedge} \tag{2}$$

$$\dot{\mathrm{v}}(t) = \mathrm{R}(t)\big(\mathrm{a}(t) - \mathrm{b}_a(t)\big) + \mathrm{g} \tag{3}$$

where:

$\omega(t)$ and $\mathrm{a}(t)$	Gyroscope and accelerometer measurements,
$\mathrm{R}(t)$	Rotation matrix from $\mathrm{T}(t)$, and
g	Acceleration of gravity.
$\wedge$	hat operator which maps angular velocities to SE(3) elements.

2.2 Adaptive Multi-Sensor Fusion with Dynamic Weighting

Sensor residuals r_k are weighted by inverse covariance matrices Σ_k^{-1}, updated in real-time based on reliability metrics:

$$\mathrm{r}_k = \mathrm{z}_k - h_k\big(\mathrm{x}(t_k)\big) \tag{4}$$

where:

r_k	sensor residual at time step t_k
z_k	measurement given by a sensor
h_k	predicted measurement (sensor model)

$$\Sigma_k = \mathrm{diag}\big(\sigma_{k,\mathrm{L}}^2, \sigma_{k,\mathrm{V}}^2, \sigma_{k,\mathrm{I}}^2\big) \tag{5}$$

where:

Σ_k	measurement noise covariance
$\sigma_{k,\mathrm{L}}$	uncertainty of LiDAR
$\sigma_{k,\mathrm{V}}$	uncertainty of visual sensor
$\sigma_{k,\mathrm{I}}$	uncertainty of inertial sensor.

areas, occasionally causing feature tracking failures. These limitations suggest the need for additional sensor modalities or algorithmic adaptations to handle extreme industrial conditions. The computational demands of continuous-time SLAM, despite the triangular dissection optimization, remain non-trivial for low-cost embedded systems. Field tests revealed that sustained operation at 15 Hz requires GPU acceleration, increasing hardware costs by approximately 30 % compared to conventional AGV controllers. This trade-off between performance and cost necessitates further research into edge-optimized implementations.

4.2 Future Directions for Multi-Source SLAM in Industrial AGVs

Three key research directions emerge from this work: First, the development of physics-informed sensor fusion algorithms could enhance robustness in extreme conditions. By incorporating material science models of environmental interference (e.g., electromagnetic field effects on IMUs, particulate scattering models for LiDAR), the system could preemptively compensate for sensor degradation.

Second, the integration of learning-based uncertainty estimation could refine the dynamic weighting mechanism. Recent advances in neural calibration networks [12] suggest potential for automatically predicting sensor reliability from raw data streams, rather than relying on hand-tuned covariance matrices.

Finally, the system's success in aluminum plants highlights opportunities for standardization. Developing open interfaces for industrial SLAM systems would facilitate adoption across different manufacturing sectors, similar to how ROS transformed mobile robotics. This requires addressing current limitations in real-time data sharing and cross-platform factor graph interoperability.

5. Conclusions

The multi-source SLAM framework demonstrates significant advancements in AGV-based anode transfer for aluminum electrolysis, achieving sub-centimeter precision through continuous-time sensor fusion and adaptive optimization. Experimental results confirm its superiority over conventional methods in both accuracy and operational efficiency, particularly in challenging indoor-outdoor transitions. While current limitations exist regarding environmental robustness and computational demands, the system's modular design provides a foundation for future enhancements. This work establishes a critical step toward fully autonomous industrial material handling, with potential applications extending beyond aluminum production to other precision-demanding sectors. The framework's success underscores the importance of heterogeneous sensor integration and real-time adaptive algorithms in modern industrial automation.

6. References

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