Risk-Aware Wireless Positioning in Maritime Environment

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Abstract: The evolution of wireless communications systems has promoted various applications that require user positions in various environments including indoor, maritime and aerial environments. This progress has also brought advanced wireless location tracking (i.e., positioning) schemes for many purposes such as military, accident prevention and facility management. In this paper, we propose a risk-aware wireless positioning scheme, where the position information is required for safety. Especially for the maritime environment, we model the risk of the user at each position as a function of location accuracy, geometry, ocean current speed and so forth. Considering the power budget of each user, we optimize the user’s wireless positioning signal frequency (i.e., the positioning signal broadcasting rate) at each position so that our positioning scheme can minimize the average risk for each user.

Keywords: wireless positioning; maritime safety; risk; power budget

1. Introduction

In our daily lives, we can observe positioning (i.e., location tracking) techniques that have been widely adopted in many applications for various purposes, which include location-based service (LBS) [1] and emergency location alarms [2]. One of the most popular positioning systems is the global positioning system (GPS) [3], which utilizes global satellites. The GPS can accurately estimate the location of an object in an outdoor environment but it requires high power consumption, a long delay time and high maintenance costs. Moreover, the GPS is generally not applicable for indoor environments. The infrared ray based positioning is also widely used in short-range applications when a line-of-sight (LoS) is present [4].

As wireless devices have become very common, wireless positioning techniques that utilizes radio frequency (RF) for localization have been intensively studied [5]. The wireless positioning schemes estimate the location of an object using wireless signals, so it can be utilized in both outdoor and indoor environments at various ranges. There are various wireless positioning schemes based on various measures such as received signal strength (RSS), the angle of arrival (AoA), the time of arrival (ToA), the time difference of arrival (TDoA) and fingerprinting (i.e., database).

Wireless positioning schemes can be classified in many ways, for example, into range-based and range-free techniques [5]. Range-based techniques estimate the position using some metrics such as RSS, AoA, ToA and TDoA so that the metrics are directly mapped into ranges. In range-free techniques, on the other hand, the measurement cannot be directly converted into a range and the position is obtained with the aid of additional information such as a database. There are two major range-free
techniques: the fingerprinting scheme and the hop count scheme. These techniques will be briefly explained in Section 2.

The fingerprinting scheme is widely used in both outdoor and indoor environments thanks to its simple and cost-effective implementation [6]. The fingerprinting scheme also shows accurate positioning performance against multipath fading and non-line-of-sight (NLoS) condition in challenging environments [7]. There are various fingerprinting schemes according to the measurement databases used, such as visual fingerprinting, motion fingerprinting, signal fingerprinting and hybrid fingerprinting, for which each scheme has pros and cons under different situations [8].

In this paper, we propose an efficient fingerprinting-based wireless positioning scheme that is aware of user safety conditions in the maritime environment. There is a mobile user in a maritime area comprising safe and unsafe zones and the base stations (BSs) monitor the user position to prevent the user from getting into an unsafe zone. In this case, the safe zone is divided into many cells and the BSs have a received signal strength (RSS) map consisting of the average RSS sequences for each cell. Thus, once the BSs measure the RSS values from the user, the BSs can jointly estimate the user’s current cell (i.e., user position) from the RSS map. Thus, our positioning scheme adaptively controls the user’s positioning signal frequency with respect to the risk at the current position, whereas the conventional scheme maintains the same signaling frequency oblivious to the risk. As a result, with our scheme the positioning signal the user transmits becomes more frequent as the user approaches more dangerous locations to allow BSs to obtain more accurate user position. Meanwhile, the mobile user has a limited power budget, so our proposed scheme reduces the user’s average risk under the same total power consumption. We model the risk of the user considering many factors including geometry (i.e., water depth) and the positioning signal frequency. Then, we optimize the user positioning signal frequency to minimize the user’s overall risk, which is the average risk of the user over all positions.

Our paper is organized as follows. In Section 2, we briefly summarize various wireless positioning schemes. In Section 3, we explain our system model and formulate our problem. In Section 4, we propose a wireless positioning scheme by solving the problem. In Section 5, we evaluate our proposed wireless positioning scheme. Finally, we conclude our paper in Section 6.

