Abstract—Knowing channel sight condition is important as it has a great impact on localization performance. In this paper, a RSS-based localization algorithm, which jointly takes into consideration the effect of channel sight conditions, is investigated. In our approach, the channel sight conditions experience by a moving target to all sensors is modeled as a hidden Markov model (HMM), with the quantized measured RSSs as its observation. The parameters of HMM are obtained by an off-line training assuming that the LOS/NLOS can be identified during the training phase. With the HMM matrices, a forward-only algorithm can be utilized for real-time sight conditions identification. The target is localized by extended Kalman Filter (EKF) by suitably combining with the sight conditions. Simulation results show that our proposed localization strategy can provide good identification to channel sight conditions, hence results in a better localization estimation.

I. INTRODUCTION

Wireless sensor networks (WSNs) have many important applications [1], [2], among all, localization using WSNs [2], [3], [4] has attracted significant research interest. A large amount of localization systems have been developed based on various measurements, e.g., received signal strength (RSS) [3], [5], [6], time of arrival (TOA) [7], time difference of arrival (TDOA) [8] and angle of arrival (AOA) [9]. Because of low configuration and cost requirement, RSS-based localization techniques have been widely used in wireless localization. The relative distance between the target and a sensor can be obtained by measuring the RSS, then be used to perform localization.

In some harsh environments, e.g., indoors areas, urban areas, the wireless channel will be blocked by walls or other obstacles, resulting the so-called non-line-of-sight (NLOS) propagation. The occurrence of NLOS will induce a degradation of localization accuracy if we do not take this into consideration when designing localization algorithm. Therefore, it is of great significance to identify the NLOS conditions and mitigate their effects.

To perform the NLOS identification, there are several methods which are mainly divided into two categories: one is based on range estimates [10] and the other one is based on channel statistics [11], [12], [13]. In [10], a sequence of range measurements are performed to estimate the range variances and compare with a predefined threshold. This methods will incur a latency because of the collection of measurements, and hence imposes limitations in a time-varying NLOS/LOS (line-of-sight) situation. As to the channel statistics based methods [11], [12], [13], by analysing the joint probability distributions of some given parameters, e.g., the mean delay, excess delay and power of the received signal, the sight condition can be identified by hypothesis testing. However, it is challenging to determine the joint probability distribution and unclear on how to set the threshold.

Various techniques are proposed for NLOS error mitigation when performing localization. In [14], a residual weighting method is proposed, in which, the estimation is a weighted combination of all least square estimations on all the possible measurement combinations. The complexity of this algorithm grows with the number of measurements. Authors in [15] develop a direct path detection methods which iteratively estimates direct path and calibrates all paths based on LOS measurements, but the computation will need a long period of time. In [16], Kalman Filter is applied to smooth the mixed LOS/NLOS conditioned measurement data by adjusting the measurement noise covariance, it is applicable for real-time localization.

Apart from the separative two-step process of NLOS identification and error mitigation, [17] proposes a method which jointly tracks the target position and channel sight conditions. It assumes both the target motion and the sight conditions are Markov process, and a grid-based Bayesian algorithm is used to estimate the hidden state. As the target positions are assumed to be the discrete grid points in the field of interest (FOI), the localization accuracy is closely related to the resolution of the grids.

In this paper, we propose a localization strategy combining Hidden Markov Model (HMM) and extended Kalman Filter (EKF) to identify sight conditions and mitigate NLOS error. Different from [17], the hidden state of HMM is only the channel sight conditions without the target state. Besides, in [17], the sight condition of each target-sensor link is assumed to be time-varying Markov process independent from the target’s position. Whilst in our paper, the sight conditions change spatially along with the target’s position. The main contributions are summarised as follows:

- We model the sight conditions between target and sensors as an HMM by assuming that the FOI can be divided into distinct non-overlapped cells, with each cell has...
a stable channel sight conditions to sensors. Based on the quantized RSS measurements, an off-line training is executed to obtain the HMM parameters.

- A forward-only algorithm is adopted for the on-line sight condition identification based on the off-line trained parameters, which owns a good performance on real time estimation.

