Target Tracking with Size Estimation in Wireless Sensor Networks

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***Abstract*—The information of target size is useful for a lot of target tracking applications of wireless sensor networks, however, it has been neglected in most existing work. This paper considers the problem of target tracking with size estimation by ultrasonic sensors, which are able to measure the relative distance with satisfactory accuracy. We first propose a recursive algorithm for single target tracking and size estimation by adopting the Extended Kalman Filter (EKF) method. For the multiple-target case, a novel target identification algorithm, which aims to minimize the consecutive square estimate error, is given to track multiple targets and estimate the corresponding size simultaneously at each time step. Extensive simulations demonstrate the effectiveness of the proposed algorithms.**

***Keywords*-target tracking; ultrasonic sensor; target size; extended kalman filter**

I. Introduction

The rapid advances in micro-electro-mechanical systems (MEMS) technology, digital computing technology, and wireless communication technology have attracted substantial research in wireless sensor networks (WSNs). The applications of WSNs can be found in a number of areas, such as environment surveillance, health-care, automobiles, power distribution, industrial automation, etc. [1]. Target tracking is a fundamental requirement for the applications mentioned above [2]–[6].

Typically, according to the number of targets, the related work can be categorized into two classes: single-target tracking [7] and multiple-target tracking [8]. For single-target tracking, there have been different approaches by considering the tradeoff between limited resources and certain tracking accuracy. In [9], a novel weighted distance based sensor selection method is proposed for target tracking, which aims to reduce the computational cost while reserving certain tracking accuracy. An adaptive activation algorithm is given in [10] for dynamically activating the sensors. Another adaptive sensor scheduling scheme, is proposed in [11] where the distributed multi-sensor scheduling scheme is considered for collaborative target tracking. On the other hand, multiple-target tracking is widely encountered in many real applications and hence has been attracting the interests of many researchers. Some multiple-target tracking algorithms have been proposed [12], such as nearest neighbor (NN), probabilistic data association (PDA), the joint probabilistic data association (JPDA), multiple hypothesis tracking (MHT), Fuzzy Cluster Means (FCM) and Markov Chain Monte Carlo Data Association (MCMCDA). In [13], a Markov chain Monte Carlo data association (MCMCDA) algorithm is presented, which solves the data association problems arising in multi-target tracking in a cluttered environment. A distributed data association algorithm for multi-target tracking is proposed in [14] by combining joint probabilistic data association and the Kalman filter based consensus algorithm.

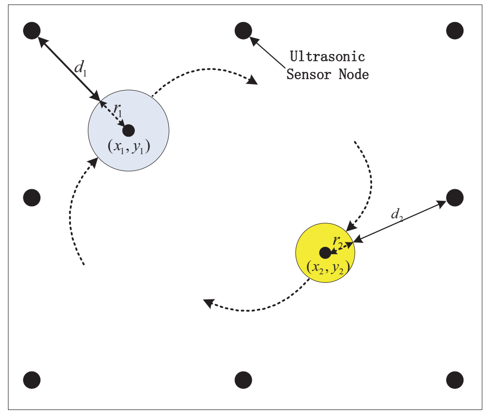

Fig. 1. Illustration of mobile target tracking with size estimation in ultrasonic sensor networks

Note that in most of the existing work on target tracking, the target is considered as a mass point, however, the size of target may not be neglected in many applications, for example, vehicles in the battle field, animals in the area [15] [16]. Such size information should be able to help to enhance the performance of systems. Moreover, it may be further utilized to help identify and track multiple targets. It should be noticed that although there have been some related work for estimating the shape and size of objects e.g., [17], where computer vision has been used to identify the shape and size, the method is not suitable for WSNs where the computational capability and energy supply are always constrained.

Consider a WSN based target tracking system as illustrated in Fig. 1. where ultrasonic sensors are deployed to measure the relative distance between the reflection point of non-cooperative mobile target and the corresponding sensor. Note that the ultrasonic sensors can obtain the relative distance with both high accuracy and low cost compared with other kinds of

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measurements, e.g., RSSI, infrared or laser. The shape of target is approximated by a circle, and the size of targets is assumed to vary differently. By consecutively measuring the relative distances between the targets and corresponding sensors, we aim to accurately identify and track the targets with size estimation in a recursive way. Our work is categorized into two parts. First, the algorithm for single-target tracking and size estimation is proposed by adopting the extended Kalman filter (EKF). In the second part, a novel target identification algorithm is presented for deal with the multiple-target case, which is further combined with the EKF to track multiple targets and estimate their size at the same time.