2. Preliminary: Various Wireless Positioning Schemes

In this section, we summarize various wireless positioning schemes such as the received signal strength (RSS) scheme [9–12], the angle of arrival (AoA) scheme [13–16], the time of arrival (ToA) scheme [17–20], the time difference of arrival (TDoA) scheme [21] and the fingerprinting scheme [22,23]. In addition, there are some schemes that using hybrid solutions for the positioning [24–28].

2.1. Received Signal Strength (RSS)

There are many positioning schemes based on received signal strength (RSS) considering various channel fading models including many path loss models [9–12]. The distance between BSs and the user can be directly obtained from the the strengths of received signal, so it is simple to implement. However, there are many channel fading models according to the dominance of a visible path (i.e., LoS) and the propagation environment, so RSS based positioning schemes require the accurate information on fading model.

2.2. Angle of Arrival (AoA)

The AoA scheme is the wireless positioning method that estimates the signal source position from the angle of arrival of the received signal. The AoA schemes can be divided into two categories, where the antennas are fixed and rotating, respectively. It is a more typical approach to use fixed (linear or general) antenna arrays for direction of arrival estimation and beamforming [13–15]. Another approach is to use rotating directional antennas, where there are multiple BSs and each of them transmits its own positioning signal with a directional beam rotating with a constant angular velocity [16]. Then, the receiver estimates azimuths (i.e., directions) of the positioning signals
from the BSs according to the times at which they are received. If there are more than three base stations, the receiver can determine its own position from the directions of the BS signals using the triangulation method.

Figure 1 illustrates the AoA scheme in a two-dimensional plane. In Figure 1, the receiver is at the position $(X_p, Y_p)$, while there are four BSs at $(L, M)$, $(0, M)$, $(0, 0)$, and $(L, 0)$. The four BSs transmit directional beams with the angular velocity $\omega$, but with the different phases of $\angle 0$, $\angle \phi$, $\angle 2\phi$ and $\angle 3\phi$.

![Figure 1. The Angle of Arrival (AoA) scheme.](image)

The receiver first measures the arrival times of the positioning signals. Then, from the differences in the arrival times, the receiver can determine the differences in the azimuths of the BSs. For example, let $(t_1, t_2, t_3, t_4)$ be the arrival times of the positioning signals and let $\alpha$, $\beta$ and $\gamma$ be the differences of the azimuth angles of $(BS_1, BS_2)$, $(BS_2, BS_3)$ and $(BS_3, BS_4)$, respectively. Then, the receiver can find $\alpha = \phi - \omega(t_2 - t_1)$, $\beta = \phi - \omega(t_3 - t_2)$ and $\gamma = \phi - \omega(t_4 - t_3)$. Finally, the receiver finds its own position given by $X_p = Y \cos(\delta)$ and $Y_p = M - Y(\delta)$, where

\[
\delta = \arctan \left[ \frac{M \sin(\alpha) \cos(\beta) - L \sin(\alpha) \sin(\beta)}{L \cos(\alpha) \sin(\beta) - M \sin(\alpha) \sin(\beta)} \right],
\]

and transmits the position information to the BSs.

2.3. Time of Arrival (ToA)

The ToA scheme is a wireless positioning method that estimates a signal source position from the arrival times of the positioning signal at the receivers. In this case, all the signal sources and receivers should be synchronized \[17,18\], while the positioning signal should contain a time stamp.

The ToA scheme is illustrated in Figure 2. In a two-dimensional plane, there are three BSs and a single user and the BSs attempt to measure the user position. Meanwhile, the user is at position $(x, y)$ and the three BSs are at $(X_1, Y_1)$, $(X_2, Y_2)$ and $(X_3, Y_3)$, respectively. From the time of arrival (ToA) at the $i$th BS (denoted by $\tau_i$), the $BS_i$ can determine the distance between them, as given by

\[
d_i = c \cdot \tau_i,
\]

where $c$ is the speed of light. Then, the position of the user $(x, y)$ satisfies that
$$\sqrt{(x - X_i)^2 + (y - Y_i)^2} = d_i \quad \forall i \in \{1, 2, 3\}. \quad (4)$$

Thus, the BSs can determine the user position because it is at the intersection of the circles centered at each BS with the corresponding radius of $d_i$. Note that although we explained the ToA scheme in synchronous networks, they are also studied in asynchronous networks [19,20].

