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Tracking Multiple Objects in Wireless Sensor Networks

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***Abstract* – Wireless sensor networks (WSN) depends on the algorithms and protocols for Communication and computation. In this paper, we implement sensors that sense the environment actively by emitting energy and measuring the reflected energy, a novel collaborative sensing scheme is used to sense multiple targets and high maneuvering targets in an energy efficient method. Joint sensing can increase the sensing region of an individual emitting sensor and generate multiple sensor measurements simultaneously. In order to conserve energy the sensors is used to estimate the target state using sensor measurements and to predict the target location and hence the tracking accuracy, as compared to individual sensing. Multiple and high maneuvering targets are identified with energy efficient.**

***Index Terms*—quality of information; target tracking; joint sensing; sensor scheduling; Kalman filter**

1. INTRODUCTION

With the introduction of wireless communication capable sensing platforms, Typical sensor-based systems comprise lower-level sensing modules that take environmental measurements and transform these measurements into useful information. Whenever the information derived from the sensed data indicates that an event of interest has occurred a decision maker will make a decision which will cause an action to be taken.

Typically, a wireless sensor network (WSN) is application-driven and mission-critical. Therefore, the information quality (IQ) is critical for the end users, service providers and the system designers. To provide accurate IQ in WSNs is challenging due to the resource-constrained, dynamic and distributed nature of the network.

Recently, IQ is receiving increasing interests for various WSN applications. The relationship between the sensor sampling rate and the QoI metric of timeliness and confidence is derived. In deciding how to proceed, decision makers make decisions based on the quality *of* the information (QoI). The quality of the sensed data is captured via a collection of attributes that includes *Timeliness, Accuracy, Throughput* and *Cost*.

2. LITERATURE SURVEY

2.1 Multi-step adaptive sensor scheduling for target tracking in Wireless sensor networks

Sensor scheduling is essential to collaborative target tracking in Wireless Sensor Networks (WSNs). In this paper, they present a Multi-step Adaptive Sensor Scheduling algorithm (MASS) by selecting the next tasking sensor and its associated sampling interval based on the prediction of tracking accuracy and energy cost. Simulation results show that, compared with the traditional non-adaptive sensor scheduling algorithm and the single-step adaptive sensor scheduling algorithm, MASS can achieve fast tracking speed and superior energy efficiency without degrading the tracking accuracy. As the future work, more advanced techniques are required for adaptive sensor scheduling .

2.2 Energy-Efficient Distributed Adaptive Multisensor Scheduling for Target Tracking in Wireless Sensor Networks

Single-sensor-based collaborative target tracking in wireless sensor networks (WSNs) suffers from low tracking accuracy and lack of reliability In this paper, an adaptive energy-efficient multisensor scheduling scheme is proposed for collaborative target tracking in WSNs. It calculates the optimal sampling interval to satisfy a specification on predicted tracking accuracy, selects the cluster of tasking sensors according to their joint detection probability, and designates one of the tasking sensors as the cluster head for estimation update and sensor scheduling according to a cluster head energy measure (CHEM) function. The performance is low due to the limited bandwidth constraint, the quantization problem is another challenging problem for further investigations.

2.3 A Prototype Ultrasonic Sensor Network for Tracking of Moving Targets

This paper describes the design and implementation details of target tracking system using ultrasonic sensor network. It reports our findings of inter-sensor interference, and suggests a time-division based sensor scheduling strategy to avoid it. Extended Kalman Filter (EKF) algorithm is proposed as the tracking algorithm with the characteristic of variable time difference between successive time steps and variable measurement equation due to different sensors used at different time steps. Comparisons between different tracking algorithms are given. The following will be the future research and development issues:

1. More efficient sensor scheduling strategy to achieve high tracking accuracy and low energy cost.
2. Adaptive tracking and data association algorithms for high maneuvering targets.
3. More advanced distributed data association algorithms.
4. Extending the test-bed to large scale.
5.

3. MULTI-TARGET TRACKING

3.1 Joint sensing

In this paper, we assume that each ultrasonic sensor installs the sound wave emitter and receiver, and all the sensors in the network are homogeneous and time synchronized.

Normally an ultrasonic sensor adopts the active sensing mechanism where the sensor emits sound wave and measures the reflected echo from the target. The time of flight (TOF) is converted into range information towards the target. In this paper, we adopt a simplified cone shape detection region model for a typical ultrasonic sensor, where one ultrasonic sensor i is characterized by its location (X_{si}, Y_{si}), orientation Θ_i, detection angle α , and detection range d. The TOF equals to the round trip time of the wave from the emitting sensor to the target and then back to the emitting sensor, which corresponds to the round trip distance of the sound wave that is bounded by 2d.

In this paper, we assume that the target can be jointly sensed by two sensors, if the following joint sensing conditions are satisfied:

1. The target is within the detection angles of both sensors;
2. The sum of distances from the target to the sensors is less than 2d;
3. The two sensors are not within line of sight with each other (i.e., not within the detection angle of each other).

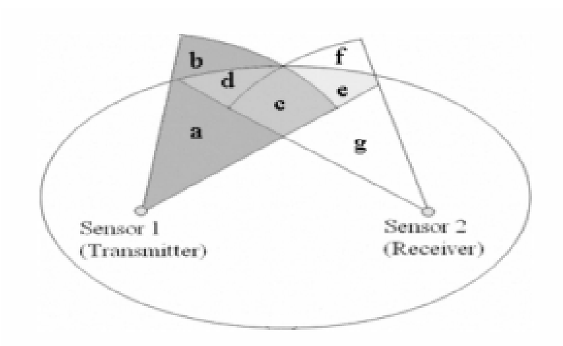

Figure 3.2 Joint sensing region

According to the above joint sensing conditions, no matter which sensor in these two sensors is the emitter, the signal can be received by the other sensor.

