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To cite this article: Yuanxing Fang *et al* 2025 *J. Phys.: Conf. Ser.* **3169** 012043

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An aeromagnetic compensation method based on the extended Tolles Lawson model

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Abstract. Aeromagnetic survey is widely applied in mineral exploration, shipwreck salvage, and unexploded ordnance detection. To maintain optimal system detection performance, it is essential to compensate for magnetic interference originating from the airborne platform and external environments. The conventional TLG compensation model can only suppress platform-induced dynamic magnetic interference and geomagnetic gradient interference, but fails to account for magnetic interference caused by geological anomalies within the survey area, which limits further improvements in system performance. To address this limitation, this paper proposes a magnetic interference compensation method specifically designed for airborne detection in regions with complex geological magnetic anomalies. First, a high-precision spatial reconstruction of the geological magnetic anomaly distribution is achieved using an ensemble machine learning-based spatial field reconstruction approach. Subsequently, the conventional TLG compensation model is extended by incorporating the reconstructed anomaly distribution, resulting in a novel TLGF compensation model. Finally, by utilizing the platform's positional information in conjunction with the TLGF model, simultaneous suppression of platform-induced dynamic interference, geomagnetic gradient interference, and regional geological magnetic interference is realized. Experimental results demonstrate that, compared to conventional methods, the proposed approach reduces the standard deviation of residual magnetic fields by 52.4-62.1%, significantly improving the system's detection robustness in complex geological environments.

1. Introduction

Aeromagnetic detection plays a crucial role in various fields, including mineral resource exploration [1-2], unexploded ordnance detection [3], and underwater target detection [4]. In practical applications, the intensity of magnetic interference caused by platform motion and external environmental factors is significantly greater than that of the target signal, and their frequency spectra heavily overlap with the target signal, leading to a substantial degradation in detection performance. Therefore, effective compensation of magnetic interference is of paramount importance in aeromagnetic surveying. In 1950, Tolles decomposed the platform-induced magnetic interference into three components: permanent field, induced field, and eddy current field, establishing the conventional TL model [5]. In 1961, Leliak proposed a calibration flight procedure to estimate the compensation coefficients of the TL model [6], a methodology that has been widely adopted and extended by subsequent researchers [7]. To enhance the accuracy of coefficient estimation, advanced mathematical techniques such as the least squares method [8] and Lasso-regularized Newton iteration [9] have been introduced into the field of aeromagnetic compensation. Du et al. extended the TL equations by incorporating additional terms to account for interference from onboard electrical equipment and control surface movements [10]. Yu et al. proposed a dynamic-coefficient TL equation to compensate for structural deformations occurring during flight [11]. Zhang et al. developed a one-dimensional convolutional neural network-based approach to mitigate



interference caused by airframe vibrations ^[12]. With regard to environmental geomagnetic gradient interference, Dou et al. incorporated the spatial variation of the geomagnetic field with respect to latitude, longitude, and altitude as three additional terms into the TL equation, thereby developing an enhanced TLG model that achieves improved compensation performance ^[13].

Scholars both domestically and internationally have conducted extensive research on compensating for magnetic interference arising from airframe vibrations, onboard electrical equipment, and geomagnetic gradients. However, existing aeromagnetic compensation methods have not yet accounted for geological magnetic interference. Geological magnetic interference primarily originates from ferromagnetic minerals in the upper crust and is characterized by a small spatial scale and strong nonlinearity compared to the slowly varying background geomagnetic field. Due to the relatively small spatial extent of such regional geological anomalies, the International Geomagnetic Reference Field (IGRF) model, which describes the Earth's main magnetic field, lacks sufficient resolution to accurately represent these localized interferences. In practical surveys, the spatial distribution of geological magnetic interference can only be reconstructed based on limited measurement points within the survey region. Machine learning methods are capable of capturing complex nonlinear mapping relationships between sample point coordinates and magnetic field values. By leveraging data-driven modeling, these methods can establish nonlinear functions to estimate field values at unmeasured locations, and have already been successfully applied in meteorology ^[14] and geophysics ^[15]. Given the highly nonlinear and spatially localized nature of geological magnetic interference, this paper adopts an ensemble machine learning approach to reconstruct the spatial distribution of such interference within the survey area. This study proposes a geological magnetic anomaly compensation method based on the TLGF model. After acquiring magnetic measurement data along survey lines within the region, an ensemble machine learning framework integrating support vector machines (SVM) and random forest (RF) is employed to reconstruct the spatial distribution of geological magnetic interference. Subsequently, a compensation term representing the geological magnetic disturbance at the platform's current position is incorporated into the conventional TLG model, yielding an enhanced compensation model, termed the TLGF model. The proposed model retains the effectiveness of the original TLG model in mitigating platform-induced dynamic interference and geomagnetic gradient effects, while additionally enabling effective compensation for regional geological magnetic interference. Experimental results demonstrate that, compared to the TLG model, the proposed TLGF model improves magnetic interference compensation performance by 52.4-62.1%, significantly enhancing the system's detection capability under complex geological interference conditions.

