Closas *et al.*
EURASIP Journal on Advances in Signal Processing (2024) 2024:84
https://doi.org/10.1186/s13634-024-01182-8

EURASIP Journal on Advances
in Signal Processing

EDITORIAL

Open Access

Emerging trends in signal processing and machine learning for positioning, navigation and timing information: special issue editorial

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Location-based services, safety-critical applications, and modern intelligent transportation systems require reliable, continuous, and precise positioning, navigation, and timing (PNT) information. Global Navigation Satellite Systems (GNSS) are the main source of positioning data in open sky conditions; however, their vulnerabilities to radio interferences and signal propagation limit their use in challenging environments. Consequently, enhancing conventional GNSS-based PNT solutions to incorporate additional sensing modalities and exploit other available signals of opportunity has become necessary for continuous and reliable navigation.

Articles in the special issue span detection methods, estimation algorithms, signal optimization, and the application of machine learning, providing comprehensive insights into enhancing navigation and positioning accuracy.

1 PNT technology

Positioning, navigation, and timing (PNT) technologies form the backbone of many of today's most critical applications, spanning various sectors and impacting everyday life. Modern PNT solutions rely on a sophisticated interplay of diverse sensors and systems to deliver precise and reliable information about position, navigation, and time [11]. In this introduction, we discuss the fundamental components that constitute these advanced PNT systems and explore their wide array of applications.

One of the cornerstones of PNT technology is Global Navigation Satellite Systems (GNSS) [31, 40]. GNSS involve satellite constellations that provide timing and positioning signals to receivers on Earth. These signals are pivotal in numerous domains, including personal navigation, geolocation services, agriculture, and search and rescue operations. GNSS enable users to determine their exact location anywhere on the globe with remarkable accuracy and reliability. Complementing GNSS are Inertial Navigation Systems (INS) [7], which consist of accelerometers, gyroscopes, and magnetometers. These systems measure inertial forces to provide orientation, velocity, and position data. This technology is particularly essential for applications such as aircraft navigation, autonomous vehicles, marine navigation, and robotics, where continuous and precise navigation information is critical, even in the absence of external signals.

Another key technology in modern PNT solutions is Light Detection and Ranging (LiDAR) [36]. LiDAR utilizes laser sensors to emit laser light and process the reflections to measure ranges. LiDAR is invaluable in autonomous vehicles, environmental monitoring, mapping, and geospatial analysis, providing high-resolution, three-dimensional information about the surroundings. Computer vision and camera systems [19] also play a crucial role in PNT. These systems are based on image sensors and advanced processing algorithms, which analyze the environment. This technology finds applications in augmented reality, robotics, autonomous vehicles, and surveillance, enabling machines to interpret and respond to visual information with high precision.

Additionally, wired and wireless communication networks [30] are integral to modern PNT solutions. Technologies such as 5G, Wi-Fi, and Bluetooth enable data exchange between devices and systems. While some of these networks are not explicitly designed for PNT, they can be utilized as Signals of Opportunity (SoO) to enhance dedicated PNT systems. Typical applications include the Internet of Things (IoT), smart cities, real-time traffic management, and remote sensing.

In summary, modern PNT solutions represent an intricate blend of various advanced technologies. Each component—whether GNSS, INS, LiDAR, computer vision, or communication networks—plays a vital role in delivering the precise and reliable PNT information that underpins countless applications in our daily lives and across numerous industries. As these technologies continue to evolve, their integration and capabilities will expand, driving further innovation and transforming how we navigate and understand the world.

2 Challenges in PNT technology

Traditional PNT methods, while revolutionary, have inherent limitations that necessitate the integration of diverse sensors and systems to achieve continuous and reliable information. Each of these traditional technologies, such as GNSS, INS, LiDAR, computer vision, and communication networks, has its unique strengths and weaknesses, shaped by their inherent characteristics and environmental interactions. Understanding these limitations underscores the need for a multifaceted approach to PNT solutions.

GNSS are susceptible to several limitations that can impair its accuracy and reliability. Signal obstructions and multipath effects, common in urban environments, forests, and indoor settings, lead to signal loss or degradation resulting in reduced positional accuracy and reliability. Additionally, GNSS signals are vulnerable to interference and jamming from other electronic devices or malicious users, which can lead to the loss or corruption of useful signals. Atmospheric conditions, particularly ionospheric and tropospheric delays, can also affect signal propagation, causing positioning errors, which are aggravated near the equator or during solar activity. Moreover, GNSS rely on the visibility of a sufficient number of satellites. In environments such as tunnels or urban canyons, the number of visible satellites can drastically reduce, hindering the system's ability to resolve the navigation problem.