![Figure 2. The Time of Arrival (ToA) scheme.](image)

### 2.4. Time Difference of Arrival (TDoA)

The TDoA scheme is a positioning scheme that uses the arrival time differences of positioning signal at the receivers [21]. Unlike the ToA scheme, the TDoA scheme only measures the absolute difference between the arrival times, so is easier to implement than the ToA scheme. The TDoA scheme is illustrated in Figure 3.

![Figure 3. The Time Difference of Arrival (TDoA) scheme.](image)
There are three BSs of which the positions are \((X_1, Y_1), (X_2, Y_2)\) and \((X_3, Y_3)\). We denote by \((x, y)\) the position of a source node and by \(d_i\) the position of the BS\(_i\). Then, from the arrival time difference, we can obtain the distance differences, that is, \(d_i - d_j\) for \(i \neq j\). Therefore, the position of the signal source can be estimated from the intersection of hyperbolas.

### 2.5. Fingerprinting

The fingerprinting scheme is the positioning scheme that estimates the user position from a database, which has already been measured [22,23]. The implementation of the fingerprinting scheme is divided into the training phase and the positioning phase. In the training phase, all BSs make a database by collecting the propagation characteristics of received signals (e.g., RSSs) from RF devices at known positions. Then, in the positioning phase, the BSs estimate the position of an RF device by comparing the propagation characteristic of the received signal with the database. The fingerprinting scheme is widely investigated especially for indoor environment, where the signal propagation model based distance estimation is hard. Compared to other positioning schemes, the fingerprinting scheme is more robust, accurate and cost-efficient for indoor positioning [6]. The fingerprinting scheme also has accurate position estimation for multipath issues and NLoS propagation in challenging environment [7]. In recent years, the fingerprinting scheme has also been widely utilized for outdoor positioning due to its accuracy, energy efficiency and low latency. For outdoor positioning, the fingerprinting scheme used, varies with the operating environment and performance. These schemes can be classified as visual fingerprinting, motion fingerprinting, signal fingerprinting and hybrid fingerprinting. Each scheme has pros and cons for different situations [8].

### 2.6. Hybrid Schemes

As we explained, various parameters such as RSS, AoA and TDoA can be used for positioning and hybrid positioning schemes use more than two parameters for more accurate position information. The TDoA/AoA scheme roughly estimates the distance between BSs and the user with TDoA and then determines a more accurate user’s position with AoA [24]. Also, the ToA/RSS schemes are studied in Reference [25–27], and the RSS/AoA scheme was studied in Reference [28]. Hybrid positioning schemes can obtain more accurate position information, so enables to provide a stable location-based service (LBS). However, they are hard to implement and requires more time for estimation.

### 3. Problem Formulation

In this section, we formulate our problem and propose an efficient location tracking scheme.

#### 3.1. System Model

Our system model is depicted in Figure 4. There are \(K\) BSs and a single user in a certain area comprising a safe zone and an unsafe zone. The user is moving around the safe zone and the BSs trace the user position to prevent the user from entering the unsafe zone. To help the BS monitoring, the user periodically broadcasts a positioning signal. Thus, the BSs can determine the user position from the received signal strengths (RSSs). For example, there can be a user swimming on the water with a wireless device in a life jacket. In this case, the BSs need to monitor the user position for safety and the user’s mobile device broadcasts the positioning signal for the BS’s monitoring.