2. Proposed aeromagnetic compensation model

2.1. Conventional compensation model

The conventional TL equation attributes platform-induced magnetic interference to three distinct sources: (1) Permanent field, originating from the permanent remanent magnetization of ferromagnetic materials in the aircraft structure. This interference remains relatively constant in magnitude and direction within the body-fixed coordinate system; (2) Induced field, arising from the magnetization of soft magnetic materials in the aircraft under the influence of the ambient geomagnetic field. Its magnitude and direction vary with changes in the aircraft's orientation, as the external field transforms in the body frame; (3) Eddy current field, generated by currents induced in conductive metallic components of the aircraft as they move through the Earth's magnetic field. The magnitude and direction of this field are related to the time derivatives of the three-dimensional projections of the ambient magnetic field.

The fundamental form of the TL equation is expressed as follows:

$$\vec{B}_{R1} = [t_1, t_2, t_3] \quad (1)$$

$$\vec{B}_{R2} = \left\{ \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} T_x \\ T_y \\ T_z \end{bmatrix} \right\}^T \begin{bmatrix} \vec{i} \\ \vec{j} \\ \vec{k} \end{bmatrix} = (A\vec{T})^T \begin{bmatrix} \vec{i} \\ \vec{j} \\ \vec{k} \end{bmatrix} \quad (2)$$

$$\vec{B}_{R3} = \left\{ \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix} \begin{bmatrix} \frac{dT_x}{dt} \\ \frac{dT_y}{dt} \\ \frac{dT_z}{dt} \end{bmatrix} \right\}^T \begin{bmatrix} \vec{i} \\ \vec{j} \\ \vec{k} \end{bmatrix} = (B\frac{d\vec{T}}{dt})^T \begin{bmatrix} \vec{i} \\ \vec{j} \\ \vec{k} \end{bmatrix} \quad (3)$$

$$\vec{B}_{TL} = \vec{B}_{R1} + \vec{B}_{R2} + \vec{B}_{R3} \quad (4)$$

where $\vec{B}_{TL}$ denotes the platform-induced magnetic interference; $\vec{B}_{R1}$, $\vec{B}_{R2}$, and $\vec{B}_{R3}$ represent the permanent field, induced field, and eddy field, respectively; T_x , T_y , and T_z denote the projections of the total external magnetic field onto the three axes of the aircraft body-fixed coordinate system.

The conventional TL equation employs 21 coefficients to compensate for the magnetic interference generated by the aircraft platform:

$$\hat{B}_{TL} = \sum_{i=1}^3 p_i u_i + \sum_{i=1}^3 \sum_{j=1}^3 a_{ij} u_i u_j + \sum_{i=1}^3 \sum_{j=1}^3 b_{ij} \dot{u}_i u_j \quad (5)$$

where u_i denotes the direction cosines of the external magnetic field with respect to each axis of the aircraft body-fixed coordinate system; $\dot{u}_i$ represents the time derivatives of u_i .

To minimize the influence of geological magnetic interference during the calibration flight, the coefficients t_i , a_{ij} , and b_{ij} are determined through high-altitude calibration flights [16-17]. The conventional TL equation assumes that the Earth's main magnetic field remains constant within the survey area. However, in practice, significant geomagnetic gradients exist across the operational region. To address this limitation, Dou et al. proposed an extended TLG model to compensate for the effects of spatial geomagnetic gradients within the survey area [13]:

$$\hat{B}_{TLG} = \hat{B}_{TL} + \tau S + \rho R + \kappa D \quad (6)$$

where S , R , and D are functions of the platform's position coordinates, including longitude, latitude, and altitude, respectively; τ , ρ , and κ denote the corresponding compensation coefficients. By incorporating these three terms into the TL equation as additional components, the extended TLG equation is formulated, enabling effective compensation for geomagnetic gradient interference.