As an example, Fig. 3.2 shows the joint sensing region of sensors 1 and 2, when sensor 1 is the emitting sensor and sensor 2 is the receiving sensor. The ellipse consists of all points where the sum of its distances to sensor 1 and sensor 2 is 2d. The target must be inside this ellipse if sensor 1 and sensor 2 can jointly sense the target.

In Fig. 3.2, areas a and b can only be sensed by sensor I individually, as any point in area a is not in the detection angle of sensor 2 (i.e., not satisfy joint sensing condition 1) and the sum of the distances from any point in area b to sensor 1 and sensor 2 is larger than 2d (i.e., not satisfy joint sensing condition 2). Areas c, d, and e can be jointly sensed by sensor 1 and sensor 2 as any point in them satisfies the three joint sensing conditions.

The target located in area e can also be jointly sensed, which indicates that joint sensing can increase the detection region of individual sensors. In addition, if the target is located in area c or d, we can obtain two sensor measurements, one is the distance from sensor 1 to the target, and the other one is the sum of the distances from sensor 1 to the target and from the target to sensor 2.

3.2 EKF Tracking Algorithm

The EKF algorithm is adopted to fuse the joint sensing measurements and the measurements taken at different time steps. The following constant velocity target motion model is used in this paper

$X(k+l) = F_k(k) + G_kU(k)$ with

$$X(k) = \begin{pmatrix} x(k+1) \\ x_v(k+1) \\ y(k+1) \\ y_v(k+1) \end{pmatrix}$$

$$F_k = \begin{pmatrix} 1 & \Delta t_k & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & \Delta t_k \\ 0 & 0 & 0 & 1 \end{pmatrix}$$

$$G(k) = \begin{pmatrix} \Delta t_k/2 & 0 \\ \Delta t_k & 0 \\ 0 & \Delta t_k/2 \\ 0 & \Delta t_k \end{pmatrix}$$

and $$U(k) = \begin{pmatrix} u_x(k) \\ u_y(k) \end{pmatrix}$$

where x(k) and y(k) are x and y coordinates of the target at time step k; $x_v(k)$ and $y_v(k)$ are respectively the velocities of the target k is the time difference between the measurement times at steps k and k+ 1. Here U(k) is the Gaussian white acceleration noise .

At each time step, the scheduled sensor emits the sound wave and all other sensor nodes collects and forwards the measurements to the fusion centre. The fusion centre will run EKF to give updates of the state estimation using the new measurements and schedule the emitting sensor for the next

time step. Then it informs the scheduled sensor to perform the emitting operation in the next time step, together with the state estimation and covariance matrix information in the distributed structure. We assume that the fusion centre knows the location and orientation of each sensor. In the distributed structure, each sensor knows the information of other nodes because each sensor is possible to be the fusion centre.
Different measures can be used as the performance indices to select the emitting sensor, including the joint sensing detection probability, tracking accuracy, and energy efficiency. For simplification, in this paper, we schedule the emitting sensor according to the individual sensor detection probability.
For each time step, energy consumption happens mainly in the following operations:
1) Sensing by sensors;
2) transmitting/receiving measurement data from sensors to the cluster head;
3) broadcasting/receiving by the current cluster head and sensors in the next cluster.

4. RESULTS

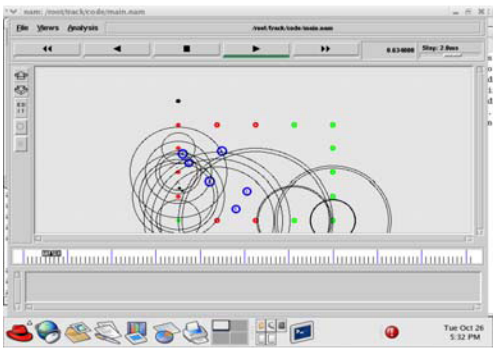

Fig 4.1. Multi-target Tracking in WSN

The figure 4.1 shows the result of multi-target racking in wireless sensor networks.

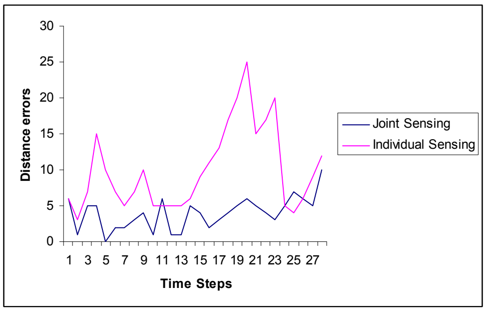

Figure 4.2. Tracking errors for adaptive sensor scheduling

The evolutions of tracking errors, i.e., the IQ, are shown in Figure. 4.2. The gain of the joint sensing is observed. The maximal and averaged tracking error of individual sensing is about 25 cm and 10.05 cm respectively, whereas that of the joint sensing is about 8 cm and 3.55 cm respectively, a significant improvement.

CONCLUSIONS

This proposed scheme increases the detection region of an individual sensor and saves the energy of a sensor by sleeping mode. The proposed algorithm finds maneuvering targets and multi-target. It is shown by simulations that the IQ of the WSN can be improved significantly using joint sensing. Future research issues include sensor scheduling for real test-bed development and to reduce the error rate.

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