- Combining the estimated LOS/NLOS sight conditions, EKF is utilized for target localization, which makes use of the identified NLOS/LOS channel conditions to effectively improve estimation accuracy.

The remainder of this paper is organized as follows. In Section.II, the system model and localization problem is described. Section.III introduces the localization strategy, including HMM formulation and training, real time sight condition identification and EKF localization algorithm. Simulation results are provided to illustrate the performance of our proposed algorithm in Section.IV. Then conclusions are drawn in Section.V.

II. PROBLEM FORMULATION

Assume the target makes a random walk in our 2-D FOI, its state at time $t$ is expressed as

$$ x_t = x_{t-1} + \nu_t $$

where $x_t = [x_t, y_t]^T$ is the target’s position at time $t$, and $\nu_t$ is a 2-D driving process with known distribution. Here, we assume $\nu_t = [\nu_{xt}, \nu_{yt}]^T$ being a white Gaussian process with zero mean and covariance matrix $Q_\nu$.

There are $N$ sensors deployed in FOI, and their positions are assumed to be known as $(x_n, y_n), n = 1, 2, \cdots, N$. When the target moves into the FOI, it transmits signals to the sensors. Then the signals are processed for localization. In this paper, RSS is utilized as our measurements. Consider the example shows in Fig.1, where $N = 4$ and the sensors are placed at the four corners of the FOI. Due to the presence of concrete walls and obstacles, it is reasonable to assume that certain region in the FOI will have NLOS propagation to some of the sensors. According to [18], the RSS of sensor $n$ at time $t$ is

$$ z_n(t) = \begin{cases} P_0,los - 10\alpha_los \log_{10}(\frac{d_n(t)}{d_0}) + \omega_{los}, & \text{LOS} \\ P_0,nlos - 10\alpha_{nlos} \log_{10}(\frac{d_n(t)}{d_0}) + \omega_{nlos}, & \text{NLOS} \end{cases} $$

where $P_{0,los}$, $\alpha_{los}$ and $\omega_{los}$ are respectively the known referenced RSS at referenced distance $d_0$, path loss exponent and the measurement noise under LOS. Similarly, $P_{0,nlos}$, $\alpha_{nlos}$ and $\omega_{nlos}$ are respectively the known referenced RSS at referenced distance $d_0$, path loss exponent and the measurement noise under NLOS. $d_n(t) = \sqrt{(x_n - x_t)^2 + (y_n - y_t)^2}$ is the true distance between sensor $n$ and the target.

Actually the channel sight conditions are related to the target position and vary with the change of target’s position. Hence, it is reasonable to assume that over the FOI, the area can be partitioned into $N_c$ cells, with each cell has a distinct NLOS/LOS sight conditions to various sensors. We can collect all these sight conditions to sensors and represent it by a $N$-tuple vectors, where $N$ is the number of sensors. In this paper, we assume the physical layout of FOI is static, and the mapping relationship between cells and sight conditions are known. When the target is at cell $q \in \{1, 2, \cdots, N_c\}$, the corresponding sight condition vector is $s_q = [s_1, s_2, \cdots, s_n, \cdots, s_N]^T$, where $s_n = 1$ stands for that the sight condition of the target relative to sensor $n$ is LOS, while $s_n = 0$ stands for that the sight condition of the target relative to sensor $n$ is NLOS. For the example shows in Fig.1, the FOI is divided into 8 cells, each cell represents a fixed sight condition vector of the target relative to all the sensors.

Remark 1

In practice, there may not have a clear boundary since the mapping relationship between the target position and sight conditions maybe not so straightforward like what is shown in Fig.1. However, this should not affect our solution. The number of states (cells) and its corresponding sight conditions can be dynamically built up with the help of a training device which is equipped with NLOS/LOS identification algorithms.