2.2. Construction of regional geological magnetic interference distribution based on ensemble machine learning

Geological magnetic interference, originating from ferromagnetic mineral deposits in the shallow crust, is characterized by its small spatial scale, strong nonlinearity, and rapid variation. To reconstruct the continuous spatial field from discrete measurement samples, machine learning methods can be employed to model these nonlinear and non-stationary characteristics. By learning the complex nonlinear relationships between the coordinates and field values of sample points, these methods can accurately estimate the field values at unobserved locations.

To reconstruct the spatial distribution of the magnetic field from discrete measurement samples, this paper adopts a stacking ensemble learning method. This approach leverages a meta-learner to intelligently fuse the predictive capabilities of multiple base machine learning models, thereby achieving higher prediction accuracy and robustness than any single model. The method consists of a two-layer

architecture: the first layer comprises two parallel base learners trained on the sample data, while the second layer consists of a meta-learner tasked with learning the optimal non-linear integration of the base learners' predictions. The workflow is divided into the following key steps:

1. **Training of Base Learners:** In the first layer, Random Forest (RF) and Support Vector Machine (SVM) are selected as base learners to capture the complex nonlinear relationship between the geological interference field values and their locations. SVM effectively handles data nonlinearity by mapping the data into a high-dimensional space via a kernel function, where a linear separation becomes possible. RF, by integrating a large number of decision trees, is capable of capturing both linear and nonlinear patterns in the data. In this step, the dataset is formed from the known discrete sample points within the region, with coordinates as input features and magnetic field intensity as the target value. A five-fold cross-validation procedure is used to independently train and perform hyperparameter tuning for each base learner, ensuring that each one achieves its optimal performance.

2. **Preliminary Predictions on Interpolation Points:** In this step, the trained base learners from the previous step are used to predict the magnetic field values for all interpolation points within the target region, establishing a set of preliminary predictions from each base learner covering the entire area.

3. **Training of the Meta-learner on Sample Point Data:** The predictions of the base learners on the sample points constitute the input feature set (i.e., meta-features) for the meta-learner. The ensemble machine learning method proposed in this paper employs a Gradient Boosting Machine (GBM) as the meta-learner, aiming to learn the optimal adaptive combination strategy for the base learners' predictions to achieve more accurate results. GBM is an additive model constructed through an iterative process, with its mathematical form as follows:

$$f_{GBM}(x) = F_M(x) = \sum_{m=1}^M \gamma \cdot h_m(x) \quad (7)$$

where $f_{GBM}(x)$ is the complex nonlinear function obtained by training the GBM as a meta-learner based on the known magnetic field at the sample points and the corresponding predictions from the base learners; x is the input vector composed of the base learners' predictions; $F_M(x)$ is the final model consisting of M decision trees; $h_m(x)$ represents the m -th decision tree; γ is a global learning rate used to control the step size of each iteration to prevent overfitting.

The model is trained using a forward stagewise algorithm. In each iteration, a new decision tree is trained to specifically fit the residuals between the predictions of the current ensemble model and the true values. This new tree is then added to the current model after being weighted by the learning rate, updating the model until the iterations are completed. This paper utilizes MATLAB's built-in Bayesian optimization framework, with the average error from five-fold cross-validation as the evaluation metric, to automatically search for and confirm the optimal combination of three hyperparameters: the number of decision trees, the learning rate, and the complexity of each tree. This process aims to construct an optimal meta-learner that, by learning the relationship between the base learners' predictions on the sample points and the true values, builds a complex nonlinear mapping function with strong generalization ability. This function is subsequently applied to the preliminary predictions over the entire region, performing its learned intelligent combination rules to ensure the accuracy and robustness of the results.

4. **Prediction on the Regional Interpolation Grid:** After the meta-learner is trained, the preliminary predictions for the entire interpolation grid (obtained in Step 2) are fed into the trained GBM meta-learner. The GBM then applies the complex nonlinear function $f_{GBM}(\bullet)$ which has learned to perform the final intelligent combination on these preliminary predictions, thereby generating a high-precision spatial distribution of the magnetic field that covers the entire region.

