Fast Localization Using Robust UWB Coding in Wireless Sensor Networks

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***Abstract*—Localization has many important applications in wireless sensor networks. A variety of wireless technologies, such as acoustic, infrared, and ultra-wide band (UWB) media have been applied for localization purposes. This paper consists of two parts. The first part presents new UWB-based communication protocols for received signal strength (RSS) information collection, namely, a robust UWB coding method called U-BOTH (UWB based on Orthogonal Variable Spreading Factor and Time Hopping), an ALOHA-type channel access method and a message exchange protocol to collect location information. The second part presents the localization algorithm, which is applied in coal mine environments. The localization algorithm first derives the corresponding UWB path loss model, then applies the maximum likelihood estimation (MLE) method to compute the distances to the reference sensors using the RSS information, and to estimate the coordinate of the moving sensor using least squares (LS) method. The performance of the system is validated using theoretic analysis and simulations. Results show that U-BOTH transmission technique can effectively reduce the bit error rate under the path loss model, and the corresponding ranging and localization algorithms can accurately compute object locations in coal mine environments.**

***Keywords*-Coal mine channel modeling; orthogonal variable spreading factor (OVSF); time hopping (TH); ultra-wide band (UWB); localization; ranging;**

I. Introduction

Large-scale economic wireless sensor networks (WSNs) become increasing attractive to environmental monitoring, control and interaction applications. Object tracking and localization is one of the key challenge for these applications. Various solutions have been proposed based on ranging techniques, such as time of arrival (ToA), which is used by GPS, or radio or acoustic received signal strength (RSS) using certain path loss models. Sometimes, range-free techniques are also applied to estimation locations, such as hop count or centroid methods [4].

Most existing localization methods were based on rather generic signal propagation and network formation assumptions. In this paper, we explore localization techniques that are targetted at monitoring and tracking human and vehicle locations in coal mine environments. This research is especially valuable when helping people in the emergency situations and reducing the costs of coal mine operations.

Coal mines present extremely harsh conditions for wireless communications. First, the power of the transmitter must be reduced to the lowest level to avoid sparkling gas explosions. Secondly, signal propagations are especially prone to multipath effects. Third, wireless networks are more dynamic than surface networks due to signal attenuation, movements, etc. Lastly, WSNs in coal mines is a multiple users system, and the MUI (multiple users interference) has dramatic impacts on the precision of the localization system.

UWB (ultra-wide band) transmission and coding technologies were proven an ideal solution to the coal mine environment. UWB exhibits excellent characteristics in reducing co-channel interference [12]. IEEE 802.15.4a is the *de facto* standards to provide low power long distant low data-rate service for real-time communication and precise localization applications [1], [8]. In UWB, coding is an important method to depress MUI. Different UWB coding algorithms have been proposed so far, such as DS-UWB (Direct Sequence UWB) and TH-UWB (Time Hopping UWB) [7]. However, none was shown to guarantee high quality localization when the multipath and MUI exist.

In this paper, we present a UWB based ranging and localization system, which consists of two components. First, we propose a new UWB coding method that applies the OVSF (orthogonal variable spread factor) coding to reduce bit error rate (BER), while mitigating the multi-users-interference (MUI) and Gaussian noise interference, thus improving the accuracy of RSS rangings and achieving fast localization results. Secondly, we propose an MLE (maximum likelihood estimation) method to compute the distances between neighbor nodes using the RSS information, and present an iterative LS (least squares) based localization algorithm using limited number of reference points [11].

Overall, the contribution of this work is the novel integration of multiple advanced UWB transmission and reception techniques, and their application for localization purposes in underground coal mine environments.

The rest of the paper is organized as follows. Section II describes the basic assumptions of the localization system. Section III presents U-BOTH coding method, and provides the UWB signal processing model in coal mine environments. Section IV specified a WSN communication protocol in order to collect reference point location information. According to the path loss model and the RSS information collected by the mobile target, Section V and Section VI present the ranging and localization algorithms using the MLE and the LS methods, respectively. Section VII evaluates the system using simulations. Section VIII concludes the paper.

II. System Assumptions

We assume coal mine WSN (wireless sensor network) deployment. The key difference between such an assumption and other deployment scenarios is that the signal propagation presents unique characteristics, which determines the path loss model that is used for ranging and localization purposes. Furthermore, we assume that a number of reference nodes are deployed the network, and have already acquired their exact location coordinates through other means, such as initial location calibrations.

The problem in our localization computation is modeled as, *given a mobile target with unknown coordinate, derive its position coordinate by collecting the RSS information from the reference nodes and running the localization algorithms on the target.*

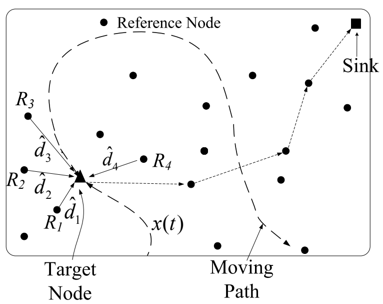


Figure 1. Wireless sensor network localization using UWB.

Fig. 1 illustrate a WSN with one target mobile node, denoted by triangle, and multiple reference nodes R_1, R_2, R_3 and R_4, denoted by dots. The target node moves across the network and collects the coordinate information of reference nodes and their corresponding signal strength. In each iteration, the target node calculates the ranges between itself and the four reference nodes, $\hat{d}_1$, $\hat{d}_2$, $\hat{d}_3$ and $\hat{d}_4$, and derives its own coordinate, which is sent to the sink, denoted by the square in Fig. 1.