In our proposed positioning scheme, the positioning signal frequency changes according to the user position. Our proposed scheme is based on the fingerprinting scheme, which we explained in Section 2. For the fingerprinting scheme, we divided the whole area into \(N\) Voronoi regions. Once the BSs locate the cell in which the user belongs (i.e., the user’s Voronoi region) from the RSS, the BSs notify the user of the new positioning signal broadcasting frequency. We denote by \(f_i\) the user’s positioning signal frequency when the user is in cell \(i\).
3.2. Risk Modeling

In our system model, the purpose of wireless positioning is to prevent the user from entering the unsafe zone. Thus, the BSs require more accurate information of user position as the user gets closer to the unsafe zone. Obviously, the user's location accuracy is proportional to the frequency of the user's positioning signal transmission (i.e., $f_i$) because we assumed that both the user speed and the ocean current speed are constants. Moreover, the risk is inversely proportional to the location accuracy. Thus, we have the following relationship:

\[
\text{Positioning signal frequency} \uparrow \leftrightarrow \text{Location accuracy} \uparrow \leftrightarrow \text{Risk} \downarrow
\]  

Next, we propose a risk model and optimize our positioning scheme under this risk model. There are many ways to model the risk of the user. Thus, we designed our risk model to be capable of generalizing many scenarios and assigning the proper factors. However, note that once the risk model is given, our proposed positioning scheme can be readily extended for the risk model.

In our risk model, we consider the following relationship.

\[
\text{Positioning signal frequency} \uparrow \implies \text{Risk} \downarrow
\]

\[
\text{Water depth} \downarrow \implies \text{Risk} \downarrow
\]

Then, we can define the risk at the cell $i$ as a function of signal transmission frequency (i.e., $f_i$) as follows:

\[
R_i(f_i) \triangleq \frac{k_i \times d_i^p}{f_i^\alpha}.
\]
In (6), \(f_i\) is the user positioning signal transmission frequency (i.e., the position information accuracy) at cell \(i\) and \(\alpha\) is a positive constant (i.e., \(\alpha > 0\)) that represents the sensitivity of the risk to the accuracy. In this case, \(d_i\) is the average water depth at cell \(i\) and \(\beta\) is the sensitivity of the risk to the water depth. The factor \(k_i\) is the weight to reflect the effects of the other factors (e.g., ocean current speed). With the definition of (6), the overall risk function is given by

\[
R(f_1, \ldots, f_N) = \sum_{i=1}^{N} [p_i \times R_i(f_i)]
\]

(7)

\[
= \sum_{i=1}^{N} \left[ p_i \times \frac{k_i \times d_i^\beta}{f_i^\alpha} \right],
\]

(8)

where \(N\) is the total number of cells and \(p_i\) is the probability that the user is in the cell \(i\). When the user’s position is uniformly distributed in the safe zone, the probability \(p_i\) becomes the ratio of the area of cell \(i\) to the area of the safe zone, that is,

\[
p_i = \frac{S_i}{\sum_{n=1}^{N} S_n}.
\]

(9)

### 3.3. Limited Power Budget

As we consider the mobile user in the marine environment, the user’s battery power budget should also be considered. The user’s positioning signal frequency should be carefully controlled considering the user’s battery power budget. We denote by \(W\) the power consumption of the user’s one time transmission of the positioning signal. Then, when the user is in cell \(i\), the user’s power consumption becomes \(W \times f_i\) per second. Thus, the user’s average power consumption per second is equal to the sum of the product of the power consumption per second in cell \(i\) and the probability of belonging to cell \(i\) for all cells is described as follows.

\[
\sum_{i=1}^{N} (p_i \times W \times f_i).
\]

(10)

When \(L\) is the expected operating time in seconds, the product of the average power consumption per second and the desired operating time should not exceed the total energy of the user, denoted by \(E\), that is,

\[
\sum_{i=1}^{N} (p_i \times W \times f_i \times L) \leq E.
\]

(11)