The procedure described above is illustrated in Figure 1.

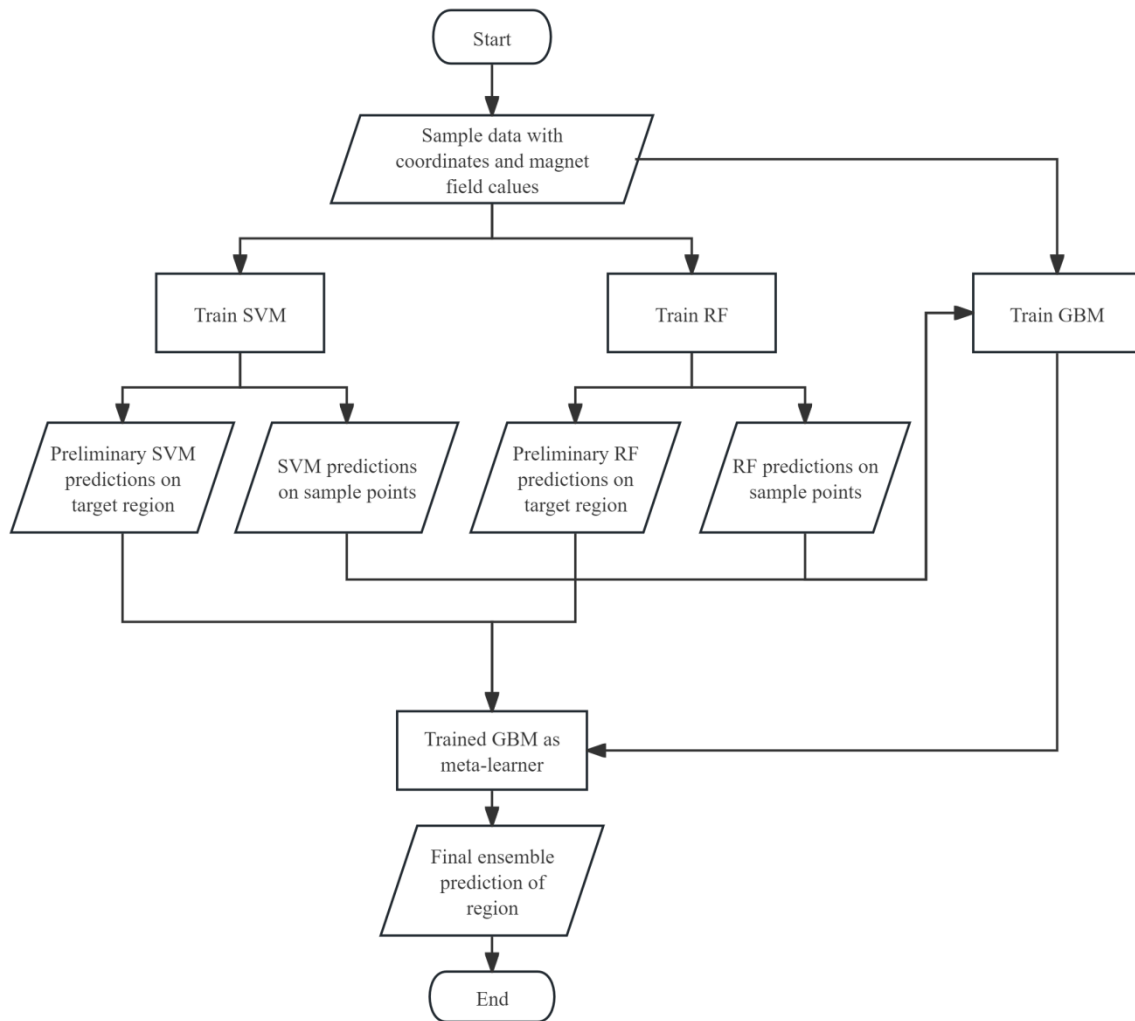


Figure 1. Workflow of the ensemble machine learning method.

The final prediction of this ensemble learning method is shown as follows:

$$B_{Final} = f_{GBM}(\hat{B}_{RF}, \hat{B}_{SVM}) \quad (8)$$

where B_{Final} denotes the final prediction result of the ensemble learning method; $\hat{B}_{RF}$ and $\hat{B}_{SVM}$ represent the prediction results of the SVM and RF base learners, respectively; $f_{GBM}(\bullet)$ (obtained from Step 3) represents the mapping function constructed by the GBM meta-learner, which is designed to model the complex nonlinear relationship between the base learner predictions and the true magnetic field values.