The objective of the design is fusing all the measured RSSs from a target to decide the actual location of the target at the fusion centre. The fusion centre needs to identify the sight condition vector based on the observed RSSs before applying the channel sight conditions to the localization algorithm. We develop a method to combine these observed RSSs and the identified sight conditions to effectively estimate the target position with better accuracy. The whole framework of our localization strategy is depicted in Fig.2, where $z_t$ is the RSS measurement vector at time $t$ and $s_q$ is the sight condition vector. After obtaining $z_t$, we use HMM to identify $s_q$, then combining $z_t$ and $s_q$, the target position can be estimated by EKF.
III. HMM-BASED LOCALIZATION

A. HMM-based Sight Condition Identification

1) HMM Formulation: To identify the sight conditions, an HMM is formulated. The state of HMM is defined as the cell where target’s position belongs to, i.e., \( q_t \in \{1, 2, \ldots, N_c\} \). It also corresponds to a fixed sight condition vector \( S_q \), which is decided by the geographical layout of the FOI. The basic parameters of HMM is defined as \( \lambda = (\pi, A, B) \), where \( \pi \) denotes the initial probabilities where the target belongs, it is proportional to the area of each cell, then \( \pi \) is formulated as

\[
\pi = \frac{A_q}{\sum A_q}, \quad q = 1, 2, \ldots, N_c
\]

where \( A_q \) is the area of cell \( q \) and \( \sum A_q \) is the overall area of our FOI.

The transition matrix \( A \) is a \( N_c \times N_c \) matrix denoting the probabilities of transition between states, which is expressed as

\[
A = \begin{bmatrix}
a_{11} & \cdots & a_{1N_c} \\
\vdots & & \vdots \\
a_{N_c,1} & \cdots & a_{N_c,N_c}
\end{bmatrix}
\]

where \( a_{ij} = P(q_t = j | q_{t-1} = i), i, j \in \{1, 2, \ldots, N_c\} \).

As to the observation matrix \( B \), for simplicity, the measured RSS is quantized into \( M \) levels. An uneven step size is used to quantize the measurements. In the FOI, the maximum target-sensor distance is known as \( d_{\text{max}} \), then the distance range is \([0, d_{\text{max}}]\). The whole range is evenly divided into \( M \) sections, \([0, d_1], [d_1, d_2], \ldots, [d_{M-1}, d_M]\), where \( d_M = d_{\text{max}} \). Each range is represented by a certain level of RSS. The \( m \)th RSS level \( [P_{m-1}, P_m] \) can be computed as

\[
P_{m-1} = \begin{cases} \infty, & m = 1 \\ P_0 - 10\alpha \log_{10} \left( \frac{d_{m-1}}{d_0} \right), & m = 2, \ldots, M \\
\end{cases}
\]

\[
P_m = \begin{cases} P_0 - 10\alpha \log_{10} \left( \frac{d_m}{d_0} \right), & m = 1, \ldots, M - 1 \\ \infty, & m = M \\
\end{cases}
\]

It can be seen that the RSS levels are computed under the assumption that all the sight conditions are LOS. Actually, the sight conditions do not have much effect on the quantization. No matter what sight conditions, the quantized RSS level can reflect the distance to some extent.

Then all the measurements are quantized into their corresponding RSS levels. Considering there are \( N \) sensors, then our observation is a \( N \)-dimension vector \( \boldsymbol{o}_t = [o_{1}(t), \ldots, o_{N}(t)]^T \), \( o_{n}(t) \in \{1, 2, \ldots, M\} \). As there are \( M \) possible observations for each sensor, then number of overall set of observation vectors is \( K = M^N \). Consequently, the observation matrix \( B \) of our proposed HMM is a \( N_c \times K \) matrix, which is expressed as

\[
B = \begin{bmatrix}
b_{11} & \cdots & b_{1K} \\
\vdots & & \vdots \\
b_{N_c,1} & \cdots & b_{N_c,K}
\end{bmatrix}
\]

where \( b_{ik} = P(o_t = k | q_t = i), k \in \{1, \ldots, K\}, i \in \{1, \ldots, N_c\} \). Because of the geographical constraint, some observation vectors have nearly zero-probability, hence \( B \) is a sparse matrix and its dimension can be reduced in a great deal, i.e., \( K < M^N \), thus reducing the memory storage. In Table.I, corresponding to the scenario in Fig.1, when we quantized RSS into different levels, i.e., \( M = 3, 4, 5, 6 \), the original dimension of \( B \) is incredibly large, while after removing the rows with all zeros, its dimension is largely reduced.