III. UWB Based Communication

A. UWB Signal Spreading and Modulation

In order to achieve accurate localization, we need a reliable physical layer communication technique that reduces bit error rate (BER), while mitigating the multi-users-interference (MUI) and Gaussian noise interference, which can be achieved using UWB based wireless systems.

UWB systems are usually based on time hopping (TH) as the signal modulation method. While OVSF (orthogonal variable spread factor) was extensively used in CDMA systems to provide variable spreading codes [2]. Shorter OVSF code lengths are usually optimized for short-distance high data rate transmission in less crowed environments.

We propose U-BOTH (UWB modulation Based on OVSF and Time Hopping) in this paper, which integrates the time-hopping pulse position modulation (TH-PPM) algorithm that encodes UWB pulse streams, with OVSF direct sequence to spread the user data bit stream.

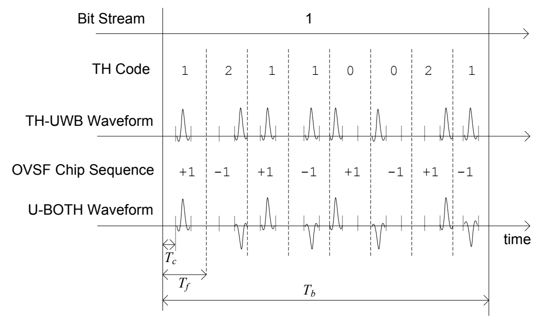


Figure 2. U-BOTH: Interference resistant UWB modulation using time hopping and OVSF.

Fig. 2 illustrates the utilization of TH-PPM and OVSF spreading to encode a single bit '1' in the user data stream. In U-BOTH, each bit is sent in bit time T_b, in which the bit is represented with a TH code, 12110021. Each digit in the TH code denotes a chip slot position within a frame time T_f to send a broadband radio pulse. The number of pulses is denoted by N_s. Therefore, each bit duration is $T_b = T_f \times N_s$. Each chip slot lasts for T_c, sufficient to send a short UWB pulse signal.

After the initial pulse position modulation using UWB signals, the pulse sequence is again applied with OVSF code so that the phases are shifted by π to provide orthogonality between multiple users. The length of the OVSF code is called the spread factor SF, which is equal to N_S.

In our system, the TH code is a pseudo-random sequence generated from foreknown seeds, such as node IDs. While the OVSF codes are selected from a well-defined set of orthogonal spreading codes.

To formally analyze the system in this paper, we represent the transmitted signal by the nth transmitter in Eq. (1).

$$s^n(t) = \sum_{j=-\infty}^{+\infty} d_j^n a^n_{\lfloor j/N_s \rfloor} \sqrt{E^n_{TX}} p_0(t - jT_f - c_j^n T_c), \quad (1)$$

in which, $d_j^n = \pm 1$ is the OVSF code with the period N_s, E^n_{TX} is the energy of the nth transmitter, $p_0(t)$ is the energy normalized pulse waveform, $c_j^n \in [0, N_c - 1]$ is the TH code with period N_s and $a^n_{\lfloor j/N_s \rfloor}$ indicates the data stream bit. If the data bit is 1, $a^n_{\lfloor j/N_s \rfloor} = +1$. Otherwise, $a^n_{\lfloor j/N_s \rfloor} = -1$.

At the receiver side, the received signal consists three source of information:

$$r(t) = r_u(t) + r_{mui}(t) + n(t),$$

in which, $r_u(t)$ is the desired user signal, $r_{mui}(t)$ is co-channel interference from multiple users, and $n(t)$ is the additive white Gaussian noise (AWGN).

The pulse energy of the n-th transmitter is denoted as E^n_{RX}. Without loss of generality, we assume that the first user's transmission is the desired signal at the receiver for simplicity, then Eq. (2) provides the desired signal function at the receiver:

$$r_u(t) = \sum_{j=-\infty}^{+\infty} d_j^1 a^1_{\lfloor j/N_s \rfloor} \sqrt{E^1_{RX}} p_0(t - jT_f - c_j^1 T_c). \quad (2)$$

We define the correlation template of the receiver:

$$m(t) = \sum_{j=iN_s}^{(i+1)N_s-1} d_j^1 p_0(t - jT_f - c_j^1 T_c); i \in (-\infty, +\infty). \quad (3)$$

In order to evaluate the performance of U-BOTH, we calculate the bit error rate (BER) of wireless systems using U-BOTH under two scenarios, single user and multiple users to analyze the impact of noise and MUI, respectively, both under a multipath-free assumption.

B. Single User System Analysis

In the single user scenarios, we assume that the channel is AWGN multipath-free channel, and that the transmitter and the receiver are synchronized. In a single user signal processing system, the input of the receiver consists two parts, $r_u(t)$ and $n(t)$, and the output of the receiver in time interval $[0, T_b]$ is represented by:

$$Z = Z_u + Z_n = \int_0^{T_b} (r_u(t) + n(t)) m(t) dt. \quad (4)$$

In Eq. (4), the useful output signal is:

$$Z_u = \sum_{j=0}^{N_s-1} \int_{jT_f + c_j^1 T_c}^{jT_f + c_j^1 T_c + T_c} d_j^1 d_j^1 a_{\lfloor j/N_s \rfloor}^1 \sqrt{E_{RX}^1} \omega(t) dt,$$

where $\omega(t) = p_0(t - jT_f - c_j^1 T_c) p_0(t - jT_f - c_j^1 T_c)$.