2.3. Extended TLGF compensation model

The conventional TLG model considers only geomagnetic gradients and does not account for the influence of regional geological magnetic interference. To address this limitation, a geological compensation term can be incorporated into the TLG equation, thereby yielding a new compensation model: the TLGF model. The geological compensation term is derived by combining the platform's position with the reconstructed distribution of regional geological magnetic interference, effectively representing the local geological magnetic disturbance at the current location. By introducing this term,

the model is capable of simultaneously compensating for platform-induced dynamic interference, geomagnetic gradient interference, and regional geological magnetic interference. The TLGF model proposed in this paper, extended from the TLG model, can be expressed as follows:

$$B_{TLGF} = \hat{B}_{TLG} + B_{Geo}(x, y, h) \quad (9)$$

where the geological magnetic interference compensation term B_{Geo} is a function of the coordinates x , y , and h . It is obtained from the pre-constructed spatial distribution of regional geological magnetic interference.

After constructing the distribution of geological magnetic interference within the survey area, the corresponding compensation term at the platform's current location is extracted from this distribution. By incorporating B_{Geo} into the TLGF model, effective compensation for geological magnetic interference is achieved.

3. Experiment and result analysis

To evaluate the performance of the TLGF model, a field experiment was conducted, in which the TLG model and the proposed TLGF model were compared to assess the effectiveness and reliability of the proposed method in magnetic interference compensation. The standard deviation (STD) and improvement ratio (IR) of the residual magnetic field after compensation, within the frequency band of 0.01-0.5 Hz, were selected as the metric for evaluating compensation performance.

The experiment was carried out in Shenmu City, Shaanxi Province, China, using a fixed-wing UAV as the test platform. The noise level of the triaxial fluxgate magnetometer is 6 pT/√Hz, while that of the cesium vapor optically pumped magnetometer is 0.6 pT/√Hz. Both sensors were mounted on an extended boom at the rear of the aircraft to minimize magnetic interference from the airframe. The specific sensor configuration is illustrated in Figure 2.

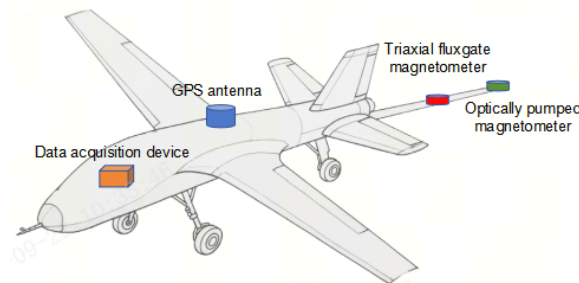


Figure 2. Schematic illustration of the aircraft platform.

First, a calibration flight was conducted at an altitude of 3,000 m. The aircraft performed pitch, roll, and yaw maneuvers in the east, south, west, and north directions, respectively, to solve for the TLG compensation coefficients. The schematic diagram and actual trajectory of the calibration flight are shown in Figure 3.

To compensate for magnetic interference induced by aircraft maneuvering, the compensation coefficients of the TLG model were first estimated using calibration flight data, followed by suppression of the platform-induced dynamic interference. Subsequently, seven north-south-oriented survey lines were established within the survey area for geological magnetic anomaly measurement, each approximately 2.3 km in length and flown at an altitude of 300 m above ground level. Magnetic data collected along these lines were used to construct a spatial distribution model of regional geological magnetic interference. Based on this model, two independent north-south-oriented test lines were established within the same area, also surveyed at a height of 300 m. The TLGF model was then applied to magnetic compensation on the test lines using the reconstructed geological interference distribution, and the results were compared with those obtained using the TLG model to evaluate the compensation performance of both methods under complex geomagnetic conditions.

