A Coding and Decoding Scheme for Energy-based Target Localization in Wireless Sensor Networks

Zhenxing Luo

Abstract*—*A coding and decoding scheme for energy-based target localization in wireless sensor networks (WSNs) is presented in this paper. This scheme can improve target localziation performance when WSNs are deployed in noisy environments. Simulation results showed that the energy-based target localization method using this coding and decoding scheme could produce better localization performance than the energy-based target localziation method which did not use this scheme. Moreover, the root mean square (RMS) errors given by the proposed method were close to the Cramer-Rao lower bound (CRLB).

Index Terms*—*Cramer-Rao lower bound, maximum likelihood estimation, quantization, Wireless sensor networks.

I. INTRODUCTION

Wireless sensor networks (WSNs) have drawn significantly attentions recently and target localization is a very popular research topic in WSNs [1-7]. The fusion center can estimate the target position by gathering information from sensors and employing appropriate estimation methods.

To solve the target localization problem in WSNS, an energy-based target localization method was presented in [8]. In this method, sensors measure the signal from a target. If the target is close to the sensor, the signal received will be strong. If the target is far away from the target, the signal received will be weak. Then, sensors send the measurements to the fusion centre. The fusion centre estimates the target position using the maximum likelihood estimation (MLE) method based on the measurements from sensors [8].

However, the energy-based target localization method suffers from some problems. For example, usually, WSNs are deployed in environments, where noise, interference and disturbances frequently make the sensor fail. To counter sensor failure, in [9][10], the sensor failure model was incorporated into the energy-based target localization method. To counter the communication channel errors, three communication channel models were included in the MLE method for a nonlinear estimation model [11]. For a linear estimation model, one method to counter communication channel errors was presented in [12]. However, if severe noise and interference are present, the MLE method may not produce satisfactory results.

A coding and decoding scheme is needed to counter severe noise and interference. This paper will present a coding and decoding scheme for the energy-based target localization method.

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The main contribution of this paper is the presentation of a coding and decoding scheme for the energy-based target localization method. Due to the limitation of computational resources, sensors can only use a simple coding and decoding scheme. In this paper, we use a simple repetition code and the majority decision rule. Simulation results showed that a coding and decoding scheme can improve target localization performance.

Section II presents the coding and decoding scheme for the energy-based target localization method. In Section III, we discuss the simulation setup, followed by simulation results and analysis in Section IV. Section V delivers concluding remarks.

II. A CODING AND DECODING SCHEME FOR THE ENERGY-BASED TARGET LOCALIZATION METHOD

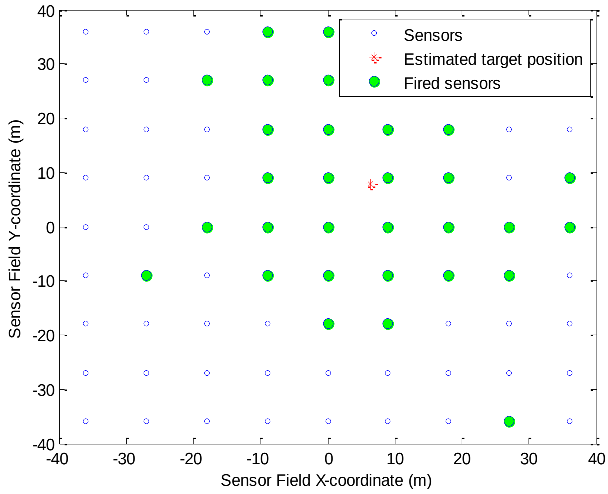

Figure 1: Sensor field

In the sensor field shown in Figure 1, small circles indicate non-fired sensors and big circles indicate fired sensors. Following the setup in [8], signals received by sensors from a target can be calculated by the signal decay model

$$a_i^2 = \frac{G_i P_0^{'}}{\left(d_i / d_0\right)^2}. \qquad (1)$$

In (1), d_0 is a reference distance, P_0 is the signal power from the target measured at d_0, and the gain of the ith sensor is G_i. If we assume that $G_i = 1$ and $d_0 = 1$, then, model (1) can be simplified as

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$$a_i^2 = \frac{P_0}{d_i^2} . \qquad (2)$$

For a given P_0, the signal received by the ith sensor is a function of the distance between the target at (x_t, y_t) and the ith sensor at (x_i, y_i). The distance can be determined by

$$d_i = \sqrt{(x_i - x_t)^2 + (y_i - y_t)^2} . \qquad (3)$$

In this paper, to avoid numerical problems, we assume that the minimum value of d_i is 1 [8].