INS, while powerful, face challenges primarily related to drift over time. The principle of INS involves integrating acceleration and angular rates over time, leading to cumulative errors known as drifts. Without periodic calibration or correction from external sources, these errors can accumulate, reducing the system's accuracy. Furthermore, high-precision INS are complex and expensive, limiting their suitability for low-cost applications.

LiDAR systems, though effective, encounter limitations due to environmental conditions and intrinsic characteristics. Weather conditions such as rain, fog, or smog can degrade LiDAR performance, reducing its accuracy. LiDAR also has limitations in range and resolution, making it difficult to detect distant or small objects. Additionally, high-quality LiDAR systems are often expensive and require significant power, posing challenges for low-cost or low-consumption applications.

Computer vision and camera-based systems are dependent on the lighting conditions of the scene they capture. Low light or highly dynamic lighting conditions can lead to poor quality images, affecting the system's performance. Occlusion and field of view limitations can result in incomplete images, hindering accurate analysis. Moreover, image processing algorithms are computationally intensive, requiring substantial power and memory, which can be challenging for real-time or low-cost applications.

Communication networks also face several limitations that impact PNT solutions. Latency and bandwidth constraints can affect real-time data transmission and processing, introducing delays and bottlenecks, especially in data-intensive applications. Network coverage can be inconsistent, particularly in underserved areas, reducing the availability and reliability of PNT solutions.

The limitations of traditional PNT methods highlight the necessity of integrating a diverse array of sensors and systems. Each technology brings unique capabilities and constraints. By combining these technologies, we can mitigate individual weaknesses and enhance overall PNT performance. This multifaceted approach is essential to meet the growing demand for precise, reliable, and continuous PNT information across various applications and environments.

3 Emerging trends

The evolving landscape of PNT technology is driven by the need to overcome the limitations of traditional methods. Emerging trends in signal processing, multi-sensor fusion, machine learning, and distributed networks offer promising solutions to enhance the accuracy, reliability, and robustness of PNT systems.

To address the shortcomings of individual sensors and provide more accurate and reliable PNT solutions, multi-sensor fusion algorithms have been developed. These algorithms combine the strengths of various systems [5, 13]. However, improvements are also made at the single-sensor level. A remarkable example is in GNSS, where the pursuit of higher precision has led to the development of techniques such as Precise Point Positioning (PPP) and Real-Time Kinematic (RTK) [39]. PPP relies on highly accurate global correction models delivered to users in near real time, significantly enhancing positional accuracy. RTK, on the other hand, uses local correction models from a known reference station, providing precise positioning for nearby users.

In a more general framework, modern signal processing techniques have also been adapted for PNT to improve robustness of solutions in degraded environments. Examples include misspecified estimation theory [15] and robust estimation techniques [27], which improve the resilience of PNT systems to outliers and improve overall data reliability. Classical estimation methods are also used for attenuating and mitigating abnormal phenomena [22] and for filtering techniques in degraded conditions [53].

Finally, the introduction of Riemannian estimation methods [1] has been a breakthrough in filtering techniques for orientation estimation in navigation systems. This theory applies Riemannian geometry, which studies curved spaces (manifolds) where the usual rules of Euclidean geometry do not apply. An excellent example is the estimation framework on Lie groups [2], which facilitates filtering techniques for attitude computation.

Moreover, Machine Learning (ML) has become a game-changing technology in the field of PNT. By utilizing extensive data sets and advanced algorithms, ML significantly improves the accuracy, robustness, and adaptability of PNT systems [25, 37]. Consequently, the latest advancements in ML are overcoming the limitations of traditional PNT methods and creating new opportunities for application and innovation.

Traditional PNT systems, like GNSS, frequently encounter issues like signal obstructions, interference, and atmospheric delays. To address these challenges, ML techniques have been employed to create data-driven positioning solutions capable of predicting and correcting these problems. For instance, ML models can analyze both historical and real-time data to detect patterns and anomalies, thereby enhancing the accuracy of position estimates even in challenging environments like urban canyons or dense forests [50]. Additionally, ML algorithms can integrate data from multiple sensors to interpret and adapt to the surrounding environment. This capability is especially beneficial in smart city applications, where integrating data from Internet of Things (IoT) devices facilitates more efficient traffic management and urban planning [16, 43, 47].

