Maneuvering Target Tracking in Wireless Sensor Network with Range Only Measurement

Yufeng Wang, Xinx Feng*

Information and Navigation College Air Force Engineering University, Xi’an, 710077, P. R. China

Email: numberyufeng1994@163.com, *Email: 1930854410@qq.com

Abstract- In this paper, we consider the condition of range-only measurement, and propose a novel maneuvering target algorithm in wireless sensor network (WSN) that can estimate the position and velocity of the target. Our algorithm combines maximum likelihood estimation and interacting multiple model filtering. Based on range information that the sensors measured, we use maximum likelihood method with constraint information to estimate the position, and then adopt interacting multiple model filtering to further improve the tracking accuracy. Simulation results shows that our algorithm can track maneuvering target effectively in wireless sensor network when we can obtain only range information.

1. INTRODUCTION

In the recent years, with the progress in micro-electro-mechanical technology and wireless communication, wireless sensor network has been widely used in environmental monitoring[1], habitat monitoring[2], military surveillance and reconnaissance[3], intelligent robotic system[4] etc. Apart from sensing the surrounding environment, these sensors with small size and low cost usually integrate with some other functions such as communication, data processing. In practice, a massive account of sensors can be deployed quickly in specific area, and complete planed task collaboratively by sharing information through multi-hop network they established before. Target tracking is one of the most important yet fundamental use in wireless sensor network, which interests more and more researchers due to its characteristic of distributed, flexibility, wide-sensing[5-8].

For wireless sensor network target tracking, some relevant research has improved tracking performance from different aspects. Most tracking algorithms track and localize targets from range measurement, bearing measurement, position measurement or hybrid measurement. In some conditions, such as acoustic system or GPS deny environment, we can only get the ranging information between sensors and target, or there is only distance information that in use. Hence, to these conditions, more and more researchers devote to study cooperative localization and target tracking in wireless sensor network using range only measurement[9-11]. For example, Evangelos B.Mazomenos, Jeffrey S. Reeve, and Neil M. White proposed a set of target tracking algorithms that can estimate the position and velocity of the target based on particle filter in their series of researchs[1,5]. Xingbo Wang, Minyue Fu, and Huanshui Zhang proposed a maximum likelihood estimation algorithm to achieve prelocalization of the target on the basis of triangulation idea that is commonly used, and then combines standard Kalman filter to estimate the position and velocity of target, their tracking accuracy is better than classical EKF(Extend Kalman Filter, EKF) algorithm or pure maximum likelihood estimation[2]. Apart
from this, some other algorithms can solve the problem of indoor cooperative localization or estimate the position of the target with RSSI information or other ranging methods such as TDOA[8,9]. Generally speaking, there are two challenging problems in pure distance target tracking. The first challenge is that we need to face the nonlinear range measurement equation of the target state(which usually consist of position and velocity), meanwhile, the moving target may switch their motion mode continually, which decrease the possibility of tracking maneuvering target in single model method, and even divergence. Although the algorithms mentioned above can track uniform or weak maneuvering targets, it is necessary for us to explore new algorithms to track maneuvering targets.

For maneuvering target tracking, Li X R's series of researches has already been widely used in radar target tracking, which can track maneuvering target and point a direction for other researchers[12-14]. S.Vasuhi and V.Vaidehi introduced the multi-model method in radar target tracking into wireless sensor networks target tracking, which can track maneuvering target better than standard Kalman Filter in simulation and experiment[7]. However, the above studies usually use the measurement of position or hybrid (distance and bearing), their results is not suitable for target tracking in wireless sensor networks under the condition of pure range measurement.

In this paper, we consider the scenario of range-only measurement and maneuvering target tracking, propose a novel algorithm named CMLE-IMM that combine the constrained maximum likelihood estimation and interacting multiple model filtering. Our basic idea is to estimate the position of the target using MLE method, and then we adopt IMM filtering to further improve the position accuracy and get the velocity of the target. Simulation result demonstrate our effectiveness which can solve the problem of tracking maneuvering target in wireless sensor networks with range only measurement better.