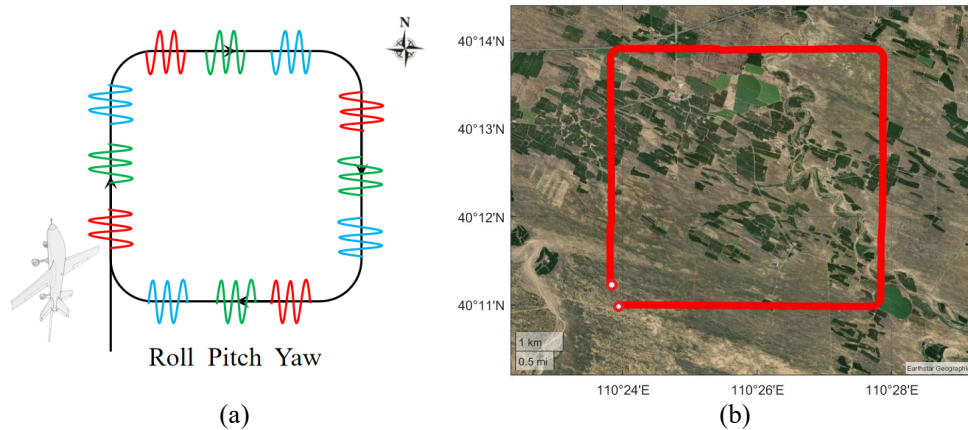


Figure 3. (a) Schematic of the calibration flight path at 3,000 m altitude; (b) Actual flight trajectory.

The layout of the survey lines within the survey area and the background of the local geomagnetic environment are shown in Figures 4 (a) and 4 (b), respectively. The residual magnetic fields after compensation using the TLG and TLGF models along the two test lines are presented in Figures 5 (a) and 5 (b), respectively.

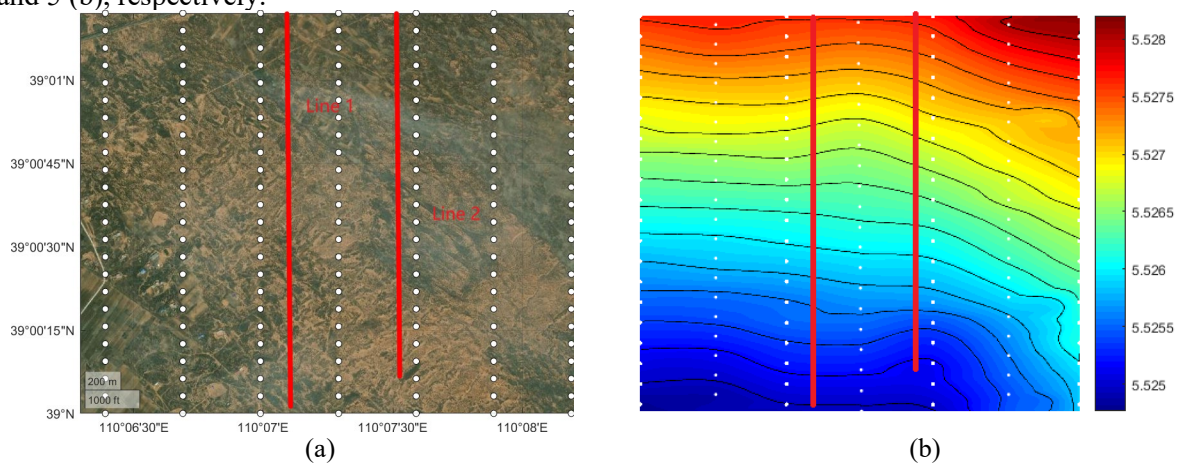
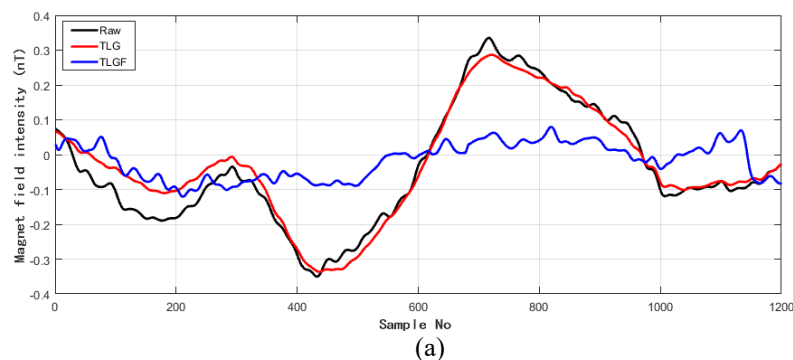


Figure 4. (a) Distribution of survey lines and test flight paths; (b) Geomagnetic background of the survey area.