In this context, the integration of ML into PNT has significantly advanced the development of autonomous systems. For self-driving cars, drones, and other autonomous vehicles, precise positioning is crucial for navigation and safety. ML algorithms enhance these systems by delivering real-time adjustments and predictions based on the vehicle's surroundings and behavior [49].

Finally, ML also plays a crucial role in detecting and mitigating anomalies in sensor data that can compromise the accuracy of PNT systems. Techniques like supervised and unsupervised learning can identify outliers and inconsistencies in the data, enabling real-time correction and ensuring the robustness of the PNT solution [9, 42]. These methods can also enhance the resilience of PNT systems against threats like jamming and spoofing. By learning to identify and counteract these malicious activities, ML-enabled PNT systems can maintain accurate positioning and timing information, which is crucial for defense and security applications.

The final emerging trend to be discussed is PNT for space localization and exploration, which aims to revolutionize methods for navigating and exploring the cosmos. Innovations such as advanced GNSS adaptations, optical navigation, autonomous systems, quantum technologies, collaborative satellite networks, and AI integration are enhancing the precision, reliability, and autonomy of space missions. As these technologies advance, they will be pivotal in facilitating humanity's ventures to the Moon, Mars, and beyond, ensuring the success and safety of future space missions.

In this context, the creation of Low Earth Orbit (LEO) satellite constellations, like SpaceX's Starlink and OneWeb, is paving the way for innovative PNT solutions [34]. These constellations offer continuous, high-precision positioning data by utilizing inter-satellite links and ground-based infrastructure. Collaborative satellite networks contribute to more robust and resilient PNT systems, capable of functioning effectively even in challenging environments or during GNSS outages. Additionally, the design of distributed timing solutions in the context of LEO satellite swarm constellations is beginning to take shape [26].

4 Applications and impact

The latest advancements in PNT solutions are significantly transforming various industries, driving innovation and enhancing capabilities across automotive, aerospace, urban planning, and more. These improvements address recent challenges and applications, and pave the way for smarter and more efficient systems.

PNT solutions are crucial for developing smart city infrastructure. In urban planning, precise positioning aids in the efficient layout and management of resources. Advanced PNT technologies facilitate real-time traffic management, reducing congestion and improving public transportation systems. Furthermore, integrating PNT with IoT enhances situational awareness and automation. IoT devices equipped with precise positioning capabilities can monitor and manage urban systems, from energy distribution to waste management, creating a more responsive and sustainable urban environment.

In the automotive industry, advanced PNT solutions are essential for the safe and efficient operation of autonomous vehicles, including self-driving cars, drones, and other autonomous systems like public transportation and aircraft. These systems require precise positioning to navigate complex environments, avoid obstacles, and ensure passenger safety. PNT advancements contribute to the reliability and accuracy of these systems, allowing them to function seamlessly in real-world conditions.

The maritime and aviation industries operate in some of the most challenging environments, where reliable PNT is critical. Advanced PNT technologies enable precise navigation and ensure compliance with stringent regulations. In maritime contexts, accurate positioning guarantees safe passage through busy and often hazardous waters. For aviation, precise timing and positioning are essential for flight safety, navigation, and efficient air traffic management. The ability to maintain accurate positioning in these sectors enhances operational safety and efficiency, supporting both commercial and defense applications.

In defense and security, the resilience of PNT solutions is paramount, especially in GNSS-denied environments where traditional GPS signals may be unavailable or unreliable. Advanced PNT systems are designed to counteract jamming and spoofing, ensuring that military operations can rely on accurate and secure positioning information. Resilient PNT technologies support mission-critical applications, from navigation and targeting to reconnaissance and communication, providing a strategic advantage in complex and contested environments.

In conclusion, the latest advancements in PNT solutions are driving significant improvements across various industries. In smart cities, PNT enhances infrastructure and IoT integration, leading to more efficient urban management. For autonomous vehicles, precise positioning is vital for safety and functionality. In maritime and aviation, advanced PNT ensures compliance and operational safety in challenging conditions. In defense and security, resilient PNT systems provide critical support in GNSS-denied environments. As PNT technologies continue to evolve, their impact will further expand, enabling more sophisticated and reliable applications across these and other sectors.