Notation. For a wireless sensor network with \( N \) sensors, we donate \( \mathcal{S} = \{S_1, S_2, \ldots, S_N\} \) as its index set, and \(|\mathcal{S}| = N\) the cardinality of set \(|\mathcal{S}|\). \( I_n \) donates the \( n \)-dimensional identity matrix. For a matrix/vector \( X \), \( X^T \) donates its transpose, \( X^{-1} \) donates its inverse. \( N(\mu, \sigma^2) \) donates the normal distribution with \( \mu \) mean and covariance matrix \( \sigma^2 \).

2. PROBLEM FORMULATION

In this paper, we consider tracking a moving target in two-dimensional field (as shown in fig.1). At each sample time \( k \), we assume that the sensors know their current state \( X_{i,k}, i \in \{1, 2, \ldots, N\} \) that consist their position and velocity in \( x \)-coordinate and \( y \)-coordinate priori. The state of sensor \( i \) at time \( k \) defined as

\[
X_{i,k} = [x_{i,k}, v_{i,x,k}, y_{i,k}, v_{i,y,k}]^T
\]  

where \( x_{i,k}, y_{i,k} \) donates its position in \( x, y \) coordinates respectively, \( v_{i,x,k}, v_{i,y,k} \) donates its velocity in two dimensional respectively.

At sample time \( k \), we assume that there are \( M \) (\( M \leq N \)) sensors measure the distance between target \( t \) and themselves, then we get a measurement information set as

\[
D_i = \{\hat{d}_{i,1}, \hat{d}_{i,2}, \ldots, \hat{d}_{i,M} \mid d_i = d_{i,t} + e_{i,t}, i = 1, 2, \ldots, m\}
\]  

where \( \hat{d}_{i,t}, d_{i,t}, e_{i,t} \sim N(\mu, \sigma^2), i \in \{1, 2, \ldots, m\} \) donates the range measurement, real distance, measurement error from sensor \( i \) to target \( t \) respectively. The state of the target \( t \) at sample time \( k \) defined as \( X_{t,k} = [x_{t,k}, v_{t,x,k}, y_{t,k}, v_{t,y,k}]^T \), hence, the nonlinear relationship between real distance and position coordinates for target \( t \) and sensor \( i \) is

\[
d_{i,k} = \sqrt{(x_{i,k} - x_{t,k})^2 + (y_{i,k} - y_{t,k})^2}
\]  

Apart from the measurement, the sensors can share their current states, relative distance and measurement information by mutual communication in sensor network \( \mathcal{S} \). Now, based on the states of
the sensors that known priori and their range measurement, each sensor $i$ desire to track the moving target $t$, i.e., provide the state estimation $X_{i,k}$ that can get the position and velocity of the target.

![Fig.1, Target tracking in wireless sensor network](image)

3. RANGE BASED TARGET TRACKING ALGORITHM IN WSN

We now discuss our algorithm in detail. In the previous literature[2], the author designed a range-only target tracking algorithm that combined maximum likelihood estimation and Kalman filter. In our algorithm, we use maximum likelihood estimation with some constrained information to provide an initial position and calculate its covariance matrix, then we use IMM filtering to further estimate the full kinematic parameter of the target with a better accuracy.

3.1 Prelocalization using constrained maximum likelihood estimation

In two dimensional filed, we can determine the position of the target uniquely if we have at least three range measurements with zero error, but this phenomenon cannot appear in practice due to the existence of measurement noise, especially for multiple sensor measurement. Maximum likelihood estimation establishes a function according to the relationship between the distance and position coordinates. By solving this function, the position of targets can be estimated. Hence, MLE method is used to prelocalization(i.e. to provide the initial estimation for the target position) the target in this paper.

