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Anti-attack and Channel Aware Target Localization in Wireless Sensor Networks Deployed in Hostile Environments

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***Abstract*— This paper discusses the attack and communication channel problems of the energy-based target localization method in wireless sensor network. An anti-attack and channel aware (AACA) target localization method is presented to address the attack problem and the problem of communication channel errors at the same time. Particularly, the AACA method proposed in this paper focuses on the Rayleigh fading channel with coherent receiver. Moreover, the AACA method was compared with the weighted average (WA) method under attack and communication channnel errors. Results showed that the root mean square (RMS) errors presented by the AACA method were close to the CRLB. Moreover, the WA method, although not able to provide as good performance as the AACA method, could give results in much shorter time.**

***Index Terms*—Cramer-Rao lower bound, Target localization, Wireless sensor networks**

I. INTRODUCTION

Advances in hardware and software have enabled wireless sensor networks (WSNs) to be applied in many areas [1-6]. The basic structure of a WSN is a fusion center and a large number of cheap sensors deployed in the sensor field during the sensor layout process [7]. This paper will focus on the target localization problem in WSNs, in which the fusion centre estimates target position based on the information from sensors.

An energy-based maximum likelihood estimation (MLE) method for target localization was presented in [7]. The MLE method is easy to implement compared with the time-delay of arrival (TDOA) method because the MLE method does not require synchronization among sensors [7]. However, there are a few potential problems with the MLE method. First, the MLE method in [7] does not consider communication channel errors between sensors and the fusion centre. To address the problem caused by communication channel errors, the authors in [8] presented a channel aware MLE method in which communication channel models are incorporated into the MLE framework. Moreover, the channel aware MLE method was furthered by a multi-hop channel aware MLE method in [9]. The second problem of the MLE method is sensor fault. One method was presented in [14] to address the sensor fault and communication channel problem at the same time. The method in [14] considered binary symmetric channel (BSC) and Rayleigh fading channel with non-coherent receiver. The third problem of the MLE method in [7] is that it is prone to outsider attacks. If sensors are attacked by intruders, intruders can flip flop sensor decisions to foil the fusion centre [10][11]. Byzantine attacks in cognitive radio networks and in distributed detection were discussed in [10] and [11] respectively. If the attack problem is not taken into account by the fusion centre, the estimation performance will suffer. A robust energy-based target localization method was presented in [13] to address the Byzantine attack problem. In this paper, we will consider the Byzantine attack problem in together with the communication channel errors for the energy-based MLE target localization method. Our solution to both problems is an anti-attack and channel aware (AACA) method to address both the attack problem and the problem of communication channel errors simultaneously. The AACA method is similar to the method presented in [14]. However, the AACA method presented in this paper only considers Rayleigh fading channels with coherent receiver.

The main contribution of this paper is the use of the AACA method to counter both the sensor attack and communication channel errors at the same time. Furthermore, the AACA method is compared with the weighted average (WA) method in the context of Rayleigh communication channel with coherent receiver and hard decoder. Simulation results showed that the AACA method achieved performance close to the Cramer-Rao lower bound (CRLB). If the Rayleigh channel with coherent receiver and hard decoder is used, the AACA algorithm performed better than the weighted average (WA) method. However, the execution time of the AACA method was much longer than the WA method.

Section II presents the energy-based AACA MLE target localization method, followed by the heuristic WA method in Section III. In Section IV, we discuss the Rayleigh channel with coherent receiver and hard decoder. The simulation setup is discussed in Section V. Results and analysis are given in Section VI. Concluding remarks are provided in Section VII.

II. ENERGY-BASED ANTI-ATTACK AND CHANNEL AWARE MLE TARGET LOCALIZATION METHOD

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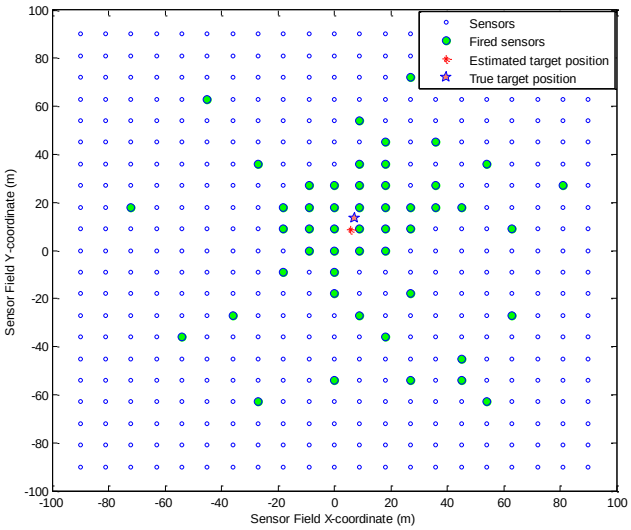

