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A Survey on Cooperation-Based Position Estimation Methods in Wireless Sensor Networks Through Probabilistic Modelling

Sujeet Pandey[1], Swatantra Tiwari[2]

M.Tech. Scholar, Rewa Institute of Technology, Rewa (M.P), India[1]

Head Of Department Electronics & Digital communications, Rewa Institute of Technology, Rewa (M.P)[2]

Abstract: The application of Wireless Sensor Networks (WSNs) in environmental monitoring, military surveillance, and industrial automation have led to broad adoption of these networks. For the proper functioning of the network, node localization is critical, which poses a challenge in harsh NLOS and noisy environments. Cooperative localization improves the reliability of position estimation using shared data between nodes due to its reliance on inter-node communication. Incorporating localization uncertainty, probabilistic models, and Gaussian Mixture Models (GMM), offers a powerful solution. This review aims to merge the main contributions in the range-based, range-free, and hybrid localization approaches, mainly focusing on probabilistic models which provide robust precision and scaling efficiency in WSNs.

Keywords: Wireless Sensor Networks (WSNs), Node Localization, Cooperative Localization, Non-Line-of-Sight (NLOS), Probabilistic Models, Gaussian Mixture Models (GMM), Range-Based Localization, Range-Free Localization, Hybrid Localization

1. INTRODUCTION

A wide variety of applications, such as environmental monitoring, industrial automation, and target tracking, are served by distributed sensor nodes, which compose Wireless Sensor Networks (WSNs). The localization of sensor nodes is equally important as the data collection to be performed, simply because of the routing and decision making that must occur. However, several issues make localization in WSNs difficult, such as NLOS (non-line-of-sight) propagation, measurement noise, and the energy constraints of the sensor nodes. To address these issues, a host of algorithms have been created, known as cooperation-based algorithms, where a cluster of nodes shares data/information to improve the overall accuracy of localisation. Furthermore, more robust and adaptive solutions can be obtained by using probabilistic models like Gaussian Mixture Models (GMM), which provide a means of incorporating uncertainties into the localisation process.

This survey captures the most critical developments in cooperation-based localisation approaches, paying particular attention to using probabilistic models to enhance the efficacy of localisation within WSNs.

2. RANGE-BASED LOCALIZATION TECHNIQUES

Like most techniques employed with WSNs, range-based localization techniques are based on the direct measurement of distance or angle between the nodes to estimate their positions. This makes these methods applicable and in wide use across WSNs. These methods have also seen substantial improvement over the years with the advent of advanced probabilistic models and other methods.

Integrating Time Difference of Arrival (TDOA) and Maximum Likelihood Estimation (MLE)
Ho (2012) presented an approach to mitigate the bias in TDOA-based localization, which increases positioning accuracy in non-line-of-sight (NLOS) conditions. This is particularly important because the NLOS effects tend to introduce large localization errors in practical scenarios. In the same direction, Qu & Xie (2012) developed a TDOA-based localization algorithm with the sensor error model for static and mobile sensors, addressing random sensor errors. Their approach employs a probabilistic treatment of sensor errors to enhance the overall robustness of the localization system.
Additionally, Weng et al. (2011) used the Total Least Squares (TLS) technique for robust TDOA-based localization in the presence of noise. This technique maintains the accuracy of the localization despite significant measurement noise, which is problematic for most wireless sensor networks (WSNs).

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Energy-Based Localization

The energy consumed by the sensor nodes is utilized in energy-based localization strategies to estimate the distances between the sensors. This improves the accuracy and energy efficiency of the localization process. In an energy localization technique proposed by Sheng & Hu (2005), energy consumption was optimized through an MLE approach, while maintaining accuracy in position estimates. This is efficient in multi-source detection because it has high energy efficiency and enables accurate estimate of positions crucial for propelling the network.

Meesookho et al. (2008) developed an energy-based localization strategy for acoustical sensors in distributed sensor networks which aimed at optimal placement of the sensors and beacons for reducing energy consumption while achieving localization. Energy based techniques for localization were also considered by Blatt & Hero (2006) which provided an approach for robust localization in noisy environments by using POCS.

Hybrid and Advanced Probabilistic Methods

An incremental Maximum Likelihood (ML) approach for source localization in sensor networks was proposed by Shi and Him (2008). This is an efficient algorithm since it updates the current estimate of a position based on new measurements. Dynamic environments have large levels of movement which makes this algorithm very useful. Meng et al. (2011) build on this work by introducing the Expectation Maximization (EM) algorithm for multi-source energy-based localization. This approach makes the estimates more accurate by considering uncertainties in measurements and better noise robustness.

3. TECHNIQUES FOR LOCALIZATION WITHOUT RANGES

The methods for localization without ranges are efficient because they do not require direct measurements of distances. Instead, they approximate the positions of sensor nodes with the help of neighbouring nodes and their spatial interrelations.