For our tracking scenario, we assume that there are $M (M \geq 3)$ sensors obtained the range information to the target, the ranging error of each sensor that are independent and distributed equally obeys the Gaussian distribution with $\mu$ mean and variance of $\sigma^2$. Hence, for each sensor $i$, based on the actual position of the target $(x_{i,k}, y_{i,k})$ and sensor position $(x_{i,k}, y_{i,k})$, the measurement $\hat{d}_{i,k}$, the conditional probability density function (PDF) defined as

$$p(\hat{d}_{i,k} \mid x_{i,k}, y_{i,k}) = \frac{1}{\sqrt{2\pi \sigma}} \exp \left\{ -\frac{(\hat{d}_{i,k} - d_{i,k} - \mu)^2}{2\sigma^2} \right\}$$

When multiple sensors obtain the measurement information at each sample time, due to the attribution of independent and distributed equally among their error, combined with the measurement information set, we establish the following function

$$p(D_\mu \mid x_{i,k}, y_{i,k}) = \prod_{i=1}^{M} p(\hat{d}_{i,k} \mid x_{i,k}, y_{i,k})$$

The MLE method is to seek the unknown target position $(x_{i,k}, y_{i,k})$ such that maximize the function (5). Since the statistical characteristics of range measurement errors for every sensors are known, equation (4) has essentially calibrated the measurement through the mean of measurement error $\mu$,
and the calibrated measurements expressed as \( \tilde{d}_{it,k} = \hat{d}_{it,k} - \mu \). Therefore, on the base of equation (4), the estimation of the target position \((\hat{x}_{tk}, \hat{y}_{tk})\) is given by the following equation:

\[
(\hat{x}_{tk}, \hat{y}_{tk}) = \arg \min_{x,y} f_2(x,y) \tag{6}
\]

where \( f_2(x,y) = \sum_{i=1}^{N} \frac{d_{it,k}^2 - \left( (x-x_{i,k})^2 + (y-y_{i,k})^2 \right)}{2 \sigma^2} \), \( d_{it,k} = \sqrt{(x-x_{i,k})^2 + (y-y_{i,k})^2} \), \( d_{it,k} \) donates the actual distance between target \( t \) and sensor \( i \). It is difficult to minimize the problem of (6). We are supposed to adopt Newton-Raphson iterative method to solve this equation to get the prelocalization value \((\hat{x}_{tk}, \hat{y}_{tk})\) (detailed procedures are omitted here due to space limitation, the interested reader can refer to[2]). At the same time, the estimation error covariance matrix \( R_k \) is available according to Hessian matrix \( H_k \):

\[
H_k = \begin{bmatrix}
\frac{\partial^2 f(x,y)}{\partial x^2} & \frac{\partial^2 f(x,y)}{\partial x \partial y} \\
\frac{\partial^2 f(x,y)}{\partial x \partial y} & \frac{\partial^2 f(x,y)}{\partial y^2}
\end{bmatrix}_{x=x_{tk}, y=y_{tk}}
\tag{7}
\]

\[
R_k = H_k^{-1} \tag{8}
\]

In the previous study, since the Newton-Raphson iterative method can only get a local minimum value, the author use one-step predict value of Kalman filter as initial iteration value when using Newton-Raphson iterative method to get a better minimum value that is closer to global minimum value. But in the multiple model method, there are more than one one-step predict value which will influence the outcomes, and the changes in target motion patterns may cause an incorrect one-step predict value which lead to worse prelocalization error. Hence, in order to find a better minimum value in solving equation (6), we add some constraint information as:

\[
\sqrt{(x_{tk} - x_i^a)^2 + (y_{tk} - y_i^a)^2} - d_{it,k} \leq \sigma^2 \quad i \in \{1, 2, \cdots m\} \tag{9}
\]

where \((\hat{x}_{tk}, \hat{y}_{tk})\) donates the prelocalization value of target \( t \).

### 3.2 Interacting Multiple Model Filtering

In the second stage, we design a IMM algorithm to further improve tracking performance[7]. The structure of IMM algorithm are shown in Fig 2.