Because $d_j^1 d_j^1 = 1$, $p_0(t)$ is the energy normalized pulse waveform, we have

$$Z_u = a_{\lfloor j/N_s \rfloor}^1 N_s \sqrt{E_{RX}^1}$$

In Eq. (4), the output noise signal is:

$$Z_n = \sum_{j=0}^{N_s-1} \int_0^{T_c} d_j^1 p_0(t) n(t) dt = \sum_{j=0}^{N_s-1} d_j^1 n_j,$$

in which n_j is Gaussian random variable with mean 0 and variance $N_0/2$. Because d_j^1 is constant, $Z_n \sim N(0, N_0 N_s/2)$.

Suppose that the statistical probabilities of data bit $b = 0$ and $b = 1$ are equal, we obtain the BER of the single user system in AWGN channel as follows:

$$Pr_b = \frac{1}{2} P(Z > 0 | b = 0) + \frac{1}{2} P(Z < 0 | b = 1) = P(Z > 0 | b = 0).$$

Because $a_{\lfloor j/N_s \rfloor}^1 = -1$ if $b = 0$, then the useful output is $Z_u = a_{\lfloor j/N_s \rfloor}^1 N_s \sqrt{E_{RX}^1} = -N_s \sqrt{E_{RX}^1}$. Using Eq. (4), the BER become:

$$Pr_b = P(Z > 0 | b = 0) = P(Z_n > N_s \sqrt{E_{RX}^1}).$$

It can be rewritten by complementary error function $\mathrm{erfc}(x)$ as follow:

$$Pr_b = \frac{1}{2} \mathrm{erfc}\left(\sqrt{\frac{N_s E_{RX}^1}{N_0}} \right).$$

Because U-BOTH is a rate variable system using OVSF, we analyze the relation between BER and the bit rate. Suppose the system's OVSF code is a code tree of 6 layers [3], and the spreading factor is 2, 4, 8, 16, 32, 64, respectively. Further suppose the basic rate of our system is R_0, then the corresponding bit rate of U-BOTH is $R_b = iR_0$ (i= 32, 16, 8, 4, 2, 1, respectively).

Denote the bit rate as R_b, where $R_b = iR_0$, $i = 1, 2, \cdots, 32$, we can get the relation between BER and the bit rate:

$$Pr_b = \frac{1}{2} \mathrm{erfc}\left(\sqrt{\frac{SF \cdot E_{RX}^1}{N_0}} \right) = \frac{1}{2} \mathrm{erfc}\left(\sqrt{\frac{64 R_0 \cdot E_{RX}^1}{R_b N_0}} \right) \quad (5)$$

Eq. (5) shows that the BER decrease when the spreading factor SF increases or when the bit rate decreases. Therefore, we can adjust SF to adapt different environments with various noise levels while maintaining the same bandwidth of the signal. This is the main reason we adjust OVSF codes in our system.

C. Multi-User Interference Analysis

In multi-user communication system, the received signal includes multi-user interference Z_{mui} and noises. The $Z_u + Z_n$ part is the same as Eq. (4), but the multi-user interference Z_{mui} is additional. Because the phase and delay τ of interfering pulses is random as shown in Fig. 3, we have to compute the interference's variance.

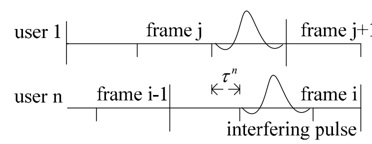


Figure 3. The interference to user 1 by the n-th user.

Suppose that τ^n is uniformly distributed over $[0, T_f)$, then the interference variance of the desired signal, *i.e.* the signal from the 1st user, caused by transmitter n is [7]:

$$\sigma_{bit}^2 = \frac{N_s}{T_f} \int_0^{T_f} \left(\sqrt{E_{RX}^n} \int_0^{T_c} d_j^1 d_i^n p_0(t - \tau^n) p_0(t) dt \right)^2 d\tau^n.$$

Therefore, the total interference variance σ_{mui}^2 from all other transmitters is:

$$\sum_{n=2}^{N_u} \left(\frac{N_s E_{RX}^n}{T_f} \int_0^{T_f} \left(\int_0^{T_c} d_j^1 d_i^n p_0(t - \tau^n) p_0(t) dt \right)^2 d\tau^n \right).$$

Because the delay τ for all transmitters has the same distribution, we get the following formula about σ_{mui}^2:

$$\left(\frac{N_s}{T_f} \sum_{n=2}^{N_u} E_{RX}^n \right) \int_0^{T_f} \left(\int_0^{T_c} d_j^1 d_i^n p_0(t - \tau^n) p_0(t) dt \right)^2 d\tau.$$

According to [7], and noticing that $R_b = \frac{1}{N_s N_f}$ and $N_s = SF = \frac{64 R_0}{R_b}$, Eq. (6) gives the BER in multi-user interference environments.

$$Pr_b = \frac{1}{2} \mathrm{erfc}\left(\sqrt{\frac{1}{2} \left(\left(\frac{128 R_0 E_{RX}^1}{R_b N_0} \right)^{-1} + \left(\frac{E_{RX}^1}{\sigma_M^2 R_b \sum_{n=2}^{N_u} E_{RX}^n} \right)^{-1} \right)^{-1}} \right). \quad (6)$$

IV. RSS Information Collection

In order to get the necessary coordinate information from adjacent reference nodes, following protocol steps are taken:

1) The mobile node broadcasts a location request message.
2) All the reference nodes send back packet with their own coordinates. During each short sampling period,

a mobile node can receive multiple responses from each of the reference nodes.