Fig. 1 Sensor field

Fig. 1 shows a typical sensor field, and our simulations were based on this field. Similar to the setup in [7], signals emitting from a target decay according to the model

$$a_i^2 = \frac{G_i P_0'}{(d_i/d_0)^2}, \tag{1}$$

in which the signal amplitude at the ith sensor is a_i, P_0 is the power of the target measured at a reference distance d_0, and G_i is the gain of the ith sensor. According to (1), if the sensor is located closer to the target, the signal received from the target will be stronger. The Euclidean distance between a target located at (x_t, y_t) and the ith sensor located at (x_i, y_i) is defined as

$$d_i = \sqrt{(x_i - x_t)^2 + (y_i - y_t)^2}\ . \tag{2}$$

In this paper, it is assumed that the target is at least d_0 meters away from any sensor in order to avoid numerical problems. If it is assumed that $G_i = 1$ and $d_0 = 1$, the model (1) can be expressed as

$$a_i^2 = \frac{P_0}{d_i^2}\ . \tag{3}$$

However, the signal received at sensor i will be corrupted by noises. The final form of received signal by sensor i is

$$s_i = a_i + w_i \tag{4}$$

where w_i is a Gaussian noise with distribution

$$w_i \sim N(0, \sigma^2)\ . \tag{5}$$

Each sensor, according to a pre-determined threshold γ_i, quantizes the signal s_i to a binary value m_i. The process is denoted by:

$$m_i = \begin{cases} -1 & -\infty < s_i < \gamma_i \\ 1 & \gamma_i \le s_i < +\infty \end{cases}\ . \tag{6}$$

The probability that m_i assumes the value m is

$$p(m_i = m|\theta) = \begin{cases} 1 - Q(\frac{\gamma_i - a_i}{\sigma}) & (m = -1) \\ Q(\frac{\gamma_i - a_i}{\sigma}) & (m = 1) \end{cases}\ . \tag{7}$$

In (7), $Q(x)$ is defined as

$$Q(x) = \int_x^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt\ . \tag{8}$$

The decision made by the ith sensor is m_i. However, due to attack, the decision $\bar{m}_i$ is transmitted to the fusion centre through the Rayleigh fading channel. The relation between m_i and $\bar{m}_i$ is defined by the attack model, which is determined by the attack probability p_a. The attack model can be expressed as:

$$p(\bar{m}_i = 0|m_i = 0) = 1 - p_a \tag{9}$$

$$p(\bar{m}_i = 1|m_i = 0) = p_a \tag{10}$$

$$p(\bar{m}_i = 0|m_i = 1) = p_a \tag{11}$$

$$p(\bar{m}_i = 1|m_i = 1) = 1 - p_a\ . \tag{12}$$

The decision received at the fusion centre is denoted by $\tilde{m}_i$. The values of m_i, $\bar{m}_i$ and $\tilde{m}_i$ can be either 1 or -1. The transition probability between m_i and $\bar{m}_i$ is defined by $p(\bar{m}_i|m_i)$ and the transition probability of communication channel is defined by $p(\tilde{m}_i|\bar{m}_i)$.

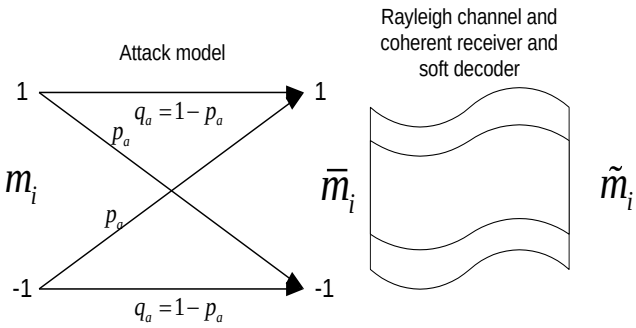

Fig. 2 Attack model and Rayleigh communication channel model

Then, the transition probabilities $p(\bar{m}_i|m_i)$ and $p(\tilde{m}_i|\bar{m}_i)$ are incorporated into the MLE framework. The probability that $\tilde{m}_i$ is equal to m is

$$p(\tilde{m}_i = m|\theta) = \sum_{\bar{m}_i \in \{-1,1\}} \sum_{m_i \in \{-1,1\}} p(\tilde{m}_i = m|\bar{m}_i) p(\bar{m}_i|m_i) p(m_i|\theta)\ . \tag{13}$$