As shown in Figure 5, after compensation using the TLG model, a residual magnetic field of approximately 0.5 nT remains and cannot be further eliminated, reflecting the presence of geological magnetic interference within the survey area. In contrast, after compensation using the proposed TLGF model, the peak-to-peak amplitude of the residual magnetic field is significantly reduced. Table 1 presents the standard deviation of the residual magnetic field along the test survey line and the corresponding improvement ratio achieved by the TLG and TLGF models, respectively.



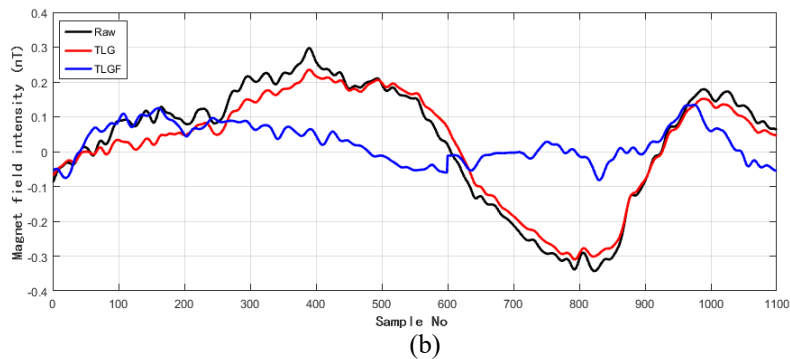


Figure 5. (a) Original magnetic data, residual magnetic field after TLG model compensation, and residual magnetic field after TLGF model compensation along Survey Line 1; (b) Original magnetic data, residual magnetic field after TLG model compensation, and residual magnetic field after TLGF model compensation along Survey Line 2.

Table 1. STD and IR of residual magnetic field along the test survey line after compensation using the TLG and TLGF models.

Data	Compensation model	STD (nT)	IR
Line 1	Raw	0.173	1
	TLG	0.161	1.07
	TLGF	0.061	2.86
Line 2	Raw	0.163	1
	TLG	0.143	1.15
	TLGF	0.068	2.40

As shown in Table 1, after compensation using the TLGF model, the STD of the residual magnetic field along Test Line 1 is reduced by 62.1% compared to the TLG model, with the IR increasing from 1.07 to 2.86. For Test Line 2, the STD is reduced by 52.4% relative to the TLG model, and the IR is enhanced from 1.15 to 2.40. These results demonstrate that the proposed TLGF model can effectively suppress geological magnetic interference within the survey area and significantly improve the system's detection performance.

4. Conclusion

This study aims to address the challenge of compensating for geological magnetic interference in aeromagnetic detection. Conventional aeromagnetic compensation methods do not account for the influence of small-scale, nonlinear, and difficult-to-model geological magnetic interference originating from shallow crustal structures, which significantly limits the detection performance.

To overcome this limitation, this paper proposes a magnetic interference compensation method tailored for complex geological magnetic anomaly regions. By employing an ensemble machine learning approach to reconstruct the spatial distribution of the regional geological interference field, a new compensation term is derived and incorporated into the conventional model, leading to the development of the enhanced TLGF compensation model. Compared with the existing TLG model, the proposed TLGF model demonstrates significantly improved capability in suppressing geological magnetic interference. Future work will focus on developing a survey-line-aware reconstruction method for the geological magnetic anomaly field to further enhance reconstruction accuracy and on integrating this refined field as an adaptive compensation term to improve the generalization ability of the TLGF model.

Acknowledgement

This study was financially supported by the Ye Qisun Science Fund of the National Natural Science Foundation of China (Grant No. U2141237) and the National Natural Science Foundation of China (Grant Nos. 62301080 and 42304091).