Because of the presence of environmental noise, the signal received at the ith sensor can be expressed as

$$s_i = a_i + w_i \qquad (4)$$

In (4), w_i is a Gaussian noise with zero mean and variance σ^2.

Usually, sensors can send the signal strength information to the fusion centre either by analog data or by quantized data [8]. Quantized data can save energy and communication bandwidths. Therefore, we will use quantized data in this paper.

According to the threshold set

$$m_i = \begin{cases} 0 & -\infty < s_i \le \gamma_{i1} \\ 1 & \gamma_{i1} < s_i \le \gamma_{i2} \\ \vdots & \vdots \\ L-2 & \gamma_{i(L-2)} < s_i \le \gamma_{i(L-1)} \\ L-1 & \gamma_{i(L-1)} < s_i < \infty \end{cases} , \qquad (5)$$

the ith sensor quantizes s_i into m_i. Given a θ, m_i takes value m with probability

$$p(m_i = m|\theta) = Q(\frac{\gamma_{il} - a_i}{\sigma}) - Q(\frac{\gamma_{i(l+1)} - a_i}{\sigma}) \quad (0 \le m \le L-1) . \qquad (6)$$

In (6), $Q(x)$ is defined as

$$Q(x) = \int_x^\infty \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt . \qquad (7)$$

The decision vector made by sensors can be expressed by

$$\mathbf{M} = [m_1 \ m_2 \ ... \ m_N]^T . \qquad (8)$$

Because sensors usually are deployed in environments where noise and interference are common, the decision vector sent to the fusion centre will be significantly distorted. Using distorted decisions to estimate the target position will degrade target localization performance. A coding and decoding scheme can improve target localization performance. The diagram of the coding and decoding scheme is shown in Figure 2.

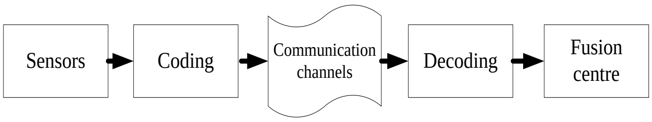

Figure 2: Diagram of the coding and decoding scheme.

However, limited by computational resources, sensors cannot use complicated coding and decoding schemes. We will use a very simple decoding and decoding scheme: repetition code and majority decision rule [14]. In the repetition code, sensors simply send the decision to the fusion n times (n is an odd number). If binary decisions 0s and 1s are used, then, the fusion centre considers the transmitted decision to be 0 if it receives more 0s than 1s. Similarly, if the fusion centre receives more 1s than 0s, it considers the transmitted decision to be 1. If the decision made by the ith sensor is m_i and the final decision made by the fusion centre is $\tilde{m}_i$, then the transition probabilities between m_i and $\tilde{m}_i$ can be calculated by

$$p(\tilde{m}_i = m_i) = \sum_{k=1}^{n-1/2} \binom{n}{k} p_b^k (1-p_b)^{n-k} \qquad (9)$$

$$p(\tilde{m}_i \ne m_i) = \sum_{k=(n+1)/2}^{n} \binom{n}{k} p_b^k (1-p_b)^{n-k} . \qquad (10)$$

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

$$\ln p(\tilde{\mathbf{M}}|\theta) = \prod_{i=1}^{N} \left[\sum_{m_i = o}^{L-1} p(\tilde{m}_i | m_i) p(m_i|\theta) \right]. \qquad (11)$$

The estimation result is $\hat{\theta}$

$$\hat{\theta} = \max_{\theta} \ln p\left(\tilde{\mathbf{M}}|\theta\right). \qquad (12)$$