In this paper, the communication channel is the Rayleigh fading channel. If coherent receiver and soft decoder are used, $p(\tilde{m}_i|\bar{m}_i)$ can be expressed as [8]

$$p(\tilde{m}_i|\bar{m}_i) = \frac{2\sigma_v}{\sqrt{2\pi}(1 + 2\sigma_v^2)} \times e^{\frac{-\tilde{m}_i^2}{2\sigma_v^2}} \left[1 + \bar{m}_i \sqrt{2\pi} \alpha \tilde{m}_i e^{\frac{(\alpha \tilde{m}_i)^2}{2}} Q(-\alpha \bar{m}_i \tilde{m}_i) \right], \tag{14}$$

in which α is

$$\alpha = 1 / (\sigma_v \sqrt{1 + 2\sigma_v^2})\ . \tag{15}$$

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If the decision vector $\tilde{\mathbf{M}} = [\tilde{m}_1\ \tilde{m}_2\ \ldots\ \tilde{m}_N]^T$ received at the fusion centre, the fusion centre estimates $\theta = [P_0\ x_t\ y_t]^T$ by finding the θ value to maximize

$$\ln p(\tilde{\mathbf{M}}|\theta) = \sum_{i=1}^{N} \ln\left[\sum_{\bar{m}_i \in \{-1,1\}} \sum_{m_i \in \{-1,1\}} p(\tilde{m}_i = m|\bar{m}_i) p(\bar{m}_i|m_i) p(m_i|\theta)\right]. \quad (16)$$

The process is expressed as

$$\hat{\theta} = \max_{\theta} \ln p\left(\tilde{\mathbf{M}}|\theta\right). \quad (17)$$

For an unbiased estimate of θ, the Cramer-Rao lower bound (CRLB) can be derived by

$$E\{[\hat{\theta}(\tilde{\mathbf{M}}) - \theta][\hat{\theta}(\tilde{\mathbf{M}}) - \theta]^T\} \geq \mathbf{J}^{-1} \quad (18)$$

$$\mathbf{J} = -E\left[\nabla_\theta \nabla_\theta^T \ln p\left(\tilde{\mathbf{M}}|\theta\right)\right]. \quad (19)$$

The derivation of the CRLB matrix is presented in Appendix.

III. HEURISTIC WA ESTIMATION METHOD

Another method to estimation target location is the WA estimation method presented in [7][12]. The calculation of the WA method can be expressed as [7][12]

$$\psi_t = \frac{\sum_{\tilde{m}_i = 1} \tilde{m}_i \psi_i}{\sum_{\tilde{m}_i = 1} \tilde{m}_i}. \quad (20)$$

In (20), the location of the ith sensor is ψ_i and the estimate of the target position is ψ_t. If the decision $\tilde{m}_i$ received by fusion centre from the ith sensor is 0, the decision will not be included to (20). If the decision $\tilde{m}_i$ received by fusion centre from the ith sensor is 1, the $\tilde{m}_i \psi_i$ value is added to the numerator of (20) and the decision $\tilde{m}_i$ is added to the denominator of (20). The attack information or any information about the communication channels between sensors and the fusion centre is not used in the WA method.

IV. RAYLEIGH CHANNEL WITH COHERENT RECEIVER AND HARD DECODER

The Rayleigh fading channel with soft receiver and hard decoder can be converted to a BSC model if the transmission signals are binary phase-shift keying (BPSK) signals [8][12]. The error probability P_e can be derived from channel SNR [8][12]

$$P_e = \frac{1}{2}\left(1 - \frac{\sqrt{SNR}}{\sqrt{1+SNR}}\right). \quad (17)$$

Therefore, if a coherent receiver and hard decoder are used, the Rayleigh channel is equal to a BSC and the crossover probability of the BSC can be determined by (21). We will use the attack model in conjunction with the Rayleigh channel with coherent receiver and hard decoder to compare the AACA method with the WA method.

V. SIMULATION SETUP

To compare the AACA method with the CRLB, we use the Rayleigh fading channel with coherent receiver and soft decoder in conjunction with the attack model. We use 1000 Monte Carlo runs and set (x_t, y_t)=(12, 13), $p_a = 0.01$, $P_0 = 10{,}000$, and $\gamma_i = 5$ for all sensors. In all other simulations, we set $\gamma_i = 4$ for all sensors, (x_t, y_t)=(12, 13), $p_a = 0.01$ and $P_0 = 10{,}000$. All simulations involving computation times were run using a Pentium-4 computer. Results of simulation times were based on 100 runs.