References

- [1] Neres M., Terrinha P., Noiva J., Brito P., Rosa M., Batista L., & Ribeiro C. (2023). New Late Cretaceous and CAMP Magmatic Sources off West Iberia, from High-Resolution Magnetic Surveys on the Continental Shelf. *TECTONICS*, 42 (7), e2022TC007637.
- [2] Mohamed A., Abdelrady M., Alshehri F., Mohammed M. A., & Abdelrady A. (2022). Detection of Mineralization Zones Using Aeromagnetic Data. *Applied Sciences*, 12 (18), 9,078.
- [3] Zhao J., Zeng Z., and Zhou S. (2025). Target Detection for Low Signal-to-Noise Ratio Scalar Magnetic Unexploded Ordnance Surveys: A Multi-Level Orthogonal Basis Function Approach, in *IEEE Sensors Journal*, doi: 10.1109/JSEN.2025.3596895.
- [4] Passaro S. (2010). Marine electrical resistivity tomography for shipwreck detection in very shallow water: a case study from Agropoli (Salerno, southern Italy). *Journal of Archaeological Science*, 37 (8), 1,989-1,998.
- [5] Tolles W. E. Compensation of Aircraft Magnetic Fields. U.S. Patent 2692970A, 26 October 1954.
- [6] Leliak P. (1961). Identification and Evaluation of Magnetic-Field Sources of Magnetic Airborne Detector-Equipped Aircraft. *IRE Transactions on Aerospace and Navigational Electronics*, Aerospace and Navigational Electronics, IRE Transactions on, IRE Trans. Aerosp. Navig. Electron, ANE-8 (3), 95-105.
- [7] Bickel S. H. (1979). Small Signal Compensation of Magnetic Fields Resulting from Aircraft Maneuvers. *IEEE Transactions on Aerospace and Electronic Systems*, Aerospace and Electronic Systems, IEEE Transactions on, IEEE Trans. Aerosp. Electron. Syst, AES-15 (4), 518-525.
- [8] Dou Z., Ren K., Han Q., and & Niu X. (2014). A Novel Real-Time Aeromagnetic Compensation Method Based on RLSQ. 2014 Tenth International Conference on Intelligent Information Hiding and Multimedia Signal Processing, Intelligent Information Hiding and Multimedia Signal Processing (IIH-MSP), 2014 Tenth International Conference On, 243-246.
- [9] Ye L., Yu Z., Zhang Y., Chi C., Cheng P., & Chen J. (2024). An Aeromagnetic Compensation Strategy for Large UAVs. *Sensors*, 24 (12), 3,775.
- [10] Du C., Wang H., Wang H., Xia M., Peng X., Han Q., Zou P., & Guo H. (2019). Extended aeromagnetic compensation modelling including non-maneuvring interferences. *IET Science, Measurement, & Technology*, 13 (7), 1,033-1,039.
- [11] Yu Z., Ye L., Ding C., Chi C., Liu C., & Cheng P. (2025). Dynamic Parameterization and Optimized Flight Paths for Enhanced Aeromagnetic Compensation in Large Unmanned Aerial Vehicles. *SENSORS*, 25 (9), 2,954.
- [12] Zhang D., Liu X., Qu X., Zhu W., Huang L., & Fang G. (2022). Analysis of aeromagnetic swing noise and corresponding compensation method. *IEEE Transactions on Geoscience and Remote Sensing*, 60, 1-10.
- [13] Dou Z., Han Q., Niu X., Peng X., & Guo H. (2016). An Aeromagnetic Compensation Coefficient-Estimating Method Robust to Geomagnetic Gradient. *IEEE Geoscience and Remote Sensing Letters*, Geoscience and Remote Sensing Letters, IEEE, IEEE Geosci. Remote Sensing Lett., 13 (5), 611-615.
- [14] Nobrega A. E. L. & Barroca Filho I. M. (2025). Analysis of Machine Learning Performance in Spatial Interpolation of Rainfall Data. *IEEE Access*, Access, IEEE, 13, 84,727-84,737.
- [15] Maurilio F. Salgado., Carlos A. M. Chaves., Henrique B. Santos., and Roberto Hirata (2025). Large-gap Seismic Data Interpolation with Generative Adversarial Networks. *Geophysics* (2025) 90 (4): V373 - V388. <https://doi.org/10.1190/geo2023-0770.1>.
- [16] Gerardo Noriega (2011). Performance measures in aeromagnetic compensation. *Leading Edge* (Tulsa, OK), 30 (10), 1,122-1,127.
- [17] Feng Y., Zhang Q., Zheng Y., Qu X., Wu F., and Guang. F. An Improved Aeromagnetic Compensation Method Robust to Geomagnetic Gradient. *Appl. Sci.* 2022, 12, 1,490. <https://doi.org/10.3390/app12031490>.