Sensor Scheduling for Target Tracking in Networks of Active Sensors[1)]

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Abstract Wireless sensor network (WSN) of active sensors suffers from serious inter-sensor interference (ISI) and imposes new design and implementation challenges. In this paper, based on the ultrasonic sensor network, two time-division based distributed sensor scheduling schemes are proposed to deal with ISI by scheduling sensors periodically and adaptively respectively. Extended Kalman filter (EKF) is used as the tracking algorithm in distributed manner. Simulation results show that the adaptive sensor scheduling scheme can achieve superior tracking accuracy with faster tracking convergence speed.

Key words Wireless sensor network, sensor scheduling, target tracking, active sensor

1 Introduction

Target tracking is an essential capability for wireless sensor networks (WSNs) and has been considered as an ideal problem for studying collaborative signal and information processing[1]. Usually the tracking system needs to dynamically schedule sensors to undertake the sensing tasks and process the distributed information with the consideration of the limited resource constraints such as power or bandwidth. Prominent target tracking approaches include the information-driven sensor querying (IDSQ)[1,2], extended Kalman filter (EKF) based zone prediction[3], and entropy based sensor selection[4].

Different from the passive sensing mechanism generally used in acoustic, seismic or thermal sensors where a sensor measures energy already in the environment[2~4], a sensor adopting the active sensing mechanism senses the environment actively by emitting energy and measuring the reflected energy. In this paper, we will consider WSNs of ultrasonic sensors where the sensors are used for ranging of the target actively.

Ultrasonic sensors have been widely used in location service or node localization in WSNs. MIT Cricket[5] is a famous in-door location-support system. It allows applications running on mobile or static users to learn their physical locations by using listeners that hear and analyze information from beacons spread throughout the building. The distance between a user and a beacon is measured using the time difference between simultaneously transmitted radio and ultrasonic signals. An active mobile architecture and a passive mobile architecture are introduced dependent on whether the mobile user is used as transmitter or receiver. An improved Cricket system is reported by developing a hybrid approach that runs EKF in the passive mobile mode and relies on an active mobile mode when the EKF state estimation is not satisfactory. In the Bat ultrasonic in-door location system[6], a wearable electronic Bat is attached with the object to be located for transmitting a short pulse of ultrasound, the times-of-flight of the pulse are measured by ultrasonic receivers mounted at known points on the ceiling. The distances from the Bat to the receivers are calculated and the location of the object is determined from three or more such distances according to the principle of trilateration.

Different from the Cricket and the Bat systems where the mobile users are collaborative with the infrastructure, a target in a WSN is non-collaborative with no information exchange with any sensor. A serious problem in WSN of active sensors is the inter-sensor interference (ISI) when nearby ultrasonic sensors work simultaneously. Such interference will result in error sensor readings and must be dealt with properly. ISI also introduces a new technological constraint in design and implementation of a WSN.

In this paper, we introduce two time-division based distributed sensor scheduling schemes to avoid ISI. In the periodic sensor scheduling scheme, each ultrasonic sensor senses the target alternatively

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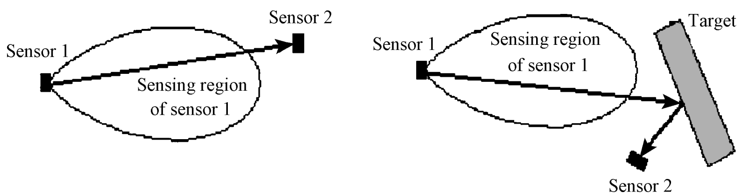
within the predefined time slots assigned to it. Whereas in the adaptive sensor scheduling scheme, similar to IDSQ, the next tasking ultrasonic sensor is selected adaptively according to the state prediction of the target.

The paper is organized as follows: ISI will be described in Section 2. EKF will be introduced in Section 3. Sensor scheduling schemes, including the periodic sensor scheduling and adaptive sensor scheduling, will be addressed in Section 4. Simulation results will be reported in Section 5. Finally conclusions and future work will be introduced in Section 6.

2 Direct ISI and indirect ISI

As shown in Fig. 1, usually the sensing region of an ultrasonic sensor can be approximated by an area with cone shape. We have identified two types of ISI, direct ISI and indirect ISI. Direct ISI happens when the sound wave propagates directly from a transmitting ultrasonic sensor (Sensor 1 in Fig. 1(a)) to another receiving ultrasonic sensor (Sensor 2 in Fig. 1 (a)). Indirect ISI happens when the sound wave propagates from a transmitter (Sensor 1 in Fig. 1 (b)) to another receiver (Sensor 2 in Fig. 1 (b)) *via* the reflection or diffusion by other objects (including the targets). Such an object can be located inside or outside the sensing range of the transmitting ultrasonic sensor.