If the size of the decision vector $\tilde{\mathbf{M}}$ is large enough, the estimation result $\hat{\theta}$ will be unbiased. The estimation performance of MLE can be compared with Cramer-Rao lower bound (CRLB), which is given by

$$E\{[\hat{\theta}(\tilde{\mathbf{M}}) - \theta][\hat{\theta}(\tilde{\mathbf{M}}) - \theta]^T\} \ge \mathbf{J}^{-1} \qquad (13)$$

$$\mathbf{J} = -E\left[\nabla_\theta \nabla_\theta^T \ln p\left(\tilde{\mathbf{M}}|\theta\right)\right] \qquad (14)$$

where $\mathbf{J}$ is the Fisher information matrix (FIM). The method to derive elements of FIM can be found in [11].

III. SIMULATION SETUP

To show the effectiveness of the coding and decoding scheme in reducing the error probability of the equivalent communication channel, the error probabilities of the equivalent communication channel were calculated. In this paper, the equivalent communication channel is the channel between the sensor and the fusion centre if the coding and decoding scheme is used. The communication channel is the physical communication channel between the sensor and the fusion centre without using the coding and decoding scheme. To generate Figure 3, we assumed the error probability of the communication channel was 0.1 and the length of code was changed from 1, 3, 5, 7, to 9.

To show the performance of the coding and decoding scheme, RMS errors given by this scheme were compared with the CRLB. The performance of the coding scheme was compared to the performance of the non-coding scheme. We set (x_t, y_t)=(12, 13), $P_0 = 10{,}000$, and $\gamma_1 = 6$ for all sensors. The error probability of the communication channel was 0.1. The sensor layout used is similar to the one shown in Figure 1. However, the size of the sensor field was [-90, -90], [-90, 90], [90, -90], and [90, 90]. The RMS errors in Figure 4 were calculated based on 100 Monte Carlo simulations.

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Similar simulations were conducted to show the effect of the error probability of the communication channel on target localization performance. In these simulations, RMS errors given by the coding and decoding scheme were compared with the CRLB. Moreover, the performance of the coding scheme was compared with performance of the non-coding scheme. In these simulations, we set (x_t, y_t)=(12, 13) , $P_0 = 10,000$, and $\gamma_1 = 6$ for all sensors. The length of the code was set to 5. All points involving RMS errors in Figure 5 were calculated based on 100 Monte Carlo simulations.

IV. RESULTS AND ANALYSIS

The error probabilities of the equivalent communication channel are shown in Figure 3. It is clear that the longer the code was, the lower the error probability was. However, longer code uses more communication bandwidth and transmitting longer code consumes more energy. Therefore, the appropriate code length should be determined based on the localization performance requirement and communication and energy resources available.

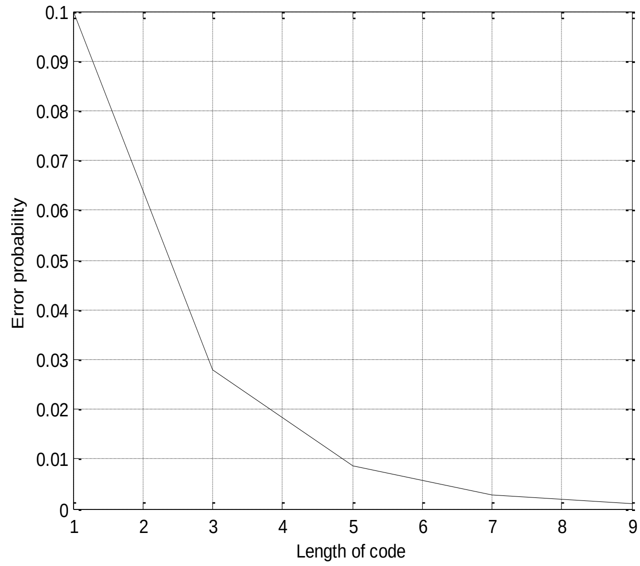

Figure 3: Error probabilities of the equivalent communication channel as a function of code length (The error probability of the physical communication channel was set to 0.1)