![Fig2](image)

**Fig2.** Structure of the IMM algorithm

We donate the previous prelocalization result as a new measurement to target \( t \) at sample time \( k \)

\[
Z_{tk,k} = [\hat{x}_{tk}, \hat{y}_{tk}]^T \tag{10}
\]

the corresponding motion equation of target and measurement equation describe as

\[
\dot{X}_{tk,k} = FX_{tk,k-1} + GW_{tk,k-1} \tag{11}
\]

\[
Z_{tk,k} = HX_{tk,k} + V_{tk,k} \tag{12}
\]
where, $F$ - State transition matrix, $G$ - disturbance gain matrix, $W_{r,k-1}$ - process noise with covariance $Q_{k-1}$, $H$ - measurement matrix, $V_{r,k}$ - measurement noise.

From sample time $k-1$ to $k$, based on the model transfer probability matrix $\Delta$, model probability $\rho_{i,k-1}^j$ of model $i$, and state estimation $\hat{X}_{i,k-1}$, covariance matrix $\Pi_{i,k-1}$ of each model $i$, a circle of IMM algorithm express as follows:

1) **Input Mixing**

\[
c_j^{i,k-1} = \sum_{i=1}^{m} \pi_{ji} c_{j,k-1}^i \quad (13)
\]

\[
\rho_{j,k-1}^i = \frac{1}{c_j^{i,k-1}} \pi_{ji} c_{j,k-1}^i \quad (14)
\]

where $\pi_{ji}$ donates the Markov transition probability from motion model $i$ to $j$, $c_{j,k-1}^i$ donates the probability of model $j$ after input mixing.

\[
\hat{X}_{i,k-1} = \sum_{i=1}^{m} \hat{X}_{i,k-1} \rho_{j,k-1}^i \quad (15)
\]

\[
\Pi_{j,k-1}^i = \sum_{i=1}^{m} \rho_{j,k-1}^i \{ \Pi_{i,k-1}^i + [\hat{X}_{i,k-1} - \hat{X}_{j,k-1}^i] [\hat{X}_{i,k-1} - \hat{X}_{j,k-1}^i]^T \} \quad (16)
\]

where $\hat{X}_{i,k-1}^j$ and $\Pi_{j,k-1}^i$ donates the state estimation of model $j$ and its estimation error covariance after input mixing respectively.

2) **Kalman Filter**

In this procedure, since measurement equation is a linear relationship according to (12), we use standard Kalman filter for each model $i$ to get their state estimation $\hat{X}_{i,k}$ and covariance matrix:

\[
\hat{X}_{i,k}^j = F_i \hat{X}_{i,k-1}^j + \hat{Z}_{i,k}^j \quad (17)
\]

\[
\Pi_{i,k}^j = F_i \Pi_{i,k-1}^j F_i^T + Q_i \quad (18)
\]

\[
\hat{Z}_{i,k}^j = H_i \hat{X}_{i,k}^j \quad (19)
\]

\[
\zeta_i^j = H_i \Pi_{i,k}^j H_i^T + R_i \quad (20)
\]

\[
K_i^j = \Pi_{i,k}^j H_i^T \zeta_i^j \quad (21)
\]

\[
\hat{X}_{i,k} = \hat{X}_{i,k} - K_i^j (Z_{i,k} - \hat{Z}_{i,k}^j) \quad (22)
\]

\[
\Pi_{i,k} = \Pi_{i,k} - K_i^j H_i \Pi_{i,k}^j \quad (23)
\]

where $F^j$ donates the state transfer matrix of model $i$.