VI. RESULTS AND ANALYSIS

Because the MLE estimator is unbiased, we use RMS estimation errors as an estimation performance criterion. For the Rayleigh channel with coherent receiver and soft decoder in conjunction with the attack model as shown in Fig. 2, the RMS errors given by the AACA method were close to the CRLB (Fig. 3). As the SNR value of communication channel increased, the RMS errors become lower due to improved communication channel condition (Fig. 3).

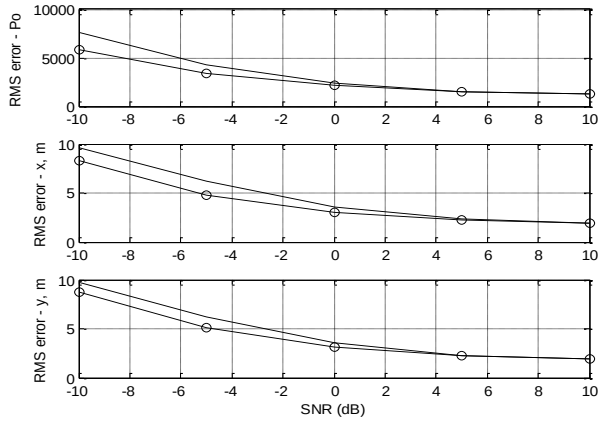

Fig. 3 RMS estimation errors corresponding to the Rayleigh communication channel with coherent receiver and soft decoder in conjunction with the attack model (solid line: AACA method, solid line+star: CRLB)

For the attack model in conjunction with the Rayleigh channel with soft decoder and hard receiver, the Rayleigh channel can be modeled as a BSC, and therefore the combined model is the BSC model in conjunction with an attack model. In this case, the AACA method (solid line) could still provide RMS errors close to the CRLB (solid line+circle), and the RMS errors given by the MLE method (solid line+square), which is channel unaware and attack unaware by nature, were higher than the RMS errors given by the AACA method (Fig. 4). This is because the MLE method does not take into account both the attack probability and the communication channel error information. The RMS errors given by the WA method (solid line+star) were higher than the RMS errors given by the MLE method (Fig. 4).

Usually, computational complexity can be reflected in computation time. For the Rayleigh channel with coherent receiver and hard decoder, the computation times of the AACA method were greater than the computation times for the MLE method (Table I). The computation times of the MLE method were much greater than for the WA method (Table I). The reason is that the WA method only needs simple calculations while the MLE method involves a time-consuming search process to find the maximum points [12].

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Moreover, the computation time of the AACA method was a little higher than for the MLE method. This is because the MLE method does not need to include additional channel probability information in (16) [12].

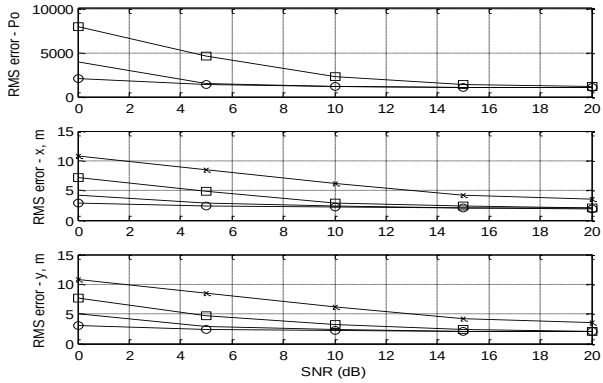

Figure 4. RMS estimation errors (solid line: AACA method, solid line+star: WA method, solid line+circle: CRLB of AACA method, solid line+square: the MLE method) Hard decoder

Table I. Computation times for aaca mle method, the mle method, and wa method (rayleigh channel with coherent receiver and hard decoder, 100 runs)

Time (seconds)	SNR (dB)				
	0	5	10	15	20
channel aware	2768.409	2678.219	2502.031	2462.927	2429.777
channel unaware	2148.551	2132.214	2120.367	1959.994	1942.652
WA	5.2220	5.1815	5.1025	5.1087	5.0700

VII. CONCLUSION

In this paper, an AACA method was presented to address the attack problem and the problem of communication channel errors at the same time. Results showed that the AACA method could provide results close to the CRLB. In practice, both attack and communication channel errors are common. The AACA algorithm can effectively address both problems.

