Group Assignment: Bayes Filter Assumptions 3

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1 Introduction

The Bayes filter is a probabilistic algorithm used in robotics and artificial intelligence to estimate an agent's belief about its state (e.g., position and orientation). This algorithm helps the robot continuously refine its position based on newly acquired sensor data, but it relies on ideal assumptions, such as independence among measurements and the Markov property. In real-world applications, however, these assumptions can break down.

2 Measurement Independence Violation Example

Consider a robotic vacuum cleaner using sonar to navigate a cluttered room. As it moves past an obstacle, the sonar sensor might pick up echoes from a nearby wall. This lingering echo effect means that the next measurement can be influenced by the prior one, leading the robot to misjudge the distance to other objects. Here, the assumption that measurements are independent does not hold, as the previous measurement interferes with the current one.

3 Example 1: Navigating City Streets

Imagine an autonomous car navigating a busy city. Constantly changing factors—like vehicles, pedestrians, and traffic signals—create an environment where sensors frequently collect incomplete or contradictory data. For instance, a sudden stop by a nearby car could result in misleading distance measurements, potentially causing the Bayes filter to yield incorrect decisions that compromise safety.
Citation: Thrun, S., Burgard, W., Fox, D. (2005). *Probabilistic Robotics.* MIT Press.

4 Example 2: Juggling Multiple Sensors

A drone navigating a park depends on GPS, motion sensors, and a camera for localization. However, when surrounded by trees, GPS signals may weaken, while motion sensors could misreport data due to interference. When the Bayes filter combines these inputs, the lack of sensor independence may lead to navigation errors, causing the drone to misinterpret its location.
Citation: Durrant-Whyte, H., Bailey, T. (2006). "Simultaneous Localization and Mapping (SLAM): Part I." *IEEE Robotics Automation Magazine*, 13(2), 99-110.

5 Example 3: Wearable Health Monitoring

A wearable health monitor tracking heart rate and oxygen levels may encounter sensor inaccuracies during exercise due to movement. The Bayes filter might interpret the inconsistent readings as health anomalies, prompting unnecessary alerts. This situation demonstrates how real-world movement affects sensor data quality, which is hard to accommodate in a static Bayes filter model.
Citation: Patel, S. N., Park, H., Kientz, J. A. (2012). "Maximizing the Accuracy of Activity Recognition Systems in Health Monitoring." *Proceedings of the 2012 ACM Conference on Ubiquitous Computing.*

6 Example 4: Sonar Interference from Previous Echoes

In sonar detection systems used in marine environments, a previous measurement may still influence current readings due to prolonged reverberation. For instance, when a sonar pulse is emitted and subsequently reflected off an underwater object, the echo can take significant time to dissipate in the water. If a new pulse is sent while the echoes from the previous measurement are still present, these lingering echoes can interfere with the interpretation of the current measurement, thus violating the assumption of measurement independence given the state.
Citation: Sha, Liewei; Nolte, Loren W. . (2005). Bayesian sonar detection performance prediction in the presence of interference in uncertain environments. The Journal of the Acoustical Society of America, 117(4), 1954–. doi:10.1121/1.1871732

7 Example 5: Non-Gaussian Noise in GPS Signals

In urban environments or "urban canyons," multipath interference introduces noise with non-Gaussian characteristics, as GPS signals reflect off buildings and other large structures. This interference results in signal delays and fluctuating signal strengths, which deviate from the Gaussian noise assumptions commonly used in Bayesian filtering models. Instead of a predictable distribution, these errors are erratic and dependent on the immediate environment, causing the Bayes filter to struggle with accurately estimating position. This often leads to sudden, large position errors that are difficult for the model to correct.
Citation: Stanford.edu. (2024). The global positioning system and inertial navigation in SearchWorks catalog. [online] Available at: https://searchworks.stanford.edu/view/4031083 [Accessed 28 Oct. 2024].

8 Conclusion

While Bayes filters are foundational for estimating probabilities in robotic systems, they rely on assumptions that are often unrealistic in dynamic environments. Real-world sensor data can be noisy, correlated, and affected by prior states, making a perfect implementation of Bayes filters challenging in practice. These examples highlight the importance of addressing sensor noise, independence, and environmental variability in future developments.