Guest Editorial

Guest Editorial for the TAES Special Section on Machine Learning Methods for Aerial and Space Positioning and Navigation

I. INTRODUCTION

Positioning and navigation plays a significant role in a wide range of fields, such as aerospace, defense, and transportation, especially due to the continuous performance enhancement of the four Global Navigation Satellite Systems (GNSS) [1], [2] and the advent of complementary local positioning systems [3], [4]. Nowadays, requirements on positioning and navigation are becoming stricter in areas such as reliability, accuracy, continuity, complexity, integrability, and safety to enable better location-based services. In many complex and harsh environments, it is still a demanding task (such as for aerial and space vehicles) to generate real-time valid location information and perform the desired navigation, which enables to fulfill the assigned duties [5].

As an example, small delivery services by unmanned aerial vehicles (UAVs) carrying products from a warehouse to a destination still present many technical challenges, such as having to travel along a trajectory near tall buildings, and in severe meteorological conditions, such as strong wind, heavy rain, or snow. The trajectory must avoid no-fly zones and possibly incorporate other constraints, such as maximum flight distance, minimum straight-line flight distance, or minimum flight altitude [6]. Another example is a space exploration robot approaching an asteroid to perform landing, excavation, and collecting mineral samples in the complete absence of GNSS signals [7]. Enabling location performance enhancement and carrying out satisfactory navigation in these demanding environments require advances in modeling and signal processing state-of-the-art techniques.

Due to the strict requirements on navigation information performance metrics and safety, the positioning, navigation, and timing (PNT) methods and systems have been prevailingly based on physics-based modeling and statistical signal processing. However, the need for improved performance of the upcoming PNT systems has led, as in a myriad of other technical or nontechnical areas, to massive application and rapid development of the machine learning (ML) methods over the past years. These ML methods mainly consist of supervised learning, unsupervised learning, and advanced learning, and there is a wide range of learning techniques, such as convolutional neural network (CNN), regression, decision tree, random forest, support vector machine (SVM), K-means clustering, or principal component analysis [8], [9]. In the context of the PNT under demanding environments, researchers and engineers have also been leveraging ML methods, especially data-driven ones, to overcome limitations of physics-based solutions.

As early as 2000, a wireless local area networks (LAN) positioning system (RADAR) was developed for indoor scenarios, which is based on the K-nearest neighbors (KNN) algorithm for position determination [10]. KNN is a nonparametric supervised ML algorithm, which is typically simple to implement. In 2005, support vector regression, an extension of SVMs, was used for fingerprint-based positioning in wireless LAN [11]. A number of early ML-assisted positioning algorithms were reported in [12], which provides a nice early review on indoor positioning techniques and systems. Meanwhile, the use of ML in GNSS positioning also started around 2000. For instance, both Bayes classifier and KNN were used in route learning, route prediction, and estimation of time of arrival in [13], and back-propagation neural networks are applied to approximating the Global Positioning System (GPS) satellite geometric dilution of precision [14]. As another example, the radial basis function neural network was employed to achieve simple architecture and fast training procedure in accurate GPS/inertial navigation systems (INS) integrated positioning [15]. Over the past two decades, various ML algorithms and methods have been, therefore, exploited for global and local positioning and navigation, which has resulted not only in improved performance and advanced concepts, but also in new challenges, such as reliability and explainability of such navigation information. These challenges have not been sufficiently solved and answered yet.

This Special Section is conceived to compile the state of the art in the theory, methodology, and software and hardware design for PNT, especially related to aerial and space vehicles which operate in demanding environments and are tied with regulations. Particularly, the emphasis is laid on using artificial intelligence and ML-enhanced solutions which have been extensively applied to a variety of fields with remarkable success. This Special Section aims to disseminate the latest research outcomes in this field and to ultimately inspire future research in such an exciting development area, with the goal of enabling more significant advances in positioning and navigation technology and boost the relevant industries as well.