(a) Direct ISI of sensor 1 on sensor 2 (b) Indirect ISI of sensor 1 on sensor 2

Fig. 1 Sensing region, direct ISI and indirect ISI

The approximate direct ISI region and the indirect ISI region of an ultrasonic sensor are illuminated in Fig. 2. Since direct ISI only requires the single trip sound wave propagation from the transmitter to the receiver of another ultrasonic sensor, which is different from the sensing mechanism where a round trip sound wave propagation is required, the direct ISI region of an ultrasonic sensor is quite larger than its sensing region. It is also shown in Fig. 2 that the indirect ISI region is much larger than its sensing region and its direct ISI region. More comprehensive ultrasonic sensing and propagation models to determine the sensing and ISI regions will be studied as future work.

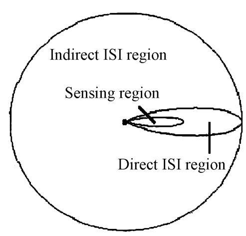


Fig. 2 Sensing, direct and indirect ISI regions of an ultrasonic sensor

3 EKF tracking algorithm

The following constant velocity target motion model is used in this paper:

$$\boldsymbol{X}(k+1) = F_k\boldsymbol{X}(k) + G_k\boldsymbol{u}(k) \tag{1}$$

with

$$\boldsymbol{X}(k) = \begin{pmatrix} x(k) \\ x_v(k) \\ y(k) \\ y_v(k) \end{pmatrix},\ \boldsymbol{u}(k) = \begin{pmatrix} u_x(k) \\ u_y(k) \end{pmatrix} F_k = \begin{pmatrix} 1 & \Delta t_k & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & \Delta t_k \\ 0 & 0 & 0 & 1 \end{pmatrix},\ G(k) = \begin{pmatrix} \dfrac{\Delta t_k^2}{2} & 0 \\ \Delta t_k & 0 \\ 0 & \dfrac{\Delta t_k^2}{2} \\ 0 & \Delta t_k \end{pmatrix}$$

where $\boldsymbol{X}(k)$ is the state of the target at the k-th time step which happens at t_k, $x(k)$, $y(k)$ are x- and y- coordinates of the target at time step k, $x_v(k)$, $y_v(k)$ are the velocities of the target along x- and y- directions at time step k, Δt_k is the time interval between the time step k and time step $k+1$. $\boldsymbol{u}(k)$ is the Gaussian white acceleration noise with zero mean and covariance matrix Q.

The observation model at time step k is

$$z_{s(k)}(k) = h_k(\boldsymbol{X}(k), s(k)) + v_s(k) \tag{2}$$

with

$$h_k(X(k), s(k)) = \sqrt{(x(k) - x_{s(k)})^2 + (y(k) - y_{s(k)})^2}$$

where $s(k)$ is the sensor that gets the range measurement $z_{s(k)}(k)$ at time step k, $(x_{s(k)}, y_{s(k)})$ is the known location of sensor $s(k)$, $v_s(k)$ is the Gaussian white measurement noise of sensor $s(k)$ with zero mean and variance $R(k)$. $s(k)$ is decided by the sensor scheduling schemes which will be described in Section 4. Δt_k is not necessary to be the same for each time step k.

EKF operates in the following way: Given the estimate $\hat{\boldsymbol{X}}(k|k)$ of $\boldsymbol{X}(k)$ with covariance matrix $P(k|k)$, the predicted state $\hat{\boldsymbol{X}}(k+1|k)$ is calculated as

$$\hat{\boldsymbol{X}}(k+1|k) = F_k \hat{\boldsymbol{X}}(k|k) \tag{3}$$

with the prediction error covariance

$$P(k+1|k) = F_k P(k|k) F_k^{\mathrm{T}} + G_k Q G_k^{\mathrm{T}} \tag{4}$$

The predicted measurement is

$$\hat{z}(k+1|k) = h_{k+1}(\hat{\boldsymbol{X}}(k+1|k), s(k+1)) \tag{5}$$

Then the innovation, *i.e.*, the difference between the measurement and the predicted measurement, is given by