VIII. APPENDIX

The CRLB is given by:

$$E\{[\hat{\theta}(\mathbf{M})-\theta][\hat{\theta}(\mathbf{M})-\theta]^T\} \geq \mathbf{J}^{-1}. \quad (22)$$

As we know, the Fisher information matrix (FIM) can be obtained as

$$\mathbf{J} = -E\left[\nabla_\theta \nabla_\theta^T \ln p\left(\mathbf{M}|\theta\right)\right]. \quad (23)$$

First we derive the (1,1) element of $\mathbf{J}$ matrix. According to (9), we have

$$\frac{\partial \ln p\left(\mathbf{M}|\theta\right)}{\partial P_0} = \sum_{i=1}^{N} \frac{1}{p(\tilde{m}_i|\theta)} \frac{\partial p(\tilde{m}_i|\theta)}{\partial P_0} \quad (24)$$

$$\frac{\partial^2 \ln p\left(\mathbf{M}|\theta\right)}{\partial P_0^2} = \sum_{i=1}^{N} -\frac{1}{p^2(\tilde{m}_i|\theta)}\left[\frac{\partial p(\tilde{m}_i|\theta)}{\partial P_0}\right]^2 + \frac{1}{p(\tilde{m}_i|\theta)}\frac{\partial^2 p(\tilde{m}_i|\theta)}{\partial P_0^2}. \quad (25)$$

The expectation of (25) is

$$\mathrm{E}\left[\frac{\partial^2 \ln p\left(\mathbf{M}|\theta\right)}{\partial P_0^2}\right] = \sum_{i=1}^{N} -\int_{-\infty}^{\infty} (\Delta_1) d\tilde{m}_i. \quad (26)$$

In (26), Δ_1 is defined as

$$\Delta_1 = \frac{1}{p^2(\tilde{m}_i|\theta)}\left[\frac{\partial p(\tilde{m}_i|\theta)}{\partial P_0}\right]^2 - \frac{1}{p(\tilde{m}_i|\theta)}\frac{\partial^2 p(\tilde{m}_i|\theta)}{\partial P_0^2}. \quad (27)$$

Because $-\int_{-\infty}^{\infty}\left(\frac{1}{p(\tilde{m}_i|\theta)}\frac{\partial^2 p(\tilde{m}_i|\theta)}{\partial P_0^2}\right)d\tilde{m}_i = 0$, we have

$$E\left[\frac{\partial^2 \ln p\left(\mathbf{M}|\theta\right)}{\partial P_0^2}\right] = \sum_{i=1}^{N}\int_{-\infty}^{\infty} -\frac{1}{p(\tilde{m}_i|\theta)}\left[\frac{\partial p(\tilde{m}_i|\theta)}{\partial P_0}\right]^2 d\tilde{m}_i. \quad (28)$$

In (28), $p(\tilde{m}_i|\theta)$ is provided by (16), and $\frac{\partial p(\tilde{m}_i|\theta)}{\partial P_0}$ is defined by

$$\frac{\partial p(\tilde{m}_i|\theta)}{\partial P_0} = \sum_{m_i \in \{-1,1\}} \sum_{\bar{m}_i \in \{-1,1\}} p(\tilde{m}_i|\bar{m}_i) p(\bar{m}_i|m_i) \frac{\partial p(m_i|\theta)}{\partial P_0}. \quad (29)$$

We have

$$\frac{\partial Q(\frac{\eta_{il}-a_i}{\sigma})}{\partial p_0} = \frac{1}{2\sqrt{2\pi}\sigma\sqrt{P_0}d_i} e^{-\frac{(\eta_{il}-a_i)^2}{2\sigma^2}} \quad (30)$$

and then $\frac{\partial p(m_i = l|\theta)}{\partial p_0}$ can be expressed as

$$\frac{\partial p(m_i = l|\theta)}{\partial p_0} = \frac{\partial}{\partial p_0}\left[Q(\frac{\eta_{il}-a_i}{\sigma}) - Q(\frac{\eta_{i(l+1)}-a_i}{\sigma})\right] = \frac{1}{2\sqrt{2\pi}\sigma\sqrt{P_0}d_i}\left(e^{-\frac{(\eta_{il}-a_i)^2}{2\sigma^2}} - e^{-\frac{(\eta_{i(l+1)}-a_i)^2}{2\sigma^2}}\right) \quad (31)$$