In ad hoc networks, code assignments are categorized into transmitter-oriented, receiver-oriented or a per-link-oriented code assignment schemes (also known as TOCA, ROCA and POCA, respectively) [6]. Depending on the ways of assigning the OVSF-TH codes and encoding the MAC data frames for transmissions, we propose two different ways to implement multiple access protocols using U-BOTH.

ROCA-Based Protocol Operations: The first approach is based on the receiver-oriented code assignment (ROCA), in which case the data packet transmissions are encoded using the unique OVSF-TH code assigned to the receiver. Beside ROCA, there is a common OVSF-TH code for bootstrapping and coordination purposes.

In ROCA scheme, when a target node needs to find out its coordinate, it sends a location request message using the common OVSF-TH code to the reference nodes. The request message includes the request command, and the receiver's OVSF-TH code. Upon receiving the request message, each reference nodes sends back a response message using the receiver's OVSF-TH code using a random backoff mechanism. The response message includes each reference node's identification information, and their own coordinates.

TOCA-Based Protocol Operations: The second approach is based on transmitter-oriented code assignment (TOCA), in which each packet transmission is encoded using two OVSF-TH codes — one is a common OVSF-TH code to encode the common physical layer frame header, and the other transmitter-specific code is to encode the physical layer frame payload. The frame head includes the transmitter-oriented OVSF-TH code for encoding the frame payload.

Because the physical layer headers are sent on a common OVSF-TH code, the physical layer header transmissions resemble those of ALOHA networks with regard to packet collision. Because the headers are usually short, the collision probability is low.

On the other hand, because the data frame payload is transmitted on unique OVSF-TH codes, the interference between the payload and other frame headers and payloads is dramatically reduced.

In both ROCA- and TOCA-based systems, packets from the reference nodes can be lost. However, this does not affect the overall performance of our localization algorithms because they tolerate such losses.

After getting the reference coordinates and the respective signal strength information, a target node calculates its coordinate in two steps — ranging and localization.

V. Ranging Algorithm

Ranging is to estimate the approximate distance between the target node and the reference nodes. We use the maximum likelihood estimation for such calculations. First of all, we need to establish the path loss model of the UWB channel in order to inversely derive the distance information from received signal qualities.

A. The Path Loss Model

The coal mine environment can be regarded as a special type of indoor environments [5]. A well-known path loss model is the log-distance path loss model in many indoor or outdoor environments in which multipath propagation is present. Eq. (7) shows the log-distance path loss model.

$$PL(d) = \left(PL_0 + 10\gamma \log_{10}(\tfrac{d}{d_0})\right) + S;\ d \geq d_0, \qquad (7)$$

in which d_0 is the reference distance (e.g. 1 meter in UWB medium), PL_0 means the path loss in dB at d_0, d is the distance between the transmitter (Tx) and receiver (Rx), γ refers to the path loss exponent which depends on channel and environment, and S is the log-normal shadow fading in dB. Usually, S is a Gaussian-distributed random variable with zero mean and standard deviation σ.

According to the residential indoor models [10], the path loss exponent γ in the aforementioned model is a random variable, and requires sufficient measurements on the spot in various residential environments before effectively being applied in generic scenarios. Therefore, in order to apply the above path loss model, IEEE 802.15.4a Task Group provided Channel Model 1-9 by taking limited real measurements to determine the values of γ, σ and other variables in different situations. When deploying real UWB networks, people could approximately choose the corresponding channel model with the parameters specified in IEEE 802.15.4a.

Especially, the standard deviation σ of the log-normal shadow fading S usually changes from locations to locations in mining environment. Even if at the same location, it may change because of the time-varying channel. Thus, for the application of localization in coal mine, we need practical method to estimate S, especially for moving targets.

In our method, the mean value of the path loss exponent γ is given for different tunnel environments, and the log-normal shadow fading S is represented through a random variable as follows:

$$S = n_1\sigma,$$

$$\sigma = \mu_\sigma + n_2\sigma_\sigma.$$

Then according to Eq. (7), the indoor UWB path loss could be expressed as:

$$P\bar{L(d)}|_{dB} = (PL_0 + 10\gamma \log_{10} d) + (n_1\mu_\sigma + n_1 n_2 \sigma_\sigma). \qquad (8)$$

In Eq. (8), μ_σ is the mean value of shadow fading's standard deviation σ. n_1 and n_2 are zero-mean Gaussian variables of unit standard deviation, $n_1, n_2 \sim N[0, 1]$. $(PL_0 + 10\gamma \log_{10} d)$ is the median path loss, and $(n_1\mu_\sigma + n_1 n_2 \sigma_\sigma)$ represents the random variation about the median path loss. According to the "3σ principle" in Gaussian distribution, the probability of a Gaussian variable lying in the range $(\mu-3\sigma, \mu+3\sigma)$ is 99.73%, even though the range of Gaussian random variable is $(-\infty, +\infty)$. That is, 99.73% value of variables n_1 and n_2 is within the range of $(-3, +3)$.