The remainder of this paper is organized as follows. The problem is formulated in Section II. The main results for target tracking with size estimation are presented in Section III, including the single-target case and the multiple-target case. Section IV evaluates the algorithms with extensive simulations. Finally, Section V concludes the paper.

II. Problem Formulation

Let N ultrasonic sensors (indexed from 1 to N) be deployed in the tracking region with the coordinate $(x_i, y_i)(i = 1, 2, ..., N)$. First consider one target case without loss of generality. The shape of target is approximated by a circle, with the center coordinate (x, y), and the radius r. At each time step, an ultrasonic sensor s_i is scheduled to measure the Euclidean distance d_i between the reflection point of target and the corresponding sensor itself, with a measurement white noise v_i, then the relative distance can be expressed by

$$||(x_i, y_i) - (x, y)|| = d_i + r + v_i \tag{1}$$

$(i = 1, 2, .., N)$, where $||(x_i, y_i) - (x, y)||$ denotes the Euclidean distance between the center of target and sensor s_i.

Denote the state of each target as $X(k) = [x, \dot{x}, y, \dot{y}, r]$, and the corresponding estimate as $\hat{X}(k)$. Note that the size of each target has been taken in as the state of the target already. The system dynamics is modeled as follows

$$X(k+1) = FX(k) + \varpi_k \tag{2}$$

where

$$F = \begin{pmatrix} 1 & T_s & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & T_s & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix} \tag{3}$$

T_s is the sampling period of the system. F is a five-dimensional state transition matrix which represents the part of constant velocity and radius. ϖ_k denotes the system noise which is Gaussian with the covariance matrix Q,

$$Q = cov(\omega_k) = q \begin{pmatrix} T_s^3/3 & T_s^2/2 & 0 & 0 & 0 \\ T_s^2/2 & T_s & 0 & 0 & 0 \\ 0 & 0 & T_s^3/3 & T_s^2/2 & 0 \\ 0 & 0 & T_s^2/2 & T_s & 0 \\ 0 & 0 & 0 & 0 & \sigma \end{pmatrix} \tag{4}$$

where q is a known scalar that represents the intensity of the process noise [11]. σ stands for the irregularity of target surface. The measurement model is nonlinear and given as follows:

$$d_i(k) = h(X(k), \nu_{i,k}) \tag{5}$$

where $d_i(k)$ is obtained by the i-th sensor at time step k.

Suppose the number of targets is m. Denote the measurement of target j as z_j, $j \in \{1, \cdots, m\}$. Note that $z_j(k) \in \{d_i(k)\}$ and the number of measurements is also m corresponding to different target respectively. Our objective is to track each target with size estimation in a recursive way. At each step, given the previous estimates $\hat{X}_j(k-1)$ as well as the current measurements $\{d_i(k)\}$, we aim to design a recursive algorithm so that the following problem can be solved efficiently:

$$\begin{aligned} min \quad & E(\Pi_{j=1,\cdots,m}||X_j(k) - \hat{X}_j(k)||_2) \\ s.t. \quad & r_i(k) = r_i(k-1), \quad r_i \neq r_j, i \neq j \\ & z_j(k) \in \{d_i(k)\}, j = \{1, \cdots, m\} \end{aligned} \tag{6}$$

where $E(\cdot)$ is the expected value.

III. Main result

In the first place, we would like to solve the problem for the single target case, which is fundamental for our solution of multi-target case. The Extended Kalman Filter will be adopted to estimate the states of target recursively. Subsequently, for the multi-target case, we further propose an efficient target identification algorithm so that the each target can be identified and tracked with size estimation.

A. Single-Target Tracking with Size Estimation

In this scenario, according to Eq. (1), the measurement function h is nonlinear and can be expressed as:

$$d_i(k) = ||(x_i(k), y_i(k)) - (x_c(k), y_c(k))|| - r_c(k) + \nu_i(k) \tag{7}$$

$(i \in \{1, 2, ..., N\}$, where $(x_c(k), y_c(k)), r_c(k)$ denote the center and radius of target at time step k respectively, and $\nu_i(k)$ denotes the measurement noise of sensor s_i with zero mean and covariance R. The corresponding Jacobian matrix H_k can be calculated by:

$$H_k = \begin{pmatrix} \frac{\partial d_i(k)}{\partial x_c(k)} & \frac{\partial d_i(k)}{\partial \dot{x}_c(k)} & \frac{\partial d_i(k)}{\partial y_c(k)} & \frac{\partial d_i(k)}{\partial \dot{x}_c(k)} & \frac{\partial d_i(k)}{\partial r_c(k)} \end{pmatrix} \tag{8}$$