3) **Model Probability Update**

In the above procedure, for each model $i$, we can get a error vector between predicted measurement and prelocalization as

\[
\tilde{Z}_k = Z_{r,k} - \hat{Z}_{i,k}^j \quad (24)
\]

and its covariance matrix $\zeta_i^j$. Hence, the likelihood function of each model calculate as

\[
\Lambda_i^k = \frac{\exp \left[-(\tilde{Z}_k^j)^T (\zeta_i^j)^{-1} \tilde{Z}_k^j / 2\right]}{\sqrt{(2\pi)^m \zeta_i^j}} \quad (25)
\]

their probability update as

\[
\rho_i^k = \Lambda_i^k c_{j,k-1}^i / C_k \quad (26)
\]

\[
C_k = \sum_{i=1}^{m} \Lambda_i^k c_{j,k-1}^i \quad (27)
\]

where $m$ donates the dimension number of the measurement model.
This step yields the overall state estimation and its covariance as the probability weighted sum of each Kalman filter as

$$\hat{X}_{i,k} = \sum_{i=1}^{n} \hat{X}_{i,k}^{j} \rho_{i}^{j}$$  \hspace{1cm} (28)$$

$$\Pi_{i} = \sum_{i=1}^{n} \rho_{i}^{j} [\Pi_{i}^{j} + (\hat{X}_{i,k}^{j} - \hat{X}_{i,k})(\hat{X}_{i,k}^{j} - \hat{X}_{i,k})^{T}]$$  \hspace{1cm} (29)$$

3.3 Algorithm

Now, according to the above procedure, CMLE-IMM target tracking algorithm can be summarized as follows.

**Off-line stage:** Establish a IMM framework, for each model $i$ choose initial state estimation $\hat{X}_{i,0}$ and its covariance $\Pi_{i,0}$.

**On-line stage:** At each sample time $k$, perform the following procedure as we obtain the measurement information set.

a) Perform the input mixing procedure from (13) to (16).

b) Calculate the one-step state prediction of the target and covariance according to (17) and (18).

c) Calculate the position of the target using range measurement information set $D_{i}$ according to (6) and (9) as follows:

$$\hat{x}_{i,k}, \hat{y}_{i,k} = \arg \min_{x, y} \sum_{n=1}^{N} \frac{[\sqrt{(x-x_{n})^{2}+(y-y_{n})^{2}}-d_{n,k}]}{2\sigma^{2}}$$

s.t. $\sqrt{(\hat{x}_{i,k} - x_{k})^{2} + (\hat{y}_{i,k} - y_{k})^{2} - d_{i,k}} \leq \sigma$

$$d)$$ Calculate prelocalization error covariance according to (8) and redefine measurement according to (10)

e) Perform the rest of procedure from (19) to (29)

4. SIMULATION EXAMPLES

To verify the effectiveness of the above proposed approach, we consider a simulation example as follows.

Consider a WSN with four sensors to track a moving target in a two dimensional field. At each sample time, we can obtain the range information with the error that obey Gaussian distribution with zero mean and covariance of 1. The target moves in nearly constant velocity (NCV) mode and nearly constant acceleration (NCA) mode in each direction. In NCV mode, the state of the target $X_{i,k}$ and some relevant parameters define as follows:

$$X_{i,k}=[x_{i,k}, v_{x,i,k}, v_{y,i,k}, v_{y,i,k}]^{T}$$

$$F_{cr} = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & T & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & T \end{bmatrix}$$

$$G_{cr} = \begin{bmatrix} T^2 & 0 \\ T & 0 \\ 0 & T \\ 0 & T \end{bmatrix}$$

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

$$Q = 0.01I_{2}$$

And in NCA mode

$$X_{i,k}=[x_{i,k}, v_{x,i,k}, a_{x,i,k}, v_{y,i,k}, v_{y,i,k}, a_{y,i,k}]^{T}$$

$$F_{cr} = \begin{bmatrix} 1 & T & 0 & 0 & 0 & 0 \\ 0 & T & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & T & 0 & 0 \\ 0 & 0 & 0 & T & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & T \end{bmatrix}$$

$$G_{cr} = \begin{bmatrix} T^2 & 0 & 0 \\ T & 0 & 0 \\ 0 & T & 0 \\ 0 & 0 & T \\ 0 & 0 & 0 & T \end{bmatrix}$$