The RMS errors given by the coding and decoding scheme were compared with the CRLB when the length of code varied (Figure 4). When the length of code was low, the RMS errors corresponding to the coding scheme were high. When the length of code was high, the RMS errors corresponding to the coding scheme were low (Figure 4). The RMS errors given by the coding scheme were close to the CRLB. Moreover, the non-coding scheme gave much higher RMS errors. The RMS errors corresponding to the non-coding scheme were constant in Figure 4 because the length of code did not affect the performance of the target localization method using the non-coding scheme.

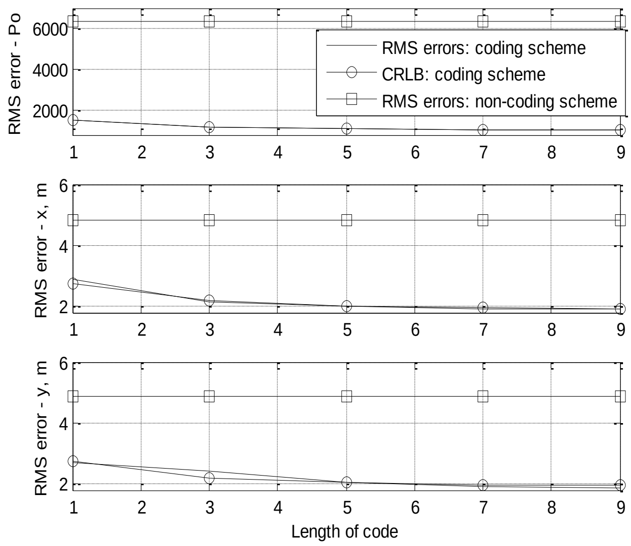

Figure 4: Target localization performance as a function of code length

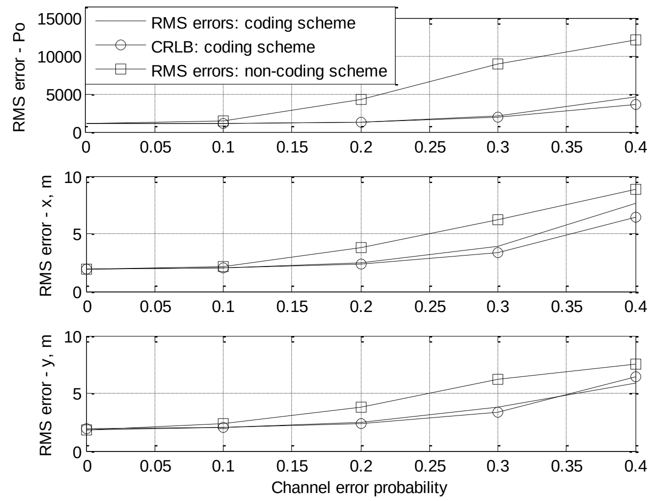

Figure 5: Target localization performance as a function of the error probability of the physical communication channel

If the error probability of the physical communication channel was varied, the RMS errors corresponding to both the coding scheme and the noncoding scheme also varied. When the error probability of the physical communication channel was low, the RMS errors corresponding to the coding scheme were also low. When the error probability of the physical communication channel was high, the RMS errors corresponding to the coding scheme were also high (Figure 5). The RMS errors given by the coding scheme were also close to the CRLB. However, the non-coding scheme gave much higher RMS errors compared with the coding scheme when the error probability of the physical communication channel was high. When the error probability of the physical communication channel was low, both schemes gave similar RMS errors (Figure 5).

V. CONCLUSIONS

In this paper, we presented a coding and decoding scheme for the energy-based target localization method.

In this coding and decoding scheme, repetition code and majority decision rule are used because of the simplicity of the repetition code and the majority decision rule. Simulation results showed that this scheme was effective at reducing the RMS estimation errors. In practice, one can choose an appropriate length of code to provide satisfactory results without wasting much computational resources and communication bandwidth.

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