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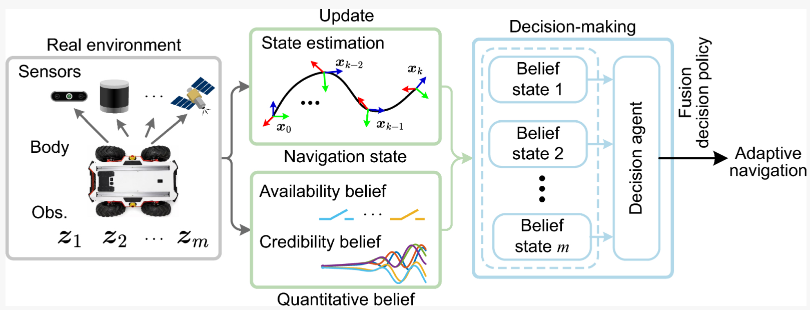
A learning-based navigation system that knows when to trust each sensor

GA, UNITED STATES, August 18, 2026 /EINPresswire.com/ -- Unmanned vehicles navigating through complex, changing environments—from urban canyons to forested trails—face a fundamental challenge: no single sensor is reliable all the time. Global navigation satellite system (GNSS) signals drop out under tree cover, cameras fail in low light or motion blur, and light detection and ranging (LiDAR) loses precision in sparse or geometrically repetitive surroundings. While multi sensor fusion has long been the standard solution, existing systems rely on fixed rules or pre set noise models that cannot adapt to rapidly shifting conditions. Researchers have now developed a method that gives navigation systems a kind of "decision making intelligence"—a quantitative belief state that tells the system how much to trust each sensor at any given moment, and a learning agent that uses that information to dynamically adjust fusion strategies.



Conceptual overview of the quantitative belief-guided intelligent decision-making method.

Existing multi-sensor fusion navigation methods typically depend on predefined fusion architectures, fixed noise models, or analytically designed parameter mappings. These approaches struggle to capture the nonlinear coupling and temporal variations among heterogeneous navigation sources such as Global navigation satellite system (GNSS), vision, light detection and ranging (LiDAR), and inertial sensors. When the operating scenario changes—say, from an open highway into a tunnel or a forest—the quality of information from each sensor can shift dramatically, rendering fixed parameters suboptimal or even harmful. Due to these challenges, there is a pressing need for an intelligent, adaptive fusion framework that can continuously evaluate the reliability of each information source and adjust its contribution accordingly.

Now, researchers from the School of Automation at Beijing Institute of Technology have published a study online 03 August 2026 in Satellite Navigation (Volume 7, Article 21), introducing a quantitative belief-guided intelligent decision-making method for adaptive multi-sensor fusion navigation. The approach builds a compact "belief state" from two complementary components—exogenous availability belief, which characterizes the quality of environmental geometric constraints, and endogenous credibility belief, which reflects the reliability of internal estimation information—and feeds this state into a learning-based decision agent that outputs adaptive information allocation policies in real time.

The core innovation lies in how the system quantifies what it does and does not know. The exogenous availability belief evaluates geometric constraint quality by propagating landmark uncertainty through an information matrix, normalizing the constraint distribution, and assessing uniformity using Shannon entropy, yielding a "degree of availability" for each sensor. The endogenous credibility belief, meanwhile, uses a sliding-window observability matrix to compare reconstructed state errors against theoretical noise propagation, producing a "degree of credibility" that tells the system how consistent its internal estimates are with observed data. Together, these two metrics form a quantitative belief state that serves as the decision input. The decision agent itself is built on a double deep Q-network (DDQN) with long short-term memory (LSTM) for temporal belief encoding—effectively, the system remembers recent belief trends and uses that memory to make smarter allocation choices. The action space is discretized into 66 prototype strategies, each representing a different way of distributing weight among GNSS, LiDAR, and vision sub-filters. The agent is trained on a blend of CARLA simulation data (about 80%) and real-world platform data (about 20%) with quasi-hardware-in-the-loop noise augmentation, helping reduce the simulation-to-reality gap. In real-world tests across a complex urban route covering parking lots, gardens, main roads, breezeways, and sidewalks, the method achieved a root mean square error (RMSE) of just 1.330 meters—outperforming the adaptive fusion baseline AFN (1.518 m), LIO-SAM (2.061 m), and VINS-Fusion (5.934 m). Even with the GNSS branch removed, the system maintained an RMSE of 1.876 m, better than LIO-SAM's 2.061 m, demonstrating that the decision-centric fusion mechanism remains effective even without global correction.

The authors said, "What we've built is essentially a navigation system that can ask itself, at every single moment, 'How much should I really trust what I'm seeing right now?' Instead of relying on fixed rules or hand-tuned weights, the system learns to read the environment and its own internal state, then makes a adaptive decision about which sensors to lean on. The beauty of this approach is that it doesn't just react—it remembers. By encoding temporal belief evolution, the agent picks up on trends and can adapt its allocation decisions as sensing conditions degrade. We were particularly encouraged to see that even when we deliberately removed GNSS, the system still outperformed established LiDAR-inertial methods. That tells us the decision framework itself is making an important contribution."

The implications extend far beyond academic benchmarks. For autonomous vehicles navigating city streets, the method could mean safer, more reliable operation through tunnels, under overpasses, and in dense urban canyons where GNSS signals are unreliable. For drones conducting infrastructure inspection or search-and-rescue missions in forests or indoors, the system's ability to dynamically re-weight visual and LiDAR inputs could maintain positioning when one sensing modality becomes degraded or unreliable. The method runs at approximately 33.6 Hz on the test platform, making it suitable for real-time deployment. Looking ahead, the team plans to explore lightweight versions for resource□constrained miniaturized platforms and to extend the decision□making framework to distributed multi□robot navigation scenarios, where multiple agents must coordinate their sensing and positioning under shared, uncertain environmental conditions.

References
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