$$\gamma(k+1) = z_{s(k+1)}(k+1) - \hat{z}(k+1|k) \tag{6}$$

with the covariance

$$S(k+1) = H_{k+1} P(k+1|k) H_{k+1}^{\mathrm{T}} + R(k+1) \tag{7}$$

where H_{k+1} is the Jacobian matrix of the observation function h_{k+1} with respect to the predicted state $\hat{\boldsymbol{X}}(k+1|k)$. The EKF gain is given by

$$K(k+1) = P(k+1|k) H_{k+1}(\hat{\boldsymbol{X}}(k+1|k), s(k+1)) S^{-1}(k+1) \tag{8}$$

and the state will be updated as

$$\hat{\boldsymbol{X}}(k+1|k+1) = \hat{\boldsymbol{X}}(k+1|k) + K(k+1)\gamma(k+1) \tag{9}$$

with the error covariance matrix

$$P(k+1|k+1) = P(k+1|k) - K(k+1) S(k+1) K^{\mathrm{T}}(k+1) \tag{10}$$

For details of EKF, the readers can be referred to [7].

4 Sensor scheduling

Sensor scheduling is used to avoid ISI and implement collaboration between sensors. We suppose the network is synchronized and the time is divided into time slots. The period for each slot should be larger than the die-out time of the ultrasonic wave in a ranging operation. In this paper, to avoid ISI, sensors are scheduled such that during any time slot only one sensor in an ISI region can sense the target. Single target tracking is considered in this paper.

4.1 Periodic sensor scheduling

In periodic sensor scheduling, as shown in Fig. 3, the time is divided into periodic cycles, and in each cycle, a sensor senses the target alternatively within the predefined time slots assigned to it. If a scheduled sensor detects the target, it will calculate the time difference between its current measurement time and the time of the previous time step, then fuse its measurement with the existing target estimation using EKF, and forward this new estimation update together with its measurement time to the next scheduled sensor.

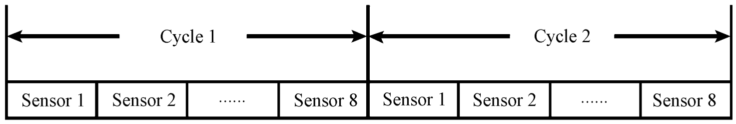


Fig. 3 Sensor scheduling according to ISID

It is not difficult to form an interference graph for a given ultrasonic sensor network in which each sensor node corresponds to a node in this graph and there is an edge between two nodes if ISI exists between them. Then the assignment of the time-slots to sensor nodes such that the total number of required time slots is minimized with the constraint that any two node of one edge can not be assigned with same time slot becomes the classic graph coloring problem which is well known to be NP-complete[8]. However optimal solutions can be found for certain networks with specific network topologies, *e.g.*, the cellular network with the hexagonal cell shape[9].

Sensor scheduling (*i.e.*, to determine the time slot for each sensor) is critical for tracking accuracy. Because it may be computational prohibitively expensive, efficient heuristics are desirable. Here we use a very simple heuristic, the incremental sensor ID (ISID) heuristic in which the time slots for sensors are assigned iteratively and in each iteration the time slot of the unassigned node with minimal sensor ID is assigned. For example, for a network of 8 nodes where each node is in the ISI region of any other node, the ISID scheduling result is shown in Fig. 3.

For a larger WSN, the same time slot can be reused by 2 different sensors if they are far away and do not interfere with each other. One example time slot assignment result for a network with a specific regular shape is shown in Fig. 4 where the time slot assigned for each sensor is marked by a digit number beside it. The sensing region of each sensor is shown and the ISI region of sensor 6 is demonstrated by a solid circle. Any sensors inside the circle can not be assigned to the same time slot with sensor 6. The reuse of the time slots is also shown in the figure when two sensors are far away.

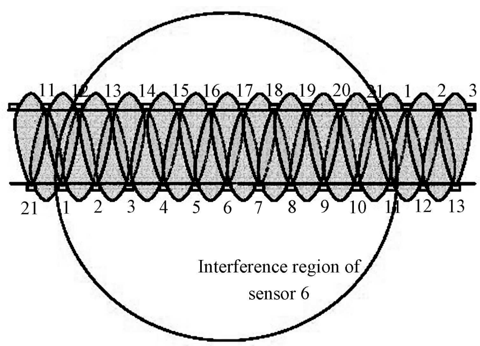


Fig. 4 Sensor scheduling for a larger WSN

It is possible that for 1 time slot, within one ISI region, an ultrasonic sensor is scheduled for sensing, but there is no target in its sensing region, as a result no detection can be available for that time slot. In this case, the current tasking sensor will forward the latest estimation update and the corresponding update time to the next scheduled sensor without new update. Therefore different from the classical EKF, the EKF tracking algorithm for periodic sensor scheduling has the following unique characteristic: 1) at most 1 range measurement data can be available at a time step for each ISI region. 2) range measurements of different time steps are generated by different sensors, *i.e.*, $s(k)$ is different at different time step, therefore the measurement equation changes at each time step. 3) The time step index k is only imposed when there is a measurement from a scheduled sensor, therefore, the time difference Δt_k between 2 successive measurements is variable due to the unavailable measurements (empty detection) at certain time slots and packet loss during communication.