Furthermore, it dramatically simplifies computation if we use truncated Gaussian distributions for n_1 and n_2 so as to keep γ and σ from taking on impractical values. According to [10], we confine $n_1, n_2 \in [-2, +2]$, and $n_1 n_2 \in [-4, +4]$.

In aforementioned model, $(n_1\mu_\sigma + n_1 n_2 \sigma_\sigma)$ is not exactly Gaussian because $n1n2$ is not Gaussian. However, this product is very small with respect to whole expression of path loss. Thus, the path loss $PL(d)$ is approximately a Gaussian-distributed random variable with:

$$n_1\mu_\sigma + n_1 n_2 \sigma_\sigma \sim N(0, \mu_\sigma^2 + \sigma_\sigma^2).$$

$$PL(d) \sim N(PL_0 + 10\gamma \log_{10} d, \mu_\sigma^2 + \sigma_\sigma^2).$$

The probability density function (*pdf*) of $PL(d)$ is:

$$p(PL|d) = \frac{e^{-\frac{[PL-(PL_0+10\gamma\log_{10} d)]^2}{2(\mu_\sigma^2+\sigma_\sigma^2)}}}{\sqrt{2\pi(\mu_\sigma^2+\sigma_\sigma^2)}}. \tag{9}$$

Compared with the model in [10], our UWB coal mine propagation model given by Eq. (9) is more convenient to carry out parameter estimation and statistic analysis because it simplifies the statistics and *pdf*. When considering the random influence of the log-normal shadow fading, this model is more generic than current models in IEEE 802.15.4a.

B. Ranging based on Maximum Likelihood Estimation

The distance between the transmitter Tx and the receiver Rx in Eq. (8) can be calculated by the general ranging method between two nodes using the RSS information:

$$\hat{d} = 10^{\frac{PL(d)-PL_0-n_1\mu_\sigma-n_1n_2\sigma_\sigma}{10\gamma}}.$$

Receiver computes the distance between the transmitter Tx and the receiver Rx using random values n_1 and n_2 in the truncated range. This method takes into account the influence of real log-normal shadow fading on ranging and decreases the ranging error compared to the models in IEEE 802.15.4a.

However, the random variables n_1 and n_2 selected by the transmitter Tx are not exactly those in the real time-variant channel. In order to avoid the ranging errors caused by the large deviation between the simulated n_1 and n_2 values and the real n_1 and n_2 values in each round of ranging estimation, we propose an iterative ranging based on maximum likelihood estimation (MLE) in UWB wireless sensor networks.

Suppose PL_i is the ith observation value, we get the joint conditional *pdf* $p(PL|d)$ using Eq. (10).

$$p(PL|d) = \prod_{i=1}^{N} \frac{e^{-\frac{[PL_i-(PL_0+10\gamma\log_{10} d)]^2}{2(\mu_\sigma^2+\sigma_\sigma^2)}}}{\sqrt{2\pi(\mu_\sigma^2+\sigma_\sigma^2)}}. \tag{10}$$

The necessary condition to compute the MLE of d is:

$$\frac{\partial \ln p(PL|d)}{\partial d} = \frac{10N\gamma}{(\mu_\sigma^2+\sigma_\sigma^2) d \ln 10}\left(\frac{1}{N}\sum_{i=1}^{N} PL_i - PL_0 - 10\gamma \log_{10} d\right) = 0. \tag{11}$$

We solve Eq. (11) and have:

$$\widehat{\log_{10}} d = \frac{1}{10N\gamma}\sum_{i=1}^{N} PL_i - \frac{PL_0}{10\gamma}.$$

Therefore, the MLE based RSS UWB ranging is:

$$\hat{d} = 10^{\frac{1}{10N\gamma}\sum_{i=1}^{N} PL_i - \frac{PL_0}{10\gamma}}. \tag{12}$$

VI. Localization Algorithm

When computing the location of a wireless sensor node, there are two types of nodes, the reference node and the target node. Suppose that we have three reference node with coordinates (x_1, y_1), (x_2, y_2) and (x_3, y_3), respectively. Traditionally, the target node computes its coordinate (x, y) using trilateration method with the coordinates of reference nodes and their ranges d_1, d_2, d_3, to the target node.

In practical situations, three reference nodes are usually insufficient to accurately derive the target coordinate due to ranging errors from thermal noise and other interferences. The least squares algorithm use multiple reference nodes and the corresponding ranges to improve accuracy in the presence of error. It first creates following equations:

$$\begin{cases} (x_1 - x)^2 + (y_1 - y)^2 = d_1^2 \\ (x_2 - x)^2 + (y_2 - y)^2 = d_2^2 \\ \qquad \vdots \\ (x_n - x)^2 + (y_n - y)^2 = d_n^2 \end{cases} \tag{13}$$

where (x_i, y_i) and d_i $(i = 1, 2, \cdots, n)$ are the coordinate of the reference nodes, and the distances to the target node.