### 3.4. Problem Description

In this paper, we find the optimal wireless positioning signal frequency that minimizes the overall risk (i.e., (7)) considering the user’s limited battery power budget (i.e., (11)) as follows:

\[
(P1) \quad \text{minimize} \quad R(f_1, \ldots, f_N)
\]

subject to

\[
\sum_{i=1}^{N} p_i f_i \leq \frac{E}{WL}.
\]
For notational simplicity, we establish the equivalent problem as follows:

\[(P1') \begin{align*} & \text{minimize} \quad \sum_{i=1}^{N} \left( \frac{p_i A_i}{f_i^\alpha} \right) \\ & \text{subject to} \quad \sum_{i=1}^{N} p_i f_i \leq B, \end{align*}\]

where \( A_i \triangleq k_i \times d_i^\beta \) is a constant related to the risk at the cell \( i \) and \( B \triangleq E/\text{WL} \) is a constant related to the power budget.

3.5. Conventional Scheme

The conventional wireless positioning scheme does not change the positioning signal frequency according to the current position. Thus, as a reference scheme, we consider the wireless positioning scheme with the same frequency at all positions, that is,

\[f_1 = \cdots = f_N = \frac{E}{\text{WL}} = B. \tag{12}\]

4. Our Proposed Risk-Aware Wireless Positioning Scheme

In this section, we find the optimal positioning signal frequency at each cell by solving the optimization problem \((P1')\). We start from the following Lemma.

**Lemma 1.** The optimization problem \((P1')\) is a convex problem.

**Proof.** We recall the objective function of the problem \((P1)\) as follows:

\[\sum_{i=1}^{N} \left( \frac{p_i A_i}{f_i^\alpha} \right) \tag{13}\]

Then, \((p_i A_i)/f_i^\alpha\) is the convex function of \( f_i \) because all of \( p_i, A_i \) and \( \alpha \) are positive constants and the term \( 1/f_i^\alpha \) is the convex function of \( f_i \) whose second derivative is positive for \( \alpha > 0 \), that is,

\[\frac{\alpha (\alpha + 1)}{f_i^{\alpha+2}} > 0. \tag{14}\]

Since the sum of convex functions is also a convex function [29], (13) is a convex function of \((f_1, \ldots, f_N)\). Also, the constraint function is convex, so the problem \((P1')\) is a convex problem. \( \square \)

To solve the convex problem, we establish the Lagrangian denoted by \( L \) as follows:

\[L = \sum_{i=1}^{N} \left( \frac{p_i A_i}{f_i^\alpha} \right) + \lambda \left( \sum_{i=1}^{N} p_i f_i - B \right), \tag{15}\]

where \( \lambda \) is the Lagrangian multiplier.

Then, we already know that from the Karush-Kuhn-Tucker (KKT) conditions, the optimal solution \((f_1^*, \ldots, f_N^*)\) satisfies that

\[\frac{\partial L}{\partial f_i} = 0 \quad \text{for all} \quad i \in \{1, \ldots, N\}. \tag{16}\]
Thus, from the equation
\[ \frac{\partial L(f^i)}{\partial f^i} = \alpha p_i A_i (f^i)^{\alpha+1} + \lambda = 0, \]
we obtain
\[ f^i = \left( \frac{\alpha A_i}{\lambda} \right)^{\frac{1}{\alpha+1}}. \]  

Also, from the constraint function of the problem (P1'), it should be satisfied that
\[ \sum_{i=1}^{N} p_i f_i^* = \sum_{i=1}^{N} p_i \left( \frac{\alpha A_i}{\lambda} \right)^{\frac{1}{\alpha+1}} = B, \]
so we obtain
\[ \lambda^{\frac{1}{\alpha+1}} = \frac{1}{B} \sum_{i=1}^{N} \left[ p_i (\alpha A_i)^{\frac{1}{\alpha+1}} \right]. \]

Finally, plugging (20) into (18), we obtain
\[ f_i^* = \frac{B \cdot (\alpha A_i)^{\frac{1}{\alpha+1}}}{\sum_{n=1}^{N} \left[ p_n (\alpha A_n)^{\frac{1}{\alpha+1}} \right]}. \]

5. Numerical Results

In this section, we evaluate our proposed wireless positioning scheme. We first explain the RSS map and the risk map modeling, by which our proposed localization scheme is evaluated and then compare our proposed scheme with the conventional one. Note that Figure 5 is based on the actual measurement and Figure 6 is based on our modeling for performance evaluation. Also, Figures 7–10 are from the simulation.