4.2 Adaptive sensor scheduling

A critical drawback of periodic sensor scheduling is the existing of the empty detection when a scheduled sensor can not generate an effective measurement which results in lower tracking accuracy and wasting power of the sensors. This problem is shown in Fig. 5 for a WSN with 6 ultrasonic sensors. In the scheduling cycle identified by the solid ellipse, the sensors are scheduled from sensor 1 to sensor 6, however, only sensors 1, 5, and 6 generate effective detections whereas sensors 2, 3, and 4 generate empty detections.

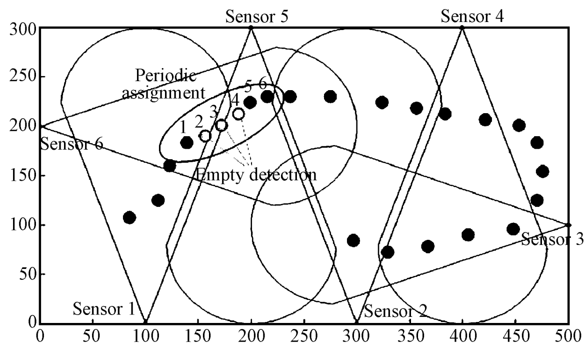


Fig. 5 Effect and empty detections in periodic sensor scheduling

Adaptive sensor scheduling is introduced to solve this problem by scheduling next tasking sensor for the next time step according to the predicted tracking accuracy[10] which is derived from the trace of the covariance matrix of the state estimation. We suppose each sensor knows the measurement characteristic of the other sensors (such as their locations, orientations and measurement functions). Using EKF, the current sensor can easily calculate the predicted covariance matrix for any other sensor according to (4), (7), (8) and (10) without the real measurement is taken using that sensor. The sensor with the best tracking accuracy is selected as the next tasking sensor. Then the current sensor shall forward its own measurement time and estimation result to the selected sensor.

Due to the uncertainties in the target motion model, even using adaptive sensor scheduling, it is still possible that the scheduled sensor can not detect the target. If this happens, this scheduled sensor will trigger the periodic sensor scheduling mechanism until the target can be captured after which the adaptive sensor scheduling will be used again.

5 Simulation results

Simulations have been done for comparisons between the 2 proposed sensor scheduling schemes. As shown in Fig. 6, the monitored field is 300cm$\times$300cm square area. The bottom-left corner of the field is with the coordinate (0, 0), whereas the upper-right corner is with the coordinate (300, 300). Each ultrasonic sensor has the maximal sensing range of 300cm and the maximal measurement angle is $\pm 22^\circ$. There are 8 ultrasonic sensors located along the edge of the area respectively with coordinates (60, 0), (180, 0), (300, 60), (300, 240), (240, 300), (120, 300), (0, 240) and (0, 120). The orientations of the sensors are respectively 80°, 90°, 170°, 180°, 260°, 270°, 350° and 0° such that the field can be covered mostly and any 2 sensors are not in the sensing ranges of each other. For example, the orientation of sensor 1 is 80° instead of 90°, such that sensor 7 can not be detected by sensor 1, otherwise the true detection region of sensor 1 will be reduced greatly because any target in the sensing range of sensor 1 with a distance greater than the distance between sensor 1 and sensor 7 can not be detected.

In this setup, each sensor is in the ISI region of any other sensor. We assume the duration of a time slot is 50 ms. In periodic sensor scheduling scheme, totally there are 8 sensors in the network, so 400ms is required for one cycle during which each sensor can sense one time in the periodic sensor scheduling scheme.

The target has the initial true state (70, 80, 70, 80) and moves according to the constant velocity model of (1) with $Q = 900I$ where I is the identity matrix. For initialization, we assume the nearest sensor (sensor 1) detects the target and initiates the tracking procedure. The initial location estimation of the target is set to the point along the central line of the beam pattern of the detecting sensor with the distance to the detecting sensor equal to the initial measurement. The initial velocity estimation of the target is set to 0. The initial covariance can be set heuristically according to the orientation and measurement of the detecting target. In this simulation experiment, it is set as Diag(200, 1000, 10, 1000).