In total, this Special Session consists of 18 papers covering both satellite-based (16 papers) and local (two papers) positioning and navigation. In particular, six papers [A1]–[A6] deal with estimation of spacecraft parameters, including position and velocity, attitude or pose, and satellite scheduling for Earth observation; five papers [A7]–[A11] focus on UAV-related applications, including target detection and mapping, pseudolite navigation ephemeris, collision avoidance and autonomous navigation, and trajectory prediction; four papers [A12]–[A15] concentrate on GNSS precise positioning and GNSS/INS integrated positioning for vehicular and train localization and tracking; one paper [A16] pays attention to GNSS interference classification, while the last two papers [A17] and [A18] address local positioning approaches for pedestrian localization, using Wi-Fi, Bluetooth, and Long-Term Evolution (LTE) signals collected by smartphone or visible light signal.

To realize the functions and tasks mentioned above, different ML algorithms and techniques were utilized. Specifically, *deep learning*, including artificial neural network, CNNs, convolutional extreme learning machine, was employed to optimize complexity and accuracy for pose estimation in [A3], to simplify image inputs for position and velocity estimation in [A4], to improve efficiency of pose estimation of noncooperative targets in [A5], to maintain sufficiently accurate ephemeris in [A8], to enhance flight trajectory prediction in [A11], to mitigate noise in GNSS/INS integrated positioning in [A14], to augment physics-based model for vehicular tracking in [A15], and to improve accuracy of phase difference estimation in [A18]. *Supervised learning*, including SVM, decision tree, random forest, back-propagation neural network, was used to establish UAV flight status recognition model in [A10], to suppress the error divergence of INS in [A12], to enable low-resource interference classification in [A16], and to classify location region in [A17]. *Unsupervised learning*, including the principal component analysis and K-means++, was used to enhance satellite pose estimation such as by addressing the issues of domain mismatch in [A1] and principal discrepancy in [A2], and to correctly resolve integer ambiguity resolution in complex environments in [A13]. *Reinforcement learning* was used to enhance low-resource satellite scheduling in [A6], to deal with joint detection and mapping in [A7], and to handle UAV autonomous navigation in dynamic environments in [A9]. Note that some of the papers made use of two or multiple ML algorithms, and some of the supervised learning, unsupervised learning, and reinforcement learning methods are also deep learning methods, or vice versa. More details about the methods and algorithms can be found in the individual papers, but the summaries of the papers are provided in the next section for a quick reference.

II. MAIN CONTRIBUTIONS OF THE ARTICLES IN THIS SPECIAL SECTION

In [A1], a self-training framework is employed for unsupervised domain adaptation in satellite pose estimation, leveraging domain-agnostic geometrical constraints to ensure consistency across domains. The framework utilizes a neural network to predict 2-D keypoints on satellite images, which are then used in conjunction with the PnP algorithm to estimate the satellite's pose. To address the challenge of information loss associated with sparse keypoints, fine-grained segmentation is introduced as an auxiliary task. Iterative optimization is performed to refine the network's predictions and adapt it to the target domain, resulting in significant accuracy improvements in satellite pose estimation without relying on real annotations.

In [A2], the vision-based monocular noncooperative spacecraft pose estimation is considered. In particular, the paper addresses the pose estimation degradation due to the principal discrepancy between training (source) data obtained by a simulator and real test (target) data. The proposed solution lies in the definition of the keypoint-based structure learning objectives and the application of an unsupervised domain adaptation algorithm based on the consensus. The proposed approach is thoroughly validated using a widely used dataset SPEED+, and it was ranked second in the two categories of the 2021 Pose Estimation Challenge (SPEC2021) organized by the European Space Agency and Stanford University.

In [A3], a direct attitude estimation method was proposed, which is called DSOAE-Net and based on CNN, to optimize the time-consuming and highly accuracy of indirect methods. The authors devised an attitude representation form, specifically tailored for the direct attitude estimation method, which is a multimodal rotation 6-D representation. The basic framework of the direct attitude estimation method was abstracted and comprehensive experiments on each module of the framework were conducted. The experimental results with the BUAA-SID-POSE1.0 dataset showed that DSOAE-Net achieved better accuracy than other direct and indirect attitude estimation methods without increasing the complexity.