**Figure 5.** The Received Signal Strength (RSS) map (dBm).
Because our proposed localization scheme is based on the fingerprinting scheme, we first model the RSS map. We consider two BSs of the IEEE802.11g (i.e., WiFi) standard, of which the positions are (−20, 0) and (20, 0), respectively, in meters. Then, we obtain the received signal strength (RSS) map by measurement. Figure 5 shows the geometry we considered with the measured RSSs at each cell. As can be seen in Figure 5, we consider a total of 28 cells (i.e., \( N = 28 \)), where each cell is a square with sides 20 m in length and the measured RSS values from BS\(_1\) and BS\(_2\) are marked from the center of each cell.

![Figure 6. The water depth modeling for the performance evaluation.](image)

Because we are considering maritime safety, we need to define the risk with respect to the user’s position. To model the risk at each cell (i.e., \( R_i(f_i) \) given in (6)), we consider the parameter \( \alpha = 1 \), which means that the risk linearly decreases with respect to the positioning signal frequency. Then, to model the risk from depth, we consider the geometry given in Figure 6 with the parameter \( \beta = 2 \), which means that the risk increases with respect to the square of the depth. For other risk factors, we simply consider \( k_1 = \ldots = k_{28} = 1 \). As a result, the risk is modeled as in Figure 7.

![Figure 7. The risk map that represents \( R_i(f_i) \) given in (6).](image)
For other parameters, we assume that the power consumption for a single time positioning signal transmission is 1 watt (i.e., $W = 1$ W). In Figure 8, we plot the achievable average risk of a user with respect to the user’s battery power budget (i.e., $E$), when the user device lifetime is two hours (i.e., $L = 7200$ s). As can be observed in Figure 8, the user’s average risk decreases as the user’s battery budget increases both in our proposed scheme and in the conventional scheme. This is because with greater battery power budget, the user can more frequently transmit the positioning signal during the device lifetime. However, with the same power budget, we observed that our proposed scheme decreases average risk by adaptively transmitting the positioning signal according to the position.

![Figure 8. The average risk with respect to the power budget of the user.](image)

**Figure 8.** The average risk with respect to the power budget of the user.

![Figure 9. The average risk with respect to the sensitivity of the risk to the position accuracy (i.e., $\alpha$).](image)

**Figure 9.** The average risk with respect to the sensitivity of the risk to the position accuracy (i.e., $\alpha$).
Figure 9 shows the average risk with respect to the different sensitivities of the risk to the accuracy (i.e., $\alpha$), where $E = 10$ Wh, $\beta = 2$ and all other parameters are same. In Figure 9, we can observe that our proposed scheme outperforms to the conventional scheme for any value of $\alpha$. Also, in Figure 10, we show the average risk per different sensitivities of the risk to the water depth (i.e., $\beta$), where $E = 10$ Wh, $\alpha = 1$ and all other parameters are same. As we can see in Figure 10, our proposed scheme outperforms to the conventional scheme for any value of $\beta$.

6. Conclusions

In this paper, we proposed a safety-aware positioning scheme based on the fingerprinting scheme, which efficiently decreases the average risk in the maritime environment. We defined a risk function, which is influenced by various factors such as location accuracy, depth, ocean current speed and geometry. Then, we found the optimal positioning signal transmission frequency that minimizes the user’s average risk. The numerical result shows that our proposed positioning scheme decreases the average risk, compared to the conventional one, assuming a user with the same battery power budget.

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Conflicts of Interest: The authors declare no conflict of interest.
Abbreviations
The following abbreviations are used in this manuscript:

- LBS  Location-based service
- GPS  Global positioning system
- LoS  Line-of-sight
- RF   Radio frequency
- AoA  Angle of arrival
- ToA  Time of arrival
- TDoA Time difference of arrival
- NLoS Non-line-of-sight
- BS   Base station
- RSS  Received signal strength

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