These equations can be linearized by subtracting the last low and performing some minor arithmetic shuffling, resulting in the following relations $AI = b$:

$$A = 2\begin{bmatrix} (x_1 - x_n) & (y_1 - y_n) \\ (x_2 - x_n) & (y_2 - y_n) \\ \vdots & \vdots \\ (x_{(n-1)} - x_n) & (y_{(n-1)} - y_n) \end{bmatrix},$$

$$I = \begin{bmatrix} x \\ y \end{bmatrix},$$

$$b = \begin{bmatrix} x_1^2 - x_n^2 + y_1^2 - y_n^2 + d_n^2 - d_1^2 \\ x_2^2 - x_n^2 + y_2^2 - y_n^2 + d_n^2 - d_2^2 \\ \vdots \\ x_{(n-1)}^2 - x_n^2 + y_{(n-1)}^2 - y_n^2 + d_n^2 - d_{(n-1)}^2 \end{bmatrix}.$$

This work employs the following solution:

$$\hat{I} = (A^T A)^{-1} A^T b. \tag{14}$$

Although the least squares algorithm could reduce the localization error, it requires a large amount of reference nodes within the communication radius of target node. Therefore, in the mining application of UWB wireless sensor networks, it is necessary to balance the cost and the accuracy.

In the following, we explore the relation between localization error and ranging error and then propose a modified algorithm based on the least squares algorithm.

Assume that the estimated distance between the target node and the ith reference node is $\hat{d}_i = d_i + \Delta_i$, where

Δ_i is the ranging error, $i \in \{1, 2, \cdots, n\}$. From Eq. (14), we have $\hat{I} = (A^T A)^{-1} A^T b = Mb$, where

$$M = (A^T A)^{-1} A^T = \begin{bmatrix} M_{1,1} & M_{1,2} & M_{1,3} & \cdots & M_{1,n-1} \\ M_{2,1} & M_{2,2} & M_{2,3} & \cdots & M_{2,n-1} \end{bmatrix},$$

Denote $B_i = x_i^2 - x_n^2 + y_i^2 - y_n^2 + d_n^2 - d_i^2$, we get the coordinate (x, y) of target node:

$$x = \sum_{i=1}^{n-1} M_{1,i} B_i + (\Delta_n^2 + 2d_n\Delta_n) \sum_{i=1}^{n-1} M_{1,i} + \sum_{i=1}^{n-1} [-M_{1,i}(\Delta_i^2 + 2d_i\Delta_i)].$$
$$y = \sum_{i=1}^{n-1} M_{2,i} B_i + (\Delta_n^2 + 2d_n\Delta_n) \sum_{i=1}^{n-1} M_{2,i} + \sum_{i=1}^{n-1} [-M_{2,i}(\Delta_i^2 + 2d_i\Delta_i)].$$

Usually, $\Delta_i \sim N(0, \sigma_i^2)$, and are mutually independent. Therefore,

$$D(x) = (2\sigma_n^4 + 4d_n^2\sigma_n^2)(\sum_{i=1}^{n-1} M_{1,i})^2 + \sum_{i=1}^{n-1} [M_{1,i}^2(2\sigma_i^4 + 4d_i^2\sigma_i^2)],$$
$$D(y) = (2\sigma_n^4 + 4d_n^2\sigma_n^2)(\sum_{i=1}^{n-1} M_{2,i})^2 + \sum_{i=1}^{n-1} [M_{2,i}^2(2\sigma_i^4 + 4d_i^2\sigma_i^2)]. \quad (15)$$

From above deduction, it is shown that localization error could be reduced proportionally to the reduction in the ranging error. According to the relation, if we guarantee the accuracy of d_i in every equation, the trilateration and the least squares algorithm could be kept similarly accurate even if the number of equations is limited. The proposed ranging solution using MLE based on RSS in this paper improves the ranging accuracy between target node and every reference node through iterative ranging, and reduces the ranging error caused by ranging based on a single round sampling. Furthermore, it reduces the influence of fixed value of γ given in our path loss model on ranging and localization in time-variant channel. Hence, our localization algorithm can provide accurate ranging and localization with less UWB reference nodes.

VII. Simulation Results

In order to verify our localization algorithms based on U-BOTH system for WSNs, we carried out simulation in the following scenarios:

1) We evaluate U-BOTH system performance in single and multi-user scenarios with regard to the BER (bit error rate).
2) We evaluate the ranging accuracy by comparing the results with the Cramer-Rao lower bounds.
3) We evaluate the impact of the number of iterations in calculating the coordinate of a specific target node, indicated by the triangle in the diagram.

A. U-BOTH System Performance

We assume the channel is AWGN multipath-free single user channel, the transmitter and the receiver are synchronized perfectly. Then we randomly generate 2000 bits, every bit uses 4 pulses to repeat coding ($N_s = 4$).

Fig. 4(a) illustrates the BER of the received signal using U-BOTH system, in contrast to DS-UWB that only uses direct sequence spreading, and TH-UWB that uses time-hopping pulse position modulation alone for UWB transmissions. We can see that the BER of U-BOTH and the DS-UWB system which use the π-phase shift keying modulation are lower than TH-UWB. This is because the distance of two signals in binary phase shift keying (BPSK) modulation is $2\sqrt{E_{pulse}}$, but $\sqrt{2E_{pulse}}$ in TH-UWB [9].