Lowest-Dimension Method: DV-Hop and Variants

Lee et al. (2010) refined the DV-Hop algorithm by incorporating a technique for reducing the error in hop-size estimation, which improves accuracy in range-free localization at scaled ranges. These modifications improve the previously mentioned problems of error in hop boundary localization methods in large networks.

Zheng et al. (2008) developed a long-range DV-Hop algorithm with improved anchor placement. The algorithm increases the localization accuracy as the anchor nodes are placed in strategic positions to enhance coverage and reduce error.

Zhong and He (2011) introduced RSD (Range-free Localisation Beyond Connectivity), which improves the accuracy of range-free methods by enhancing the basic connectivity restrictions using additional network topological information.

Fingerprinting and Machine Learning Methods

Suroso et al. (2011) applied Fuzzy C-Means clustering for fingerprint recognition via localization in indoor environments, classifying the sensor nodes according to the strength of the signals with a certain level of uncertainty.

Gogolak et al. (2011) utilized machine learning neural networks to enhance wireless sensor network fingerprint localization, showcasing the effectiveness of using advanced techniques in various machine learning applications, like localization, where there is significant interference or environmental changes.

Wang et al. (2011) constructed a differential radio map to bolster indoor positioning accuracy, thus further deepening machine learning's contribution to range-free localization systems.

4. PROBABILISTIC AND COOPERATIVE LOCALIZATION

Cooperative localization increases accuracy by allowing nodes to share their position estimates, probabilistically fused. In this case, the focus is on cooperative approaches that apply Bayesian, Kalman filtering, and particle filtering techniques.

Bayesian and Kalman Filtering Approaches

Kaplan (2006) applied Bayesian approaches to node-level selection problems for distributed sensor networks and enhanced the efficiency and accuracy of localization. Ren & Meng (2009) applied a particle filter that provided power-adaptive localization where power usage is changed according to the estimated position, thus improving energy efficiency.

Chiang et al. (2012) developed a hybrid Kalman filter for heterogeneous networks that incorporated other probabilistic approaches into Kalman filtering to enhance the robustness of localization systems to conditions like node movement and changes in the signal strength.

Distributed and Consensus-Based Methods

A decentralized localization approach via averaging Rabat et al. (2005) suggested that it enables sensor nodes to autonomously enhance their localization estimates without the need for a central server. This approach is best suited for systems with large networks because distributed processing is often inefficient and impractical performed from a central point.

Zhang and Cao (2004) developed DCTC (Dynamic Convoy Tree Collaboration) for target tracking, which uses the cooperation of nodes to enhance localization within sensor networks.

Wymeersch et al. (2009) examined the various approaches to cooperative localization. They focused on the advantages offered by cooperative localization, especially in regard to robustness and accuracy in noisy or dynamic environments.

NLOS Mitigation Techniques

Chan et al (2006) looked at the problem presented by NLOS errors in TOA-based localization. They proposed a solution for these localization errors and their reduction using a probabilistic approach.

Mazuelas et al. (2009) suggested using prior NLOS measurement correction for position refinement in the cellular wireless context of independent networked systems, which can also be used in wireless sensor networks (WSNs) suffering from similar problems.

Kim et al. (2001) applied NLOS error mitigation techniques in CDMA systems using Kalman filtering, which may be used for improving localization in WSNs under NLOS conditions.

5. CHALLENGES AND FUTURE DIRECTIONS

Though there has been distinct advancement in cooperation-based localization in WSNs, several issues still challenge researchers. These include:

Scale: Current algorithms fail to efficiently maintain control over processes as networks become larger. There is a need for research on distributed localisation and approximation techniques so that methods are feasible for large-scale networks (Goldenberg et al., 2006).

Energy Efficiency: As with other localisation methods, cooperatively obtained estimates must minimise energy expenditure. New algorithms for energy-efficient resource allocation and adaptive localization strategies must be created to prolong the life of WSNs (Zhu & Ni, 2007).

Security and Robustness: Localization systems are vulnerable to malicious attacks that can open a breach for inaccurate position estimation. Future work should focus on attack-resistant robustness and secure localization protocols (Xu et al. 2011).

6. CONCLUSION

The level of cooperation within the localization process and probabilistic modelling significantly improves the accuracy of WSN positioning. The range-based methods, TDOA and MLE, outperform in accuracy, while DV-Hop and fingerprinting, range-free techniques, outperform in ease of computation. Enhanced techniques for NLOS mitigation, Bayesian filtering, and distributed algorithms significantly improve robustness. Using machine learning for adaptive localization and quantum-inspired techniques for NLOS mitigation enhances precision and so will further research.

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