5 Challenges and opportunities

These applications present several challenges and opportunities, which we discuss below.

When considering positioning, the primary goal is often estimating the most precise location. PPP and RTK, as mentioned earlier, can achieve centimeter-level positioning accuracy. However, these technologies require significant infrastructure development and may not provide real-time positioning. One way to enhance these methods is through collaborative positioning, where information is shared between users [21, 28, 33]. Another approach to achieving the best precision could involve increasing the number of sensors–such as GNSS, INS, LiDAR, or cameras–and developing new filtering algorithms to fuse all the sensor data [45]. Ensuring intercompatibility among these sensors can be challenging due to different formats and communication protocols, and they may not be necessarily synchronized. Standardizing interfaces and developing middleware solutions can facilitate their integration. In addition, the development of open-source platforms and frameworks can promote interoperability and collaboration.

Large-scale deployments also present new challenges, such as those encountered in smart cities, which require managing vast amounts of data and ensuring consistent performance across diverse scenarios [46]. To address these scalability issues, the development of cloud-based solutions, distributed computing, and scalable algorithms and architectures will be essential to maintaining consistent performance.

Regarding safety-critical applications, such as unmanned vehicles or civil aviation, providing a precise location is of utmost importance. However, it is even more important for the system to offer a trust level for this position, known as integrity [52]. In nominal conditions, it is straightforward to provide such levels, as observation and models follow Gaussian distributions with known covariance matrices. However, in more challenging scenarios, such as those involving signal obstructions, interference, or spoofing, this is no longer the case. Therefore, in such situations, advanced and adaptive signal processing and ML techniques are required to provide robust and reliable solutions.

When it comes to ML, it is common knowledge that data are the key. Therefore, data quality and availability present significant challenges. The processed data should be of high quality, sourced from various origins and highly trustworthy. Developing robust data preprocessing and cleaning techniques, as well as creating large, well-annotated datasets, is crucial. However, managing all these data can lead to high computational complexities and increased requirements for storage and power. Leveraging advancements in hardware (e.g., use of GPUs) and optimizing algorithms (e.g., use of sparsity) can help reduce this computational burden. Cloud computing [35] and distributed learning [10] are promising research areas to explore lowering computational demands. These two technologies involve sharing information between users, which is also true in emergent fields such as collaborative positioning or crowdsourcing-based solutions, where all the user knowledge is pooled together. Consequently, ensuring data privacy is of utmost importance. This requires advanced encryption and authentication methods [14, 20, 32], anomaly detection, or the use of federated learning—a family of privacy-preserving ML methods [12, 24, 41, 48].

To address some of these challenges, we are pleased to present this special issue of the EURASIP Journal on Advances in Signal Processing entitled "Emerging Trends in Signal Processing and Machine Learning for Positioning, Navigation and Timing Information," with contributions described in the following section.

6 Summary of the special issue

This section provides a summary of the contributions the special issue received. We have received excellent papers that, after a careful peer-review process, were accepted for publication. We hope you find them interesting and, ultimately, that these papers help boost research on the timely topic targeted in this special issue.

One prominent theme is the detection and mitigation of GNSS signal interference and spoofing. In [6], deep learning models are employed at the acquisition stage to detect GNSS spoofing and, if applicable, to estimate spoofed signal parameters. The presented approach shows very encouraging results. Additionally, more traditional techniques based on expectation–maximization algorithms are applied in [23] to estimate GNSS parameters under constant modulus interference, demonstrating robust performances in simulations.

Another key area of research is the optimization of signal processing techniques. In [17], the co-design of orthogonal frequency-division multiplexing (OFDM) signals for both ranging and communication is analyzed, revealing fundamental trade-offs and optimal resource allocation strategies. Signal optimization for LEO satellites is tackled in [44], with research proposing efficient spreading code designs to minimize inter-channel interference and enhance navigation performance. Finally, [4] investigates novel methods for precise time-delay and Doppler estimation based on a calibration hypothesis and provides the corresponding estimation bounds.