where

$$\frac{\partial d_i(k)}{\partial x_c(k)} = \frac{x_c(k) - x_i(k)}{\sqrt{(x_c(k) - x_i(k))^2 + (y_c(k) - y_i(k))^2}} \tag{9}$$

$$\frac{\partial d_i(k)}{\partial y_c(k)} = \frac{y_c(k) - y_i(k)}{\sqrt{(x_c(k) - x_i(k))^2 + (y_c(k) - y_i(k))^2}} \tag{10}$$

$$\frac{\partial d_i(k)}{\partial \dot{x}_c(k)} = 0 \quad \frac{\partial d_i(k)}{\partial \dot{y}_c(k)} = 0 \quad \frac{\partial d_i(k)}{\partial r_c(k)} = -1 \tag{11}$$

$(i = 1, 2, .., N)$. Then the states of target can be estimated by using the EKF algorithm, which mainly consists of the following two parts:

Time Update (Prediction):

$$\widehat{X}_k^- = F\widehat{X}_{k-1} \tag{12}$$
$$\widehat{P}_k^- = F\widehat{P}_{k-1}F^T + Q \tag{13}$$

Measurement Update (Correction):

$$K_k = P_k^- H_k^T (H_k P_k^- H_k^T + VRV^T)^{-1} \tag{14}$$
$$\widehat{X}_k = \widehat{X}_k^- + K_k(z_k - h(X_k^-, 0)) \tag{15}$$
$$P_k = (I - K_k H_k) P_k^- \tag{16}$$

Note that K_k is the Kalman filter gain, $\widehat{X}_k^-, \widehat{X}_k$ are the priori and posteriori estimates respectively, $\widehat{P}_k^-, \widehat{P}_k$ represent the corresponding error covariance matrices. Q, R stand for the covariance matrices for the model and the measurement respectively.

B. Multiple-Target Tracking with Size Estimation

For multiple targets, one major difficulty is to determine the correct measurement for the corresponding target. In this paper, a novel target identification algorithm is proposed to identify the targets by utilizing the additional information, i.e., the differences of the size of targets. For simplicity, the algorithms for two targets case will be presented. The results are not difficult to extend for the case of more than two targets.

Suppose the estimate for the i-th target has been obtained as $\hat{X}_i(k-1)$ at time step $k-1$, and if the measurement of the j-th sensor is assigned to the i-th target, then we are able to track target i and estimate the size at time step k. Moreover, it is straightforward to define the evaluation function J_{ij} as follows:

$$J_{ij} = [\hat{x}_{ij}(k) - \hat{x}_{ij}(k-1)]^2 + [\hat{y}_{ij}(k) - \hat{y}_{ij}(k-1)]^2 + [\hat{r}_{ij}(k) - \hat{r}_{ij}(k-1)]^2 \tag{17}$$

where $i = 1, 2; j = 1, 2$, which denote the serial number of the targets and candidate measurements respectively, for example, J_{12} denotes the evaluation function of the first target related to the second measurement. $\hat{x}_{ij}(k), \hat{y}_{ij}(k), \hat{r}_{ij}(k)$ denote the optimal estimated coordinate and radius of the i-th target calculated by the j-th measurement using EKF at step k. Since the target will not move too far away from its previous position and the size keeps constant, J_{ij} can be utilized to decide the correct pair of target and measurement at each time step. The details for target identification are summarized in Algorithm 1.

Once the targets have been distinguished, the remaining problem is similar to the single-target case which has been solved previously. It should be noted that in order to guarantee successful target identification with high accuracy, we need a certain amount of information about the targets at the initial stage of Algorithm 1. Specifically, two typical scenarios are as follows.

The first scenario is that the initial states of targets are known to the estimator with high accuracy. This is possible since we can deploy a small number of smart sensors which are able to accurately distinguish and estimate the states of targets within their neighborhood. In the second scenario, the targets enter the region in succession and the time intervals between their entering are sufficient for the estimate to converge. Take the two-target case as an example. Suppose one target has entered the region for a certain period so that the estimate has converge to the steady state. Then there should be no problem to apply Algorithm 1 if a new target enters afterwards. The effectiveness of Algorithm 1 under different scenarios will be demonstrated in the simulation part.