A typical true target trajectory is shown by the central line in Fig. 6. The estimated trajectories of periodic sensor scheduling and adaptive sensor scheduling are also shown in the figure. Their time slots associated with effective detections are indicated along the true target trajectory by small circles and "+" symbols respectively. It is clear that the trajectory obtained by adaptive sensor scheduling is much closer to the true trajectory than that obtained by the periodic sensor scheduling and the adaptive sensor scheduling generates more effective detections.

In this simulation, totally there are 39 time slots. The associated sensors with effect detections using periodic sensor scheduling are shown in Fig. 7. There are only 17 effective detections with the effective detection ratio of 43.6%. For example, for the first cycle, although the sensors are scheduled from sensor 1 to sensor 8, but only sensors 1, 3, 6 and 8 generate effective detections. The associated sensors with effect detections using adaptive sensor scheduling are shown in Fig. 8. At all time slots, the selected sensors generate effective detections achieving the effective detection ratio of 100%. For example, after the initial detection of sensor 1, sensor 6 is selected and senses the target for 4 successive time slots followed by sensors 3, 6, 3, 6, 8 and so on.

The benefits of the adaptive sensor scheduling are shown in Fig. 9. Obviously the adaptive sensor scheduling can converge much faster with higher tracking accuracy than the periodic sensor scheduling.

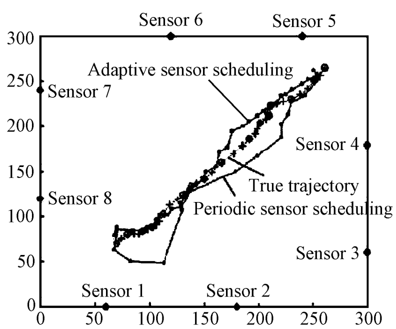


Fig. 6 True and estimated trajectories of the target

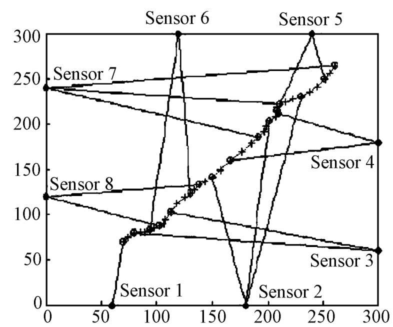


Fig. 7 Associated sensors with effect detections using periodic sensor scheduling

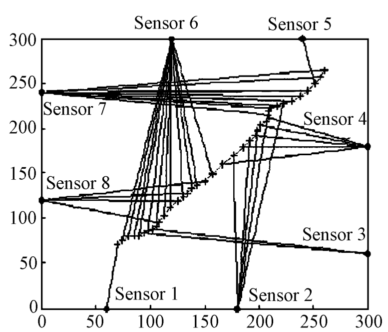


Fig. 8 Associated sensors with effect detections using adaptive sensor scheduling

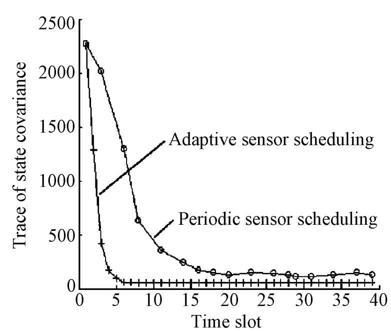


Fig. 9 Convergence of the tracking accuracy

6 Conclusions

This paper highlights the ISI problem in a WSN of active sensors and presents two time-division based distributed sensor scheduling schemes, the periodic sensor scheduling and the adaptive sensor scheduling. EKF is modified for estimation in periodic sensor scheduling, as well as estimation and covariance prediction in adaptive sensor scheduling. Simulation results show that the adaptive sensor scheduling scheme can utilize the sensors more effectively, with fast tracking convergence speed and higher tracking accuracy. As the future work, a more comprehensive ultrasonic sensor model for study ISI is required. Collaborative sensing strategies (for example by using single transmitter with multiple receivers), and certain simultaneous sensing mechanisms (for example by using code division by means of specific signal processing techniques) are promising future research topics for WSN of active sensors. This paper uses EKF as the estimation and prediction algorithm, however, it can only deal with the noises with Gaussian distributions, more advanced techniques (such as particle filter) are required for sensor scheduling with more general non-linear non-Gaussian systems. Tracking and adaptive sensor scheduling for maneuvering targets, for multiple targets, using multiple modalities are among the challenging problems for further study.

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