<table>
<thead>
<tr>
<th>( M )</th>
<th>Before Dimension Reduction</th>
<th>After Dimension Reduction</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>8 x 81</td>
<td>8 x 17</td>
</tr>
<tr>
<td>4</td>
<td>8 x 256</td>
<td>8 x 33</td>
</tr>
<tr>
<td>5</td>
<td>8 x 625</td>
<td>8 x 36</td>
</tr>
<tr>
<td>6</td>
<td>8 x 1296</td>
<td>8 x 54</td>
</tr>
</tbody>
</table>

2) HMM Training: The transition probabilities depend on the target’s motion, and the observation matrix has a direct relationship with HMM state, then for a given motion model of the target, an off-line training procedure for \( A \) and \( B \) is necessary before state estimation. Being different from the well-known Baum-Welch algorithm [19], which is of great computational complexity and time-spending, a method of discrete frequencies evaluation is applied in HMM training. Our training samples include the Markov state sequence \( \{q_1, q_2, \ldots, q_T\} \), and the corresponding quantized RSS measurement vectors \( \{o_1, o_2, \ldots, o_T\} \). The transition matrix \( A \) is constructed by counting the occurrence of state transitions. And the relative frequency of each observation vector associated with a specific Markov state is recorded as the observation probabilities. \( a_{ij} \) and \( b_{ik} \) can be computed as

\[
a_{ij} = \frac{N_{i \rightarrow j}}{N_i}
\]

\[
b_{ik} = \frac{N_{i = o = k}}{N_i}
\]

where \( N_i \) is the total number when the target is at state \( i \), \( N_{i \rightarrow j} \) stands for the number of transitions from state \( i \) to state \( j \), and \( N_{i = o = k} \) denotes the number of occurrence of the \( k \)th observation vector when the target is at state \( i \). When the amount of training samples is large enough, the discrete frequencies can replace the expected value of \( a_{ij} \) and \( b_{ik} \).
3) **Sight Condition Identification:** After the training phase, the HMM parameter set $\lambda = \{ \pi, A, B \}$ is obtained, which is associated with the given motion model described in (1). When a target appears in the FOI, the sight conditions where the target locates at each time instant should be identified before localization is performed. Here, for real-time estimation, a forward-only algorithm\cite{17}, \cite{19} is utilized to identify the sight conditions.

Given $\lambda$ and the observation vectors up to the current $t$th time step $o_{1:t}$, the probability of the target being in state $i$ at time $t$ is defined as

$$
\gamma_t(i) = p(q_t = i | o_{1:t}, \lambda)
$$

(10)

According to Bayes’ theorem,

$$
\gamma_t(i) = p(o_t | q_t = i)p(q_t = i | o_{1:t-1}, \lambda)
$$

(11)

where $p(o_t | q_t = i)$ is obtained by the observation matrix $B$, and $p(q_t = i | o_{1:t-1}, \lambda)$ can be computed as

$$
p(q_t = i | o_{1:t-1}, \lambda) = \sum_{j=1}^{N_o} p(q_t = i | q_{t-1} = j)p(q_{t-1} = j | o_{1:t-1}, \lambda)
$$

(12)

where $p(q_t = i | q_{t-1} = j)$ can be obtained by transition probability matrix $A$. Consequently,

$$
\gamma_t(i) = \delta_t p(o_t | q_t = i) \sum_{j=1}^{N_o} p(q_t = i | q_{t-1} = j) \gamma_{t-1}(j), t > 1
$$

(12)

where $\delta_t$ is an multiplied normalization term to satisfy the constraint $\sum_{i=1}^{N_o} \gamma_t(i) = 1$. When $t = 1$,

$$
\gamma_1(i) = \delta_1 p(o_1 | q_1 = i) \pi(i)
$$

(13)

Thus, the state at time $t$ is estimated as follows

$$
\hat{q}_t = \arg \max_i(\gamma_t(i))
$$

(14)

Meanwhile, the corresponding estimated sight condition vector is identified as $s_{\hat{q}_t}$.