Algorithm 1 Targets Identification Algorithm

Input: candidate measurements by corresponding sensors
Output: the state of the targets
Initialization: $X_1(0), X_2(0)$;
for target moves in the tracking region **do**
  step 1: calculate the current state of each target with candidate measurements respectively by EKF.
  step 2: calculate evaluation function J_{ij}
  step 3: decision-making
  if $J_{11} <= J_{12}$ and $J_{21} >= J_{22}$ **then**
    target 1 selects the first measurement;
    target 2 selects the second measurement;
  end if
  if $J_{11} > J_{12}$ and $J_{21} < J_{22}$ **then**
    target 1 selects the second measurement;
    target 2 selects the first measurement;
  end if
  if $J_{11} < J_{12}$ and $J_{21} < J_{22}$ **then**
    if $J_{12}/J_{11} >= J_{22}/J_{21}$ **then**
      target 1 selects the first measurement;
      target 2 is forced to select the second measurement;
    else
      target 1 is forced to select the second measurement;
      target 2 selects the first measurement;
    end if
  end if
  if $J_{11} > J_{12}$ and $J_{21} > J_{22}$ **then**
    if $J_{11}/J_{12} >= J_{21}/J_{22}$ **then**
      target 1 selects the second measurement;
      target 2 is forced to select the first measurement;
    else
      target 1 is forced to select the first measurement;
      target 2 selects the second measurement;
    end if
  end if
  step 4: calculate the current optimal estimate of each target
end for

IV. SIMULATION RESULTS

In this section, extensive simulations are conducted to validate the performance of our method. The tracking region is set to be $200 \times 200cm^2$ square area and covered by 8 range ultrasonic sensors as shown in Fig 2. Suppose the target moves along a circle with center coordinate (x_0, y_0) and radius r_0, and then the actual center coordinate (x_k, y_k) of the target at time step k can be obtained as

$$\begin{cases} x_k = x_0 + r_0 cos(\omega k) \\ y_k = y_0 + r_0 sin(\omega k) \end{cases} \tag{18}$$

where ω is the angular velocity of the target. Then the measurement of sensors can be obtained according to Eq.

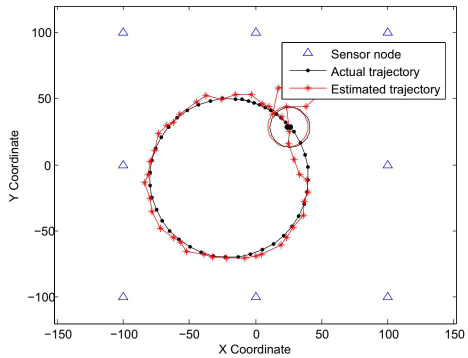

Fig. 2. The trajectory of single-target tracking

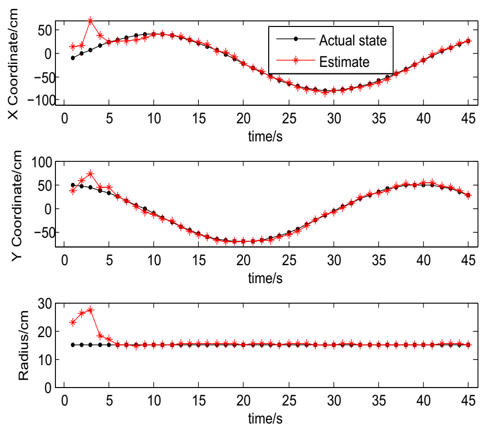

Fig. 3. The comparison of the estimate and true state of single-target tracking

(7). In simulation, the angular velocity ω of moving target is 0.15 rad/s, the sampling period of sensors is 1s, and the measurement noise covariance R is 1. The statistical simulation results for both single-target case and two-target case are done over 1000 independent trails.

For the single target case, using the algorithm depicted in section III, one typical simulation result is shown in Fig. 2 and 3. The statistical result for the trace of error covariance is shown in Fig. 4, which is an average over 1000 independent trials. Note that the estimates for the coordinates both converge to the steady state after about 10 steps, which demonstrates the efficiency of proposed algorithm. Furthermore, the estimate of radius r also approaches to the true value quickly as expected. It should be noted that the common kalman filter based tracking algorithm will treat the reflecting point as the center of target as it does not take the size of target into consideration, which will worsen the tracking accuracy.