Secondly, we let $E_b/N_0 = 0$ dB, $N_s = 4$ and generated 2000 bits randomly. Fig. 4(b) shows the relative performance of U-BOTH, TH-UWB and DS-UWB systems in multiple access scenarios. In this case, the received signal includes by noise and co-channel interference. In Fig. 4(c), although both the BER and the variance of error bits increase as the number of users increases, the performance of our U-BOTH system is still better than DS-UWB and TH-UWB, proving that the UWB coding based OVSF-TH effectively handle the burst errors.

B. Evaluation of the Ranging Algorithms

In order to evaluate the performance of the ranging algorithms, we compare the parameter estimation errors against the Cramer-Rao lower bound (CRLB).

Denote $\hat{d}$ as the unbiased estimation of the parameter d from Eq. (11), then the mean square error (MSE) of $\hat{d}$ is

$$MSE[\hat{d}] = E[(\hat{d} - d)^2] = E[(\hat{d} - E(d))^2] = var[\hat{d}]. \quad (16)$$

Hence in unbiased condition, the MSE of $\hat{d}$ is equal to the variance. The lower bound of the MSE based on UWB RSS ranging could be represented by the CRLB:

$$CRLB(d) = (-E(\frac{\partial^2 \ln p(PL|d)}{\partial d^2}))^{-1} = \frac{(\mu_\sigma^2 + \sigma_\sigma^2)d^2 \ln^2 10}{100N\gamma^2}.$$

From Eq. (11), we know that $\frac{\partial \ln p(PL|d)}{\partial d}$ can not be expressed in the form $K(d)[\hat{d}(PL) - d]$. So, the lower bound of MSE can not reach the CRLB. However, we can use the MLE based RSS ranging to enable the MSE to approach the CRLB. The MSE of UWB ranging is:

$$E[(\hat{d} - d)^2] = \int (\hat{d} - d)^2 p(PL|d) dPL. \quad (17)$$

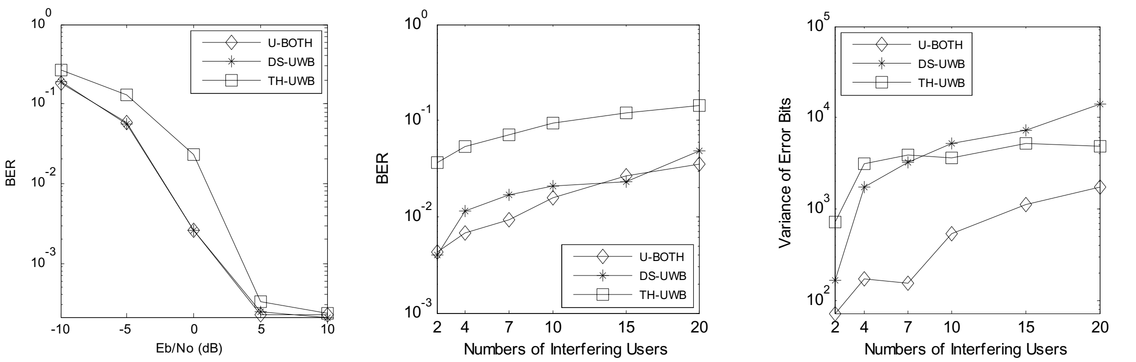
As PL_i are mutually independent, we take Eq. (10) and Eq. (12) into Eq. (17), and get the MSE of MLE based ranging using RSS information:

$$e^{\frac{2(\mu_\sigma^2 + \sigma_\sigma^2)\ln^2 10}{100N\gamma^2} + 2\log_{10} d \ln 10} - 2de^{\frac{(\mu_\sigma^2 + \sigma_\sigma^2)\ln^2 10}{200N\gamma^2} + \log_{10} d \ln 10} + d^2. \quad (18)$$

Therefore, the MSE of estimated distance $\hat{d}$ is the function of real distance d and the number of iterations N.

Based on the data in [8], [10], we set $n_1, n_2 \in [-2, +2]$, $n_1 n_2 \in [-4, +4]$, and adopt values of UWB path loss model for simulations as shown in Fig. 5.

Fig. 6(a) illustrates the relation between d and the CRLB, and the relation between d and the MSE. On one hand, it shows that the CRLB and the MSE increase when d increases, on the other, the MSE of ranging and the CRLB are always very close. When d is very small, they even

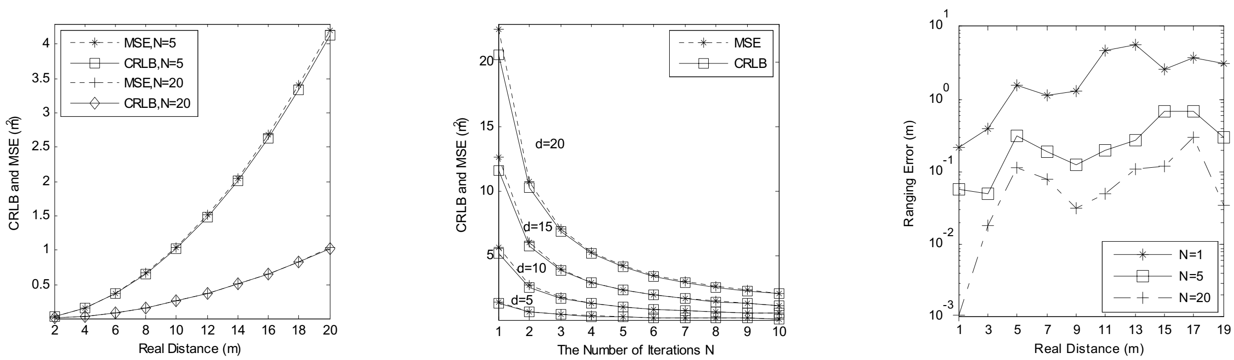


(a) BER in a single user system.