In [A4], the focus is on exploring the importance of onboard autonomous decision-making for navigation around small celestial bodies. It discusses optical-based navigation techniques, combining image processing algorithms and filtering methods for efficient navigation with cost-effective hardware. The paper proposes a novel onboard methodology utilizing segmentation masks, convolutional extreme learning machine architectures, and recurrent neural networks to simplify image inputs, map single-frame data into position estimates, and process multiple-frame sequences for position and velocity estimates. Using the Didymos binary system as a case study, with the potential integration of LiDAR data, the paper concludes that recurrent neural networks offer limited improvement in position reconstruction but can enhance velocity estimation, especially with LiDAR data integration.

In [A5], the authors highlight the importance of monocular vision-based pose estimation for noncooperative spacecraft tasks. It discusses the limitations of existing methods based on a two-stage approach and for their over-reliance on CNNs, which may lead to texture dependence and inadequate long-range modeling. To overcome these issues, it proposes DTSE-SpaceNet, a single-stage end-to-end network that fuses features dynamically and predicts keypoints. Pose parameters are derived using the PnP method, while a novel shape loss function improves geometric accuracy. Extensive experiments on public datasets demonstrate competitive performance, strong generalization, and computational advantages over two-stage methods.

In [A6], the applicability of satellite-based Earth observation is investigated. Contrary to solutions based on ground-based or low-altitude aerial platforms, satellite-borne approaches provide wider space/time coverages. One of the challenges is to efficiently use the, typically scarce, satellite resources. In this paper, a deep reinforcement learning (RL) solution for efficient onboard autonomous scheduling is proposed based on a transformer encoder–decoder architecture.

In [A7], RL for joint detection and mapping in the context of UAVs is treated. The emphasis is put on the dynamic radar network of UAVs for accurate target detection to enhance their ambient awareness by estimating the occupancy radio map. Cooperation between UAVs leads to a well-learned navigation policy, which helps to explore an unknown environment while maximizing the accuracy in detecting targets and reaching the team's goals. The proposed approach was thoroughly validated in single- and multitask scenarios.

In [A8], the concept of UAV-based pseudolites is explored. Pseudolites can act both as augmentation or alternatives to GNSS-based positioning, whereby so-called pseudosatellites provide coverage to certain areas where GNSS satellites are obstructed or not available. This article considers the challenges of having such pseudolites mounted on moving drones. In particular, one of the main differences to actual satellites resides in the difficulty of predicting the UAVs movement, which renders the generation and broadcasting of the pseudolite ephemeris a challenge. The authors propose to leverage deep learning in order to maintain sufficiently accurate ephemeris for reliable use of such UAV-based pseudolite systems

In [A9], RL is employed in the context of UAVs. The proposed solution enables autonomous navigation, runs in real-time, and accounts for a robust collision avoidance capability to safely guide UAVs through dynamic environments. Transferability of trained RL agents to real-world experiments is an important aspect that this work discusses, which is accomplished through the use of DL. The article demonstrates the validity of the proposed solution through synthetic and real data experiments.

In [A10], the stress is laid on the trajectory prediction of a UAV based on the data-driven UAV model. The developed modeling methodology consists of collecting and preprocessing flight data, designing the flight status recognition model using the principal component analysis of data, and predicting the trajectory using a trained back-propagation neural network. The proposed approach is compared with the traditional state-estimation-based approach using the real dataset.

In [A11], a novel global and local interattribute relationship based graph convolutional network model is proposed for flight trajectory prediction, which integrates local and global inter-attribute relationships by fusing local embedded features with global patterns. An attribute graph is constructed with accumulated local embeddings and augmented correlations, and integrated features are extracted using a graph convolutional network for LSTM-based prediction. The proposed model has been validated using real flight datasets, exhibiting superior performance compared to existing methods, and ablation studies have confirmed its robustness and accuracy in capturing intricate relationships between trajectory points.

In [A12], an LSTM-assisted GNSS/INS integration system was proposed, which uses recomputed Inertial Measurement Unit (IMU) error to suppress the error divergence of an INS in the case of GNSS solution nonavailability.

