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An Overview of Estimation Methods within Wireless Sensor Networks

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Abstract*— *This paper is a review of some publications that considered estimation issues within wireless sensor networks. Byzantine attacks on sensors, sensor position uncertainty, and calculation error times are some of the issues that falsify data within a wireless sensor network. Therefore, the implementation of new systematic methods that outperformed previous methods solved each estimation issue as described.

Index Terms*— *Binary Symmetric Channel (BSC), Byzantine Attack, Cramer-Rao Lower Bound (CRLB), Weighted Average (WA).

I. INTRODUCTION

A wireless sensor network (WSN) is a network in which sensors monitor distinct instances within an environmental setting. WSNs have drawn significant attentions [1]-[25]. The estimation types of wireless sensors consist of temperature, gas, sound, pressure, and any other matter or anti-matter within an environment that warrants estimation.

Wireless sensors measurement the parameters of events within an environment, encode the measurement as data, and then transports the data through a network to a main analysis center that uses different estimation techniques to estimate the parameters.

Wireless sensor networks are hot topics in engineering because of its importance [1]-[5]. The innovation of this network and the potential of making it more low cost are very important.

Usually, wireless sensors are low-cost and used in extreme environments. Therefore, errors occur within any part of WSNs [1]-[5]. To analyze sensor errors, an estimation theory called the Creamer-Rao Lower Bound (CRLB) was used as a criterion, which is the optimum performance that an estimation system can achieve. This means all estimation methods can not to outperform the bounds of the Cramer-Rao function.

In this review, some forms of errors within a wireless sensor network will be discussed along with tried strategies and analysis of those experimental findings.

II. ANTI-ATTACK AND CHANNEL AWARE METHOD

In energy based target localization, Byzantine attacks and communication problems have the probability of occurring. Byzantine attacks are manipulations of sensor data that are sent to the fusion center due to an outside intruder [1]. Communication faults are normal sensor errors that occur within the communication channels.

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An anti-attack and channel aware (AACA) target localization method was used to address both the attack and communication errors at the same time, but it only focused on the Rayleigh fading channel with coherent receiver [1].

If transmitted signals are binary phase-shift keying (BPSK) signals, the Rayleigh fading channel with soft receiver and hard decoder can be converted to a binary symmetric channel (BSC) model. This will cause the Rayleigh channel to be equal to the BSC. The probability of errors can be derived from the signal to noise ratio (SNR) channel [1].

Since the maximum likelihood estimation (MLE) estimator is unbiased, root mean square (RMS) was used. As the SNR value increased, the RMS errors decreased due to improved communications. The RMS errors given by the MLE method were higher than the RMS errors given by the AACA method, because the MLE method does not account for both the attack probability and the communication channel error information [1].

Computation time is usually correlated to complexity. So, the AACA method used more computational time than the MLE method, and both the AACA method and the MLE method were greater than the weighted average (WA) method's time, which had the shortest calculation time of the three [1]. But, the errors given by the AACA method were closer to the Cramer-Rao lower bound (CRLB) [1].

III. LINE ERROR MODEL FOR MAXIMUM LIKELIHOOD ESTIMATION

Sensor position uncertainty causes errors when the fusion center tries to locate a target using maximum likelihood estimation (MLE) in energy-based target localization. Each sensor that detects a signal has a threshold that it must reach before it transmits any information about the target.

A fusion center uses the MLE method to estimate the position of a target. The fusion center can receive inaccurate information from a sensor if it is positioned in an undetermined placement, or in motion at the time of data networking [2]. So, a new line error model maximum likelihood estimation (LEM MLE) approach is used that incorporates a model of random sensor position errors in order to reduce performance degradation caused by sensor position uncertainty [2]. This approach can be used in all models of sensor position error that are more general than the LEM.

The LEM MLE was tested using Monte Carlo simulation; We compared this approach to the MLE, LEM, TVCEM, and the CEM approach.

Based on the results, the MLE approach did not account for sensor position uncertainty.

The LEM MLE approach was close to the CRLB [2].

IV. ROBUST ENERGY-BASED TARGET LOCALIZATION

A robust energy-based target localization method in the presence of Byzantine attacked sensors was used to counter Byzantine attack issues. This method assumes that the fusion center knows the percentage of Byzantine attack probability [3].

Results from testing showed that the robust energy-based target localization method had better results than energy based target localization methods, which do not consider byzantine attacks when faced with Byzantine sensors. The majority of this out-performance is due to the robust energy-based method having the capacity to have Byzantine sensors flip decisions with probability [3]. Since both Byzantine and non-Byzantine sensor now applies at the same time and Byzantine sensors can be removed, it was easier for the robust energy-based method to localize targets.

A reputation based method was used to single out Byzantine sensors first. When a Byzantine sensor is found, the false data from the byzantine sensors will be removed so the robust energy-based target localization method can perform better. The RMS errors given by the robust energy-based target localization method were close to the CRLB. The reputation based method for identifying Byzantine sensors resulted in having found most, but not all Byzantine sensors [3]. So it all adds up to whether or not the fusion center takes into account the Byzantine sensors.

V. A NEW DIRECT SEARCH METHOD FOR DISTRIBUTED ESTIMATION

MLE is widely used in target localization, but the issues that arise from using the MLE method is its' time constraints. The MLE method takes an unwanted amount of time to calculate the location of a target because of its computation intensity.

To minimize time calculation, a new direct search method (DSM) was presented. The results showed that the DSM had a lower computation complexity while still reaching similar estimation results to that of the MLE method. The DSM is different from the mean estimator, because it uses quantized data [4]. The mean estimator uses analog data.

The estimation time of MLE increased linearly as the number of sensors increased, but this does not occur with the DSM. The normalized estimation error squared (NEES) was calculated. Then, because the MLE calculates unbiased results, root-mean-square (RMS) errors were used as the performance criterion [4]. The CRLB was used as a benchmark as well.

VI. ENERGY-BASED TARGET LOCALIZATION IN MULTI-HOP WIRELESS SENSOR NETWORKS

The multi-hop transmission scheme was modeled using a binary symmetric channel (BSC). Energy-based target localization methods do not require direction of arrival (DOA), or time delay of arrival (TDOA). But, transmissions from sensors are jumped several times before data reaches the fusion center in a multi-hop wireless sensor network [5].

The MLE framework was extended to address multi-hop transmissions by replacing the BSC model with an equivalent BSC model that considers multi-hop transmissions. A Monte Carlo simulation was used to test the effect of hops on localization performance for all sensors. The estimation errors could be close to the CRLB [5]. This method was integrated into the MLE framework making it more convenient and intuitive.

VII. CONCLUSION

Wireless sensor networks are upgrading regularly, and becoming more efficient. Sensor attacks; position uncertainties, calculation time, and other common and not so common errors are being investigated more thoroughly so that the overall system achieves the CRLB.

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