(b) BER in a multi-user system.

(c) Variance of the number of error bits.

Figure 4. U-BOTH system performance with AWGN channel.



(a) Comparisons between the Cramer-Rao lower bound (CRLB) and the mean square error (MSE) of ranging estimations at different distances.

(b) Comparisons between the Cramer-Rao lower bound (CRLB) and the mean square error (MSE) of ranging estimations, regarding the number of iterations N.

(c) The impact of the number of iterations N to the ranging errors at different distances.

Figure 6. U-BOTH ranging performance with AWGN channel.

Notation	Meaning	Value	
		LOS	NLOS
d_0	The reference distance	1 *m*	1 *m*
PL_0	The path loss at reference distance	47 *dB*	51 *dB*
γ	The path loss exponent	1.7	3.5
μ_σ	The mean value of shadow fading's standard deviation σ	1.6	2.7
σ_σ	The standard deviation of shadow fading's standard deviation σ	0.5	0.98

Figure 5. Simulation parameters.

overlap with one another. The more iterations we have for ranging, the smaller difference between the CRLB and the MSE (When $d = 4m$, $N = 20$, the CRLB is $0.0412m^2$, the corresponding MSE is $0.0414m^2$. When $d = 20m, N = 20$, the CRLB is $1.0310m^2$, the corresponding MSE is $1.0357m^2$).

In Fig. 6(a), we can see that when $N = 20, d > 20m$, the MSE of ranging estimation grows higher than $1m^2$. Therefore, it is necessary to filter out large d values in order to achieve higher ranging accuracy.

In the MLE based ranging using the RSS values, the number of iterations N is an important parameter. Fig. 6(b) gives the relation between N and the CRLB and the MSE, respectively. When N increases, the CRLB and the MSE decrease rapidly. The MSE of ranging approximates the CRLB when N is large enough (*e.g.* when $d = 5m$, $N = 10$, the CRLB is $0.1289m^2$, the corresponding MSE is $0.1300m^2$). Accordingly, we validate Eq. (18), and prove the validity of our MLE method.

Fig. 6(c) compares the MLE based ranging errors when the number of iterations N are 1, 5, and 20. Even if thermal noises and other interferences cause the error to fluctuate randomly, we can see that higher numbers of iterations dramatically increase the accuracy of ranging computations.

C. Evaluation of the Localization Algorithms

From the analysis of Cramer-Rao low bound in Eq. (16), the variance of ranging error can be shown in Eq. (18). Similarly, the localization error can be expressed as $\sqrt{(\hat{x} - x)^2 + (\hat{y} - y)^2}$.

Fig. 7 shows the relation between ranging error and localization error in Eq. (15). It is obvious that the ranging

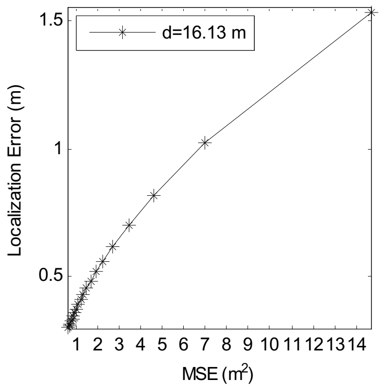


Figure 7. Relation between the mean square error (MSE) of ranging estimation and the localization error.

error and localization error decrease when N increases. The localization error when $N = 2$ is about $2/3$ of that when $N = 1$. When $N = 20$, we could get the least localization error, which is $0.3009m$.

Iteration Number N	Localization Error
$N = 1$	$1.2547m$
$N = 20$	$0.2464m$
$N = 50$	$0.1253m$
$N = 100$	$0.0885m$

Figure 8. The impact of the number of iterations N to the localization errors when distance $d = 14.9430m$.

Secondly, we choose a specific node to examine the impact of the number of iterations to the accuracy of localization computations. The triangle is the target node, and we set the communication radius as $20m$, so that the average number of reference nodes in this range is around 5, which are shown by the squares. Fig. 8 shows the localization error between the target node and a reference node that is $d = 14.9430m$ away, which shows that the impact of N increments decreases when N is greater than a few dozen.

VIII. Conclusion

We have presented a fast and accurate localization method using UWB communication techniques in wireless sensor networks under coal mine environments. The UWB communication consists of a new UWB coding method, called U-BOTH (UWB based on Orthogonal Variable Spreading Factor and Time Hopping), an ALOHA-type channel access method and a message exchange protocol to collect location information. The location method consists of the ranging algorithm, which applies the maximum likelihood estimation (MLE) method to compute the distances under the log-distance path loss model, and the coordinate computation algorithm using the least squares (LS) method. The performance of U-BOTH communication system and the localization algorithms are analyzed using communication theories and simulations. Results show that U-BOTH transmission technique can effectively reduce the bit error rate under the path loss model, and the corresponding ranging and localization algorithms can accurately compute moving object locations in coal mine environments.

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