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

$$Q = 0.01I_{6}$$
\[ F_{ca-x} = F_{ca-y} = \begin{bmatrix} 1 & T & \frac{T^2}{2} \\ 0 & 1 & T \\ 0 & 0 & 1 \end{bmatrix} \quad G_{ca-x} = G_{ca-y} = \begin{bmatrix} \frac{T^2}{2} \\ T \\ 1 \end{bmatrix} \]

\[ H = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{bmatrix} \quad Q = 0.1I_2 \]

where \( a \) donates acceleration of the target, \( F_{ca-x} \) and \( F_{ca-y} \) donates the state transfer matrix in \( x \) and \( y \) axes respectively, \( G_{ca-x} \) and \( G_{ca-y} \) donates the disturbance gain matrix in \( x \) and \( y \) axes respectively.

The target switch its motion mode with Markov probability transfer matrix
\[
\Delta = \begin{bmatrix} 0.7 & 0.3 \\ 0.3 & 0.7 \end{bmatrix}
\]
and the initial probability of each mode is 0.5.

More than 100 times Monte Carlo simulation is needed to evaluate the accuracy use RMSE (Root Mean Square Error, RMSE). The RMSE of position and velocity calculate as

\[
RMSE = \sqrt{\frac{1}{q} \sum_{i=1}^{q} (P_{t,i} - \hat{P}_{t,i})^T (P_{t,i} - \hat{P}_{t,i})} \quad (31)
\]

\[
RMSE = \sqrt{\frac{1}{q} \sum_{i=1}^{q} (V_{t,i} - \hat{V}_{t,i})^T (V_{t,i} - \hat{V}_{t,i})} \quad (32)
\]

where \( P_{t,i} = [x_{t,i}, y_{t,i}]^T \) and \( \hat{P}_{t,i} = [\hat{x}_{t,i}, \hat{y}_{t,i}]^T \) donates the real position and estimate value of the target respectively, \( V_{t,i} = [v_{x,t,i}, v_{y,t,i}]^T \) and \( \hat{V}_{t,i} = [\hat{v}_{x,t,i}, \hat{v}_{y,t,i}]^T \) donates the real velocity and estimate value respectively.

![Fig.3 Comparison of tracking trajectory](image1)

![Fig.4 Comparison of the position in x axes](image2)
We compare our algorithm CMLE-IMM with the method that combines maximum likelihood estimation and Kalman filter (MLE-KF) proposed in [2]. In Fig.3 we show the trajectory of the target, and in Fig.4, Fig.5 we show the comparison of the tracking results in $x$ coordinate and $y$ coordinate respectively. It is not easy to demonstrate our advantage in a single experiment. By 100 times Monte Carlo experiments, we can clear express our advantage in RMSE that shown in Fig.6. Our algorithm can adapt the change of motion mode better with a lower RMSE about 0.8 while MLE-KF method act 1.1 approximately. [10]
Fig. 7 and Fig. 8 show the velocity tracking results, their RMSE is shown in Fig. 9. Compared with MLE-KF method, we improve the velocity accuracy about 12% while 22% in position estimation in our algorithm.

The MLE-KF algorithm use maximum likelihood estimation to prelocalization the target and use standard Kalman filter to further improve the tracking performance. In this paper, we add some constraint information to eliminate the effect of initial iterative value to provide a relevant stable prelocalization, and then integrate the prelocalization result into IMM framework. Through the above simulation experiments, it is shown that our proposed algorithm achieve a better performance in tracking maneuvering target in WSN.

5. CONCLUSION

In this paper, we desire to track maneuvering target in WSN with range-only measurement. Our idea source from the MLE-KF approach in [2]. Under the range only condition, we propose a constrained MLE approach to eliminate one-step state prediction of the target from different model, we can obtain a prelocalization result of the target and its covariance in this step firstly. In the second step, we integrate the above result into IMM framework to get a full kinematic parameter in a better accuracy. In this paper, we demonstrate our advantage through Monte Carlo experiment in a two dimensional field, and our algorithm can be easily extend to 3 dimensional space, at the same time, we can further improve the prelocalization approach and multiple model based filter which will be studied in our future work.

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