For the two-target case, we consider two typical scenarios. In the first scenario, the initial states of targets are known to the estimator. Let the two targets move according to their own trajectories and not collide each other. By using Algorithm 1, we are able to successfully identify and track them in a recursive way. One typical simulation result is shown in Fig. 5, and an average trace of error covariance is depicted in Fig. 6. It can be observed that the two targets can be identified

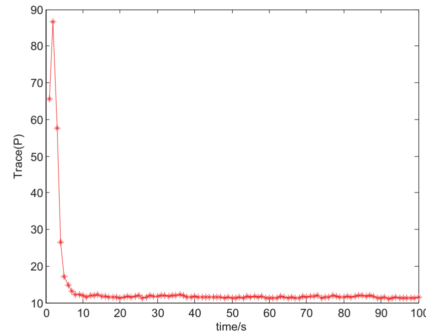

Fig. 4. The average trace of error covariance in the single-target tracking

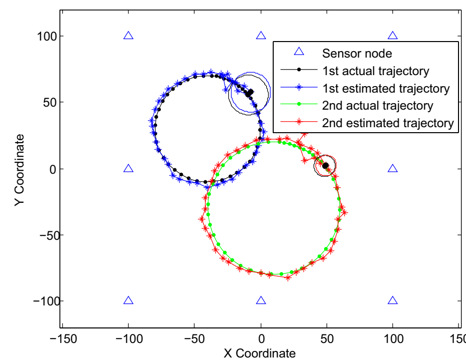

Fig. 5. The trajectories in the first scenario of two-target tracking

effectively and tracking performances of both targets are also accurate. We also test the correct decision rate of Algorithm 1, which is 98.3% over 1000 independent trials.

For the second scenario, one target appears in the region from the initial time and moves in a circle. At the 40-th time step, the second target enters the region. By using Algorithm 1, one typical trial is shown in Fig. 7 and 8. The statistical result for the trace of error covariance is shown in Fig. 9. It can be observed that for the initial 40 steps, the estimate of the first target converges to the steady state effectively which is similar to the single-target case. Furthermore, there is also no obvious disturbance for the estimates of the first target once the second target enters into the region, and the tracking performance of the second target itself is also quite accurate.

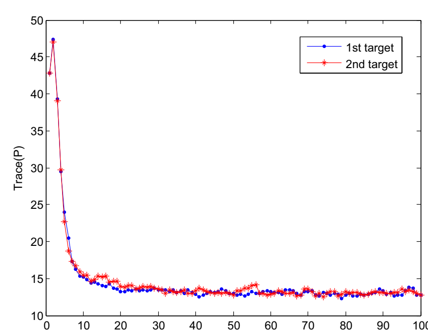

Fig. 6. The average trace of error covariance in the first scenario of two-target tracking

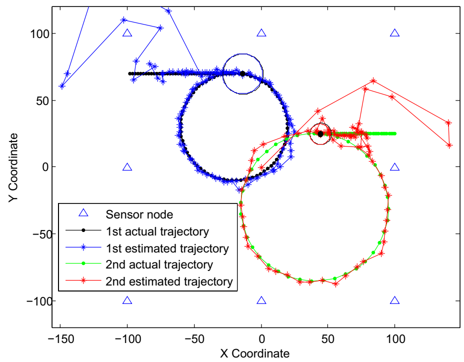

Fig. 7. The trajectories of targets in the second scenario of two-target tracking

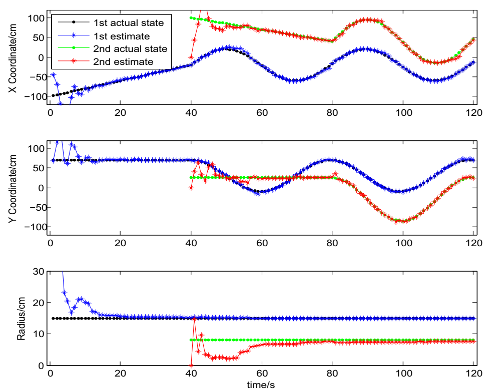

Fig. 8. The comparison of the estimate and true state in the second scenario of two-target tracking

For this scenario, the correct decision rate of Algorithm 1 over 1000 independent trials is around 92.6%.

V. Conclusion

We have studied the tracking of targets with size estimation in wireless sensor networks. For the single-target case, by adopting the EKF algorithm, an efficient algorithm has been proposed for estimating the target position and size simultaneously. For the multi-target case, a target identification algorithm has been given by minimizing the consecutive square error based on the previous estimate and current measurements

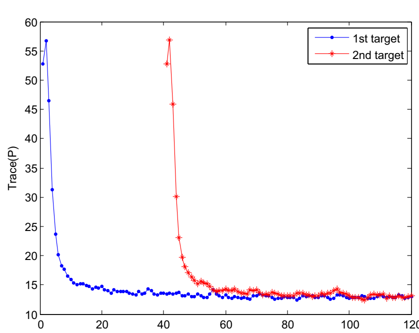

Fig. 9. The average trace of error covariance in the second scenario of two-target tracking

so that we are able to track each target and estimate the size in a recursive way. Extensive simulations have been conducted to evaluate the effectiveness of our algorithms.

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