**B. EKF Localization Algorithm**

Considering the LOS/NLOS conditions, Extended Kalman Filter (EKF) is applied for target localization. The RSS measurement of sensor $n$ at time $t$ can be expressed as

$$
z_n(t) = s_n[P_{0,los} - 10\alpha_{los} \log_{10}(d_n(t)/d_0) + \omega_{los}] + (1 - s_n)[P_{0,nlos} - 10\alpha_{nlos} \log_{10}(d_n(t)/d_0) + \omega_{nlos}]
$$

(15)

where $\omega_n(t) = s_n\omega_{los} + (1 - s_n)\omega_{nlos}$ is the measurement white Gaussian noise yielding $\omega_n(t) \sim N(\mu_n(t), \sigma_n^2(t))$ with

$$
\mu_n(t) = s_n\mu_{los} + (1 - s_n)\mu_{nlos}
$$

$$
\sigma_n^2(t) = s_n^2\sigma_{los}^2 + (1 - s_n)^2\sigma_{nlos}^2
$$

The measurement vector $z_t = [z_1(t), \ldots, z_N(t)]^T$, with white Gaussian noise, whose mean is $\mu_t = [\mu_1(t), \ldots, \mu_N(t)]^T$, and covariance matrix $R_t = \text{diag} [\sigma_1^2(t), \ldots, \sigma_N^2(t)]$. The corresponding Jacobian matrix $H$ is computed as

$$
H_t = \begin{bmatrix}
\frac{\partial h_1(t)}{\partial x_t} & \cdots & \frac{\partial h_N(t)}{\partial x_t}
\end{bmatrix}_{x_t = \hat{x}_{t|t-1}, y_t = \hat{y}_{t|t-1}}
$$

where

$$
h_n(t) = z_n(t) - \omega_n(t)
$$

and

$$
h_t = [h_1(t), h_2(t), \ldots, h_N(t)]^T
$$

Then the target position is estimated by the following EKF algorithm

$$
\hat{x}_{t|t-1} = \hat{x}_{t|t-1} + Ku_t
$$

$$
P_{t|t-1} = P_{t|t-1} + Qv
$$

$$
K_t = P_{t|t-1} H_t^T (H_t P_{t|t-1} H_t^T + R_t)^{-1}
$$

$$
\hat{x}_{t|t} = \hat{x}_{t|t-1} + K_t (z_t - h_t - \mu_t)
$$

$$
P_{t|t} = (I - K_t H_t) P_{t|t-1}
$$

where $K_t$ is the Kalman Filter gain. $\hat{x}_{t|t-1}, \hat{x}_{t|t}$ are the predicted and estimated target position respectively. $P_{t|t-1}$ and $P_{t|t}$ represent the corresponding error covariance.

**C. HMM-EKF Localization Algorithm**

The overall localization algorithm is depicted in **Algorithm 1**.

**Algorithm 1**: HMM-EKF Localization

1: Off-line training: based on the training samples, compute HMM parameter $\lambda = \{ \pi, A, B \}$ according to Eq.(3), (8) and (9) respectively.
2: On-line hidden state estimation: according to Subsection.III-A3, based on $A$, identify the sight condition vector $s_{\hat{q}_t}$ at time $t$.
3: Real time localization: combining the estimated sight conditions $s_{\hat{q}_t}$ and RSS measurements $z_t$, localize target’s position using EKF described in Subsection.III-B.