Then, (29) can be expressed as

$$\frac{\partial p(\tilde{m}_i|\theta)}{\partial P_0} = \sum_{\bar{m}_i \in \{-1,1\}} \sum_{m_i \in \{-1,1\}} p(\tilde{m}_i|\bar{m}_i) p(\bar{m}_i|m_i) \Delta_2. \quad (32)$$

In (32), Δ_2 is defined as

$$\Delta_2 = \frac{1}{2\sqrt{2\pi}\sigma\sqrt{P_0}d_i}\left(e^{-\frac{(\eta_{il}-a_i)^2}{2\sigma^2}} - e^{-\frac{(\eta_{i(l+1)}-a_i)^2}{2\sigma^2}}\right). \quad (33)$$

Take (32) and (16) into (28), we can have the final form of (26). In (32), $p(\bar{m}_i|m_i)$ is defined in (9)-(12) and $p(\tilde{m}_i|\bar{m}_i)$ is defined in (14). Other elements of $\mathbf{J}$ matrix can be derived similarly.

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REFERENCES

[1] D. Li, K. D. Wong, Y.H.Hu, and A. N. Sayeed, "Detection, Classification, and Tracking of Targets", *IEEE Signal Processing Magazine*, vol.19, no. 3, pp. 17-29, Mar. 2002.

[2] Z. X. Luo and T. C. Jannett, "Optimal Threshold for Locating Targets within a Surveillance Region Using a Binary Sensor Network", in *Proceedings of the International Joint Conferences on Computer, Information, and Systems Sciences, and Engineering* (CISSE 09), Dec. 2009.

[3] Z. X. Luo, "A censoring and quantization scheme for energy-based target localization in wireless sensor networks", To appear in *Journal of Engineering and Technology.*

[4] X. Sheng and Y. H. Hu, "Maximum Likelihood Multiple-Source Localization Using Acoustic Energy Measurements with Wireless Sensor Networks", *IEEE Transactions on Signal Processing*, vol.53, no.1, pp. 44-53, Jan. 2005.

[5] Z. X. Luo and T. C. Jannett, "A Multi-Objective Method to Balance Energy Consumption and Performance for Energy-Based Target Localization in Wireless Sensor Networks", in *Proceedings of the 2012 IEEE Southeastcon*, Orlando, FL, Mar. 2012, in press.

[6] Z. X. Luo and T. C. Jannett, "Modeling Sensor Position Uncertainty for Robust Target Localization in Wireless Sensor Networks", in Proceedings of the 2012 IEEE Radio and Wireless Symposium, Santa Clara, CA, Jan. 2012.

[7] R. X. Niu and P. K. Varshney, "Target Location Estimation in Sensor Networks with Quantized Data", *IEEE Transactions on Signal Processing*, vol. 54, pp. 4519-4528, Dec. 2006.

[8] O. Ozdemir, R. X. Niu, and P. K. Varshney, "Channel Aware Target Localization with Quantized Data in Wireless Sensor Networks", *IEEE Transactions on Signal Processing*, vol. 57, no. 3, pp. 1190-1202, Mar. 2009.

[9] Z. X. Luo and T. C. Jannett, "Energy-Based Target Localization in Multi-Hop Wireless Sensor Networks", in Proceedings of the 2012 IEEE Radio and Wireless Symposium, Santa Clara, CA, Jan. 2012.

[10] A.S. Rawat, P. Anand, H. Chen, and P.K. Varshney , "Collaborative Spectrum Sensing in the Presence of Byzantine Attacks in Cognitive Radio Networks", *IEEE Transactions on Signal Processing*, vol.59, no.2, pp.774-786, Feb. 2011.

[11] S. Marano, V. Matta, and Lang Tong, "Distributed Detection in the Presence of Byzantine Attacks", *IEEE Transactions on Signal Processing*, vol.57, no.1, pp.16-29, Jan. 2009

[12] Z. X. Luo and T. C. Jannett, "Performance Comparison between Maximum Likelihood and Heuristic Weighted Average Estimation Methods for Energy-Based Target Localization in Wireless Sensor Networks", in *Proceedings of the 2012 IEEE Southeastcon*, Orlando, FL, Mar. 2012.

[13] Z. X. Luo, "Robust Energy-based Target Localization in Wireless Sensor Networks in the Presence of Byzantine Attacks", to appear in *International Journal of Innovative Technology and Exploring Engineering.*

[14] Z. X. Luo, "Modeling and Multi-objective Optimization for Energy-based Target Localization Using Wireless Sensor Networks", PhD Dissertation, The University of Alabama at Birmingham, to be submitted.

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