A significant focus in modern PNT application is urban positioning, especially in the context of self-driving cars or Advanced Driver-Assistance Systems (ADAS). Here, cooperative localization algorithms, particularly under challenging conditions like ionospheric scintillation events, are developed to improve position estimates by leveraging message exchange between connected nodes [38]. Another crucial aspect is safety in these critical applications; integrity mechanisms should be implemented, as proposed in [18].

Filtering is also an important family of methods when it comes to navigation. The most well-known filtering solution is the Kalman filter, which is optimal under linear models with Gaussian noise. However, these assumptions may not hold in challenging environments. For example, the GNSS observation model is nonlinear, and outliers may occur due to multipaths. To address these issues, robust Kalman-type filters are designed to handle outliers in measurements and system dynamics, coupled with geometry aware estimation to ensure reliable attitude estimation in the presence of anomalies [3]. Another example is spacecraft navigation, where images obtained with interferometry are used to estimate star powers and corresponding directions of arrival to position the vessel. However, corresponding observations are correlation matrices, which do not rely explicitly on the unknown sources. To overcome this, [8] proposes a Kalman filter coupled with a linear fitting of the unknown state.

ML techniques are also covered, showcasing their potential to revolutionize GNSS-based positioning. A survey of ML in GNSS is presented in [29], and a hyperspectral target detection framework based on 3D–2D CNN and transfer learning is proposed in [51] to solve the problems of traditional supervised methods.

7 Future directions

In light of the contributions in this special issue, and our own views, we conclude this editorial by providing a non-exhaustive list of potential future directions in the PNT area.

- Artificial Intelligence: AI-driven PNT is in its early stages, and further integration of artificial intelligence techniques, including deep learning and reinforcement learning, to enhance the accuracy, robustness, and adaptability of PNT systems, will be a compelling area of study. Another field where AI can help is that of context-aware PNT: ML algorithms could help to dynamically adjust to environmental changes and user requirements.
- Diversity of information sources: Multi-sensor fusion and hybrid positioning should be prioritized in the future. Enhanced fusion techniques to combine data from diverse sources (e.g., GNSS, INS, LiDAR, cameras) for improved accuracy and reliability will be essential. Moreover, hybrid positioning systems—such as the integrating of different positioning technologies (e.g., GNSS with visual odometry, inertial sensors with environmental context)—will help mitigate the limitations of individual systems.
- Quantum technologies: It is envisioned that quantum technologies will be central to the next generation of computers. However, these technologies also pave the way for the development of new sensors, such as quantum clocks or quantum IMU, which in turn further motivate the ongoing research on s quantum signal processing.
- Edge Computing and Distributed PNT: Development of edge computing solutions to process PNT data closer to the source will help to reduce latency and improve real-time performance. Moreover, exploring distributed PNT architectures that leverage decentralized processing and communication paradigms will enhance scalability and resilience.
- Security and Resilience: Advancements in techniques to detect and mitigate spoofing and jamming attacks on PNT signals, ensuring system integrity and reliability, are key aspects of future PNT developments. The creation of secure positioning technologies with robust encryption, authentication, and anomaly detection mechanisms to protect against cyber threats should also be considered.
- Advanced applications and use cases: As discussed in this editorial, future applications of PNT will include autonomous vehicles, drones, and robotic systems. Fur-

thermore, future applications to consider are smart city infrastructure, IoT networks, and industrial automation, which will enhance urban planning, logistics, and resource management.
- Standardization and Interoperability: Promoting open standards and interoperability protocols for the seamless integration of PNT solutions across different platforms, devices, and environments will pave the way for future PNT fusion algorithms and facilitate their development. The development of middleware solutions and frameworks will also enhance the interoperability and scalability of PNT systems in diverse applications.
- Privacy Considerations: Research and implementation of privacy-preserving ML and data handling techniques are crucial for protecting user privacy while leveraging PNT data for advanced applications. Ensuring privacy during the exchange of information will be of utmost importance.

In a nutshell, future directions in signal processing and ML for PNT will focus on enhancing accuracy, robustness, and adaptability, while also addressing security and privacy concerns, developing new sensors, and increasing the range of applications.

Acknowledgments
The organizers of this special issue are very grateful to the authors whose contributions made it possible, as well as all the reviewers who volunteered their time and knowledge. We would also like to thank the journal's Editor-in-Chief, Prof. Maria Sabrina Greco, for their support and guidance. This work was partially supported by the National Science Foundation under Awards 1845833, 2326559, and 2212506.

Published online: 11 September 2024

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