Special Issue on “Recent Advances in Indoor Localization Systems and Technologies”

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Abstract: Despite the enormous technical progress seen in the past few years, the maturity of indoor localization technologies has not yet reached the level of GNSS solutions. The 23 selected papers in this special issue present recent advances and new developments in indoor localization systems and technologies, proposing novel or improved methods with increased performance, providing insight into various aspects of quality control, and also introducing some unorthodox positioning methods.

Keywords: indoor localization technologies; hybrid positioning; model based techniques; quality control

While outdoor localization solutions mainly depend on services offered by well-established Global Navigation Satellite Systems (e.g., Global Positioning System–GPS), indoor localization technologies have not yet reached this level of maturity. There has been enormous technical progress in the past decade, resulting in various competing techniques and technologies for sensing, positioning, and tracking. The two main directions of indoor localization methods contain reference-based and reference-free methods. For references, various types of anchor nodes (e.g., WiFi hotspots, light sources, or pseudo-satellites–pseudolites) [1–3], or various maps (e.g., WiFi or magnetic fingerprint maps of a building) [4,5] can be used. Reference-free approaches do not use such external aids but rather estimate the position of the tracked entity from its measured inertial properties (e.g., Pedestrian Dead Reckoning–PDR) [6].

A wide range of technologies is used to create the reference system, including audio signals [7], magnetic signals [8], visible light [9], and radio communication techniques (e.g., WiFi, Bluetooth, Bluetooth Low Energy–BLE, Radio-Frequency Identification–RFID, and Ultra-wideband–UWB), [1,10–12]. For sensing, various metrics have been proposed, including the Received Signal Strength (RSS), the Time of Flight (ToF) or Time Difference of Arrival (TDoA) of signals, the Angle of Arrival (AoA) or Angle Difference of Arrival (ADoA) of signals, or the Phase of Arrival (PoA) of signals [13]. From the measured signals' properties, the position is estimated using various analytical or iterative methods.

To increase accuracy and performance of indoor localization systems, hybrid solutions have been proposed (e.g., PDR combined by WiFi [14]). Machine learning methods (Neural Networks and Deep Learning) and various model-based techniques are widely used (e.g., various Kalman Filters, Particle Filters) [15,16].

Despite advances in technology, the main challenges in indoor localization are still present: Our current sensing systems are sensitive to the state of the environment (e.g., non-Line of Sight conditions, fading, multipath effects, reflections, noise) and also changes in the environment (e.g., the presence or absence of people, change of furniture), the detection and adaptation to such circumstances are essential in order to maintain a high quality of localization services. Energy efficiency and low cost are further enabling factors of successful localization technologies [14].
Papers in this special issue focus on recent advances and new developments in indoor localization systems and technologies. A collection of 23 papers has been selected, which address various problems of indoor positioning, propose novel or improved methods with increased performance, and also provide insights into various aspects of quality control. The papers of this special issue can be classified into the following four research areas:

**Hybrid Positioning:** The papers in this section provide enhanced positioning performance by combining some of the available sensing modalities. In [17], WiFi RSS is used to provide both fingerprinting and trilateration, and PDR is used to enhance the position estimation accuracy. In [18], a genetic-particle filter (GPF) algorithm is proposed to integrate PDR and geomagnetic positioning. In [19], common infrastructure elements and services, already present in smart environments (e.g., WiFi, access-control services, and BLE beaconing), are used to enhance the quality of indoor positioning. The solution proposed in [20] combines BLE and proximity sensors to increase coverage and accuracy in an Ambient and Assisted Living environment. The hybrid system of [21] combines PDR with occasional correctional steps using Visual Place Recognition, to eliminate the cumulative error of PDR and enhance its accuracy when vertical movement between different floors is possible. In [22], a closed-form localization algorithm is introduced for scenarios where multiple TDOA measurements and a single TOA measurement are also available. The review paper [23] introduces and compares the performance of various integrated remote sensing technologies, which combine, e.g., GPS, UWB, RFID, sensor networks, and digital imaging.

**Techniques to enhance the performance of positioning systems:** In addition to the combination of various sensing modalities, other techniques have been proposed to improve the performance of indoor localization systems. Papers [24–26] propose enhancements to systems using RSS-based WiFi fingerprinting. In [24], a dimensionality reduction technique is proposed, where non-informative anchor nodes are eliminated to reduce computation time and also increase system performance. In [25], methods are proposed to enhance the performance of the feature extraction and the fingerprinting processes, and extensions are introduced to handle the unknown-map situation. In [26], Deep Learning methods are used to enhance the performance of WiFi fingerprinting: A stacked denoising auto-encoder is applied to extract robust features from noisy measurements and other model-based techniques (Kalman filters and Hidden Markov Models) are used to improve the estimate. In [27] an Extended Kalman Filter-based solution, utilizing Channel State Information, is proposed to enhance the accuracy of RSS-based ranging in challenging indoor environments. In [28], a unified state-estimation algorithm is proposed applying finite memory structure filtering and smoothing. The proposed unified approach has attractive properties, e.g., it provides robust, unbiased, and dead-beat state estimates (e.g., position, speed, and acceleration) in noise-free cases. To improve the accuracy of PDR systems, in [29], a novel adaptive Kalman filter-based heading estimation method is proposed.

**Quality control:** The actual state of the environment may strongly influence the accuracy of measurements used for positioning, thus affect the quality of the positioning process as well. High precision localization techniques must monitor the state of both the environment and the measurement process, detect potential anomalies and adapt the estimation process accordingly. Papers in this section propose various solutions to problems emerging in laser- and radio-based positioning systems. Paper [30] investigates positioning systems using laser sensors, being sensitive to refracted and reflected beams when transparent objects are present. The authors propose a novel algorithm to detect the presence of transparent objects, by analyzing the pattern of the reflected noise. In [31], a novel method is proposed to identify the indoor/outdoor environment using GPS signals and machine learning classification techniques. Paper [32] proposes a method to ensure the accuracy and reliability of positioning results in indoor pseudolite systems: An adaptive fault-detection method is applied to find and exclude potentially faulty pseudolite measurements, influenced by multipath effects, clock drift, or noise. In papers [33–35], problems of line-of-sight (LOS) and non-line-of-sight (NLOS) situations are studied in radio-based systems, where
accurate ranging is possible with LOS. These papers propose various NLOS identification methods, which help to eliminate the influence of NLOS errors on positioning accuracy. In [33], a NLOS tracer method is proposed based on the improved Modified Probabilistic Data Association and Interacting Multiple Model algorithms. In [34], a Gaussian model is proposed to identify NLOS signals, while [35] applies machine learning methods to identify not only LOS and NLOS, but also multipath situations.

**Unorthodox Positioning and Sensing methods:** Some of the papers proposed new or unorthodox approaches both for sensing and positioning. In [36], a novel inexpensive sensing method is proposed using a Circular Photodiode Array (for sensor) along with modulated light sources (for anchor nodes), to provide an ADoA-based positioning system. Paper [37] proposes a single-camera trilateration method, which is able to estimate the 3D pose of a camera from a single image, using landmarks at known positions. The systems of [38,39] offer help for the visually impaired, using portable cameras. In [38], a marker-based localization and navigation system is proposed, using convolutional neural networks to identify markers on the camera stream. In [39], a system is proposed, which helps to identify objects on the camera image, using a novel multi-label convolutional support vector machine.

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