**IV. SIMULATION RESULTS**

In this section, extensive simulations are conducted to illustrate the performance of the proposed localization strategy. The layout of our considered FOI is illustrated in Fig.1, which is a $20m \times 20m$ area with 4 sensors located at $(-10, -10)$, $(-10, 10)$, $(10, -10)$ and $(10, 10)$, respectively. The target moves a random walk driven by a white Gaussian
process whose covariance matrix $Q_\upsilon = \text{diag}\{0.2, 0.2\}$. The referenced RSS $P_{0,\text{los}}$ and $P_{0,\text{nlos}}$ are set to be $50dBm$ and $25dBm$ at referenced distance $d_0 = 1m$. And the path loss exponent under LOS and NLOS are respectively set as $\alpha_{\text{los}} = 1.8$ and $\alpha_{\text{nlos}} = 4$, according to [18]. The corresponding measurement noise yielding $\omega_{\text{los}} \sim N(0, 0.1)$ and $\omega_{\text{nlos}} \sim N(0.1, 0.5)$. A $1 \times 10^5$ length training sequence is used for HMM parameter estimation in the training phase.

Fig.3 shows the root mean square error (RMSE) in 200 Monte Carlo runs with three different sight condition strategies: a) Our proposed HMM estimated sight condition; b) All the sight conditions are assumed to be LOS; c) All the sight conditions are assumed to be perfectly known, which acts as the performance benchmark. It can be seen that the performance of our proposed localization algorithm is much better than the case when assuming all the sight conditions are LOS. Compared with the blue line, the RMSE of our proposed algorithm is much larger, because occasionally if the sight conditions are wrongly identified, it will bring a extremely large error. Large estimation errors will occur at different time steps in different Monte Carlo runs, which enlarge the average error.

![Fig. 3. Localization performance comparison under LOS/NLOS conditions in 200 runs](image)

Fig.4 shows the localization performance in a single run. Fig.4(a) displaces the estimated position error and Fig.4(b) illustrates the variation of Markov state over time, which is the red dotted line and the HMM estimated state error, which is the green line. Comparing the two sub figures, we can see that, large position error mainly occurs when the Markov state is wrongly estimated. And it most happens where the target goes across the borderline between neighbouring cells. It also shows that, when the wrong state estimation happens, our algorithm can still rapidly correct back to the right estimation.

![Fig. 4. Localization performance under LOS/NLOS conditions in a single run](image)

The dimension of $A$ and $B$ has a great impact on the computational complexity and memory storage. $A$ is decided by the layout of the physical map we considered. In a static environment, the dimension of $A$ is fixed. While, the dimension of observation matrix $B$ is affected by the quantization of RSS. A larger number of levels $M$ brings a larger computational complexity and memory storage. As to the resulting localization performance, Fig. 5 shows that, the variation of $M$ does not incur a significant change in localization performance and a larger number of levels does not mean a better localization performance. Though the localization accuracy when $M = 3$ is mostly better than that when $M = 4$, its performance is not stable as the case when $M = 4$ since there exists extremely large errors when $M = 3$. Hence, we can say that, the best localization performance can be obtained when $M = 4$ from our simulations.

To investigate the sensitivity of our algorithm to the target’s motion, in Fig.6, we compare the localization performance when the target moves under the motion models with different velocities, i.e., different covariance matrix $Q_\upsilon = \text{diag}\{0.1, 0.1\}$, $Q_\upsilon = \text{diag}\{0.2, 0.2\}$, $Q_\upsilon = \text{diag}\{0.5, 0.5\}$ and $Q_\upsilon = \text{diag}\{1, 1\}$, respectively. We can see that, there is no obvious distinction among the four performance lines. It can be concluded that, the proposed localization algorithm owns strong robustness against the target motion.

V. CONCLUSION

In this paper, a novel strategy is proposed for the localization problem under LOS/NLOS conditions. The FOI is assumed to be able to partitioned into distinct cells, with each cell
has stable channel sight conditions relative to sensors. The change in channel sight conditions as a target moves is modeled as a HMM process. With sight conditions as hidden state and quantized RSS measurements as observations, HMM parameters are obtained by an off-line training. Then the sight conditions are identified by an on-line forward-only algorithm. Combining the estimated sight conditions, the target is localized by EKF. The proposed strategy is applicable for real time localization, and the simulation results illustrate that, with sight conditions identification, the localization performance can be improved in a great deal.

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