The recomputed error of the IMU sensors can be obtained by differencing the theoretical measurements and the actual measurements of accelerometer and gyroscope. Experiments were conducted using real data collected on the Shuozhou–Huanghua rail. Results showed that the horizontal position accuracy of the proposed method was significantly improved, and the divergence of the INS sensor error was greatly suppressed.

In [A13], an integrated approach for GNSS precise positioning and navigation is proposed to correctly resolve integer ambiguity resolution in complex environments of GNSS, which makes use of the best integer equivariant (BIE) estimation based on unsupervised ML. As an unsupervised ML strategy, the K-means++ algorithm was applied to the BIE estimation. The float, fixed, and BIE estimations are combined to achieve an integrated precise positioning and navigation. The performance of the integrated solution has been evaluated through a monitoring experiment in a mountain canyon and vehicular tracking experiment in a harsh environment with the obstruction of trees, pedestrians, and buildings.

In [A14], the integration of GNSS and INS is discussed. Particularly, the conventional approach based on the error-state extended Kalman filter is augmented with a data learning-based component to learn the nearly optimal Kalman filter gain together with the description of the actual inertial measurement errors. The proposed data-augmented integrated navigation algorithm provides highly accurate navigation information estimates while maintaining their interpretability.

In [A15], AI/ML techniques in navigation and tracking applications, which focus on the dynamical models, are typically involved in corresponding state estimation problems. By augmenting the physics-based models with data-driven components, promising solutions are proposed to tradeoff both models. The authors illustrate the benefits and challenges of different modeling choices using two examples of target tracking with synthetic and real data, which highlight the importance of reliable and accurate navigation for transportation efficiency, and discuss the limitations and challenges of AI/ML-enhanced navigation systems for safety-critical applications.

In [A16], a low-resource interference classification approach is proposed, which combines conventional statistical signal processing approaches with ML. Using the appropriate pre-processing from known classical best practices in conjunction with ML provides superior performance, as the benefits of both are leveraged. The ML simplifies threshold settings and classification logic, whereas the conventional methods provide optimal signal processing foundations. Results show that exploiting applicable signal processing methods would facilitate ML pipelines of low size, weight, power, and cost, and thus, more efficient architectures can be developed using existing signal-processing approaches.

In [A17], considering the coverage range of wireless signal and the accuracy requirement, a two-phase localization system is designed for region determination and position estimation, which uses the internal camera sensor and received LTE signal, Bluetooth signal, and Wi-Fi signal. Taking advantage of smaller coverage, the LTE signal and Bluetooth signal are fed into the SVM for region classification learning, while the Wi-Fi signal and camera image, which contains much information, are combined with CNN for position regression learning. Experimental results show that this solution achieves decimeter accuracy overall and is suitable for most of real-time localization scenarios.

In [A18], visible light positioning (VLP) is investigated for indoor environments. While VLP offers high accuracy and low cost, common methods based on received signal strength (RSS) lack generalization. The article proposes a VLP method based on time difference of arrival, eliminating the need for extensive calibration. It discusses error influences and introduces a CNN to enhance accuracy of phase difference estimation. In addition, a particle filter based on motion state improves also the robustness of the architecture. Simulated experiments demonstrate significant accuracy improvements, with over 50% enhancements in both ranging and localization accuracy compared to traditional methods.

III. CONCLUSION

ML has been utilized to cope with complex and challenging problems in positioning and navigation technologies, with the focus on accommodating the increasing demands on PNT performance, such as accuracy and reliability. This Special Section has attracted eighteen articles, mainly focusing on aerial and space positioning and navigation and related applications, highlighting the current status, and envisioning the future trends of this amazing and high-tech field.

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APPENDIX
RELATED ARTICLES

[A1] Z. Wang, M. Chen, Y. Guo, Z. Li, and Q. Yu, “Bridging the domain gap in satellite pose estimation: A self-training approach based on geometrical constraints,” *IEEE Trans. Aerosp. Electron. Syst.,* vol. 60, no. 3, pp. 2500–2514, Jun. 2014.

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