International Journal of Computer Science and Engineering Communications
Vol.3, Issue 3, 2015, Page.1034-1039, ISSN: 2347–8586

Multi Sensor Fusion Model for Detecting Movements of a Target in Wireless Sensor Networks

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ABSTRACT-Target tracking is one of the key applications of wireless sensor networks (WSNs). Existing work mostly requires organizing groups of sensor nodes with measurements of a target's movements or accurate distance measurements from the nodes to the intention, and predicting those activities. These are, however, often not easy to precisely achieve in practice, more than ever in the case of impulsive environments, sensor faults, etc. To explore efficient use of mobile sensors to address the limitations of static WSNs in target detection, in proposed system proposes a data fusion model that enables static and mobile sensors to effectively collaborate in target exposure. An optimal sensor movement scheduling algorithm is developed to minimize the total moving distance of sensors while achieving a set of spatiotemporal performance requirements including high detection probability, low method false alarm rate and enclosed detection delay. The effectiveness of proposed approach is validated by extensive simulations based on real data traces collected by 23 sensor nodes.

I. INTRODUCTION

A wireless sensor network (WSN**)** consists of spatially distributed autonomous sensors to monitor physical or ecological conditions, such as temperature, resonance, vibration, pressure, activity or pollutants and together pass their data through the network to a main locality. The more contemporary networks are bi-directional, enabling also to control the movement of the sensors. The enlargement of wireless sensor networks was stimulated by military applications such as battlefield surveillance; today such networks are used in many industrial and consumer applications, such as developed process monitor and control

Deploying wireless sensor networks (WSNs) for mission critical applications (such as intruder detection and tracking) often faces the fundamental challenge of meeting stringent spatial and temporal performance requirements imposed by users. In case of a surveillance application may require any intruder to be detected with a high probability (e.g., > 90%), a low false alarm rate (e.g., < 1%), and a bounded delay (e.g., 20s). Due to the limited capability and unreliable nature of low-power sensor nodes, over-provisioning of sensing coverage seems to be the only choice for a static sensor network to meet such stringent performance requirements. However, over-provisioning only works up to the point where the reality meets the original expectation about the characteristics of physical phenomena and environments. If a new on-demand task arise after deployment and its requirements exceed the statically designed network facility, the task could not be accomplished. For instance, in a battlefield monitoring scenario, sensor failures in a small region may lead to a perimeter breach and the sensor nodes deployed in other regions become useless.

Tracking framework, called Face Track, which employ the nodes of a spatial region bordering a target, called a face. Instead of predicting the target location separately in a face, estimate the target's moving toward another face. Introduce an edge detection algorithm to generate each face further in such a way that the nodes can prepare to the lead of the target's moving, which greatly helps tracking the goal in a timely fashion and recovering from special cases, e.g., sensor fault, loss of tracking. Also, develop an optimal selection algorithm to select which sensors of faces to query and to forward the tracking data. The challenge is to determine how to perceive the target in a WSN efficiently. the performance of variable brink lengths of the polygon versus adjustable transmission power levels in a WSN for target detection and its energy cost in the WSNs; the impact of the target's dynamic movements, brink detection, and real-time polygon forwarding in target tracking. In this, propose a data-fusion centric target detection model that features effective collaboration between static and mobile sensors.

The proposed system derives an optimal sensor movement scheduling algorithm that minimizes the total moving distance of sensors under a set of spatiotemporal performance requirements including (1) bounded revealing delay, (2) maximum target detection probability, and (3) low conduct extensive simulations based on real data traces collected by 23 sensors in the SensIT vehicle detection experiments. The results show that a small number of mobile sensors can significan1tlhe detection performance of a network.0 Moreover; the proposed movement scheduling algorithm can achieve satisfactory performance in a range of realistic scenarios.

II.RELATED WORK

Poster Abstract: Distributed RSSI Processing for Intrusion Detection in Indoor Environments says that **t**his work aims at applying distributed processing of the RSSI signals for indoor observation purposes. Through distributed processing, the nodes are able to unconventionally detect and localize moving persons. The algorithm low pass filter, pre-defined threshold, RSSIs measurements and TDMA protocol used. The advantage of distributed processing of the RSSI measurements, nodes deployed in an unknown indoor environment can detect intrusion and possibly help in localizing and tracking moving individuals. Distributed processing of the RSSI signals allows minimizing the power consumption of the nodes and the latency at the central base station. However, the disadvantage of two processing algorithms do not weight on the RAM memory of the node, since at run time only the previous filtered RSSI value is stored.

The combination of the two algorithms avoids false alarms in the case of instability of the RSSI signals, and simultaneously detects those motions which do not produce violent drops.

DCTC stands for Dynamic Convoy Tree-Based Collaboration for Target Tracking in Sensor Networks says that an optimal solution which achieves 100% coverage and minimizes the energy consumption under certain ideal situations. Concrete algorithm and Classification algorithms, Centralized algorithm and DCTC algorithm used. Hence, the advantage of using prediction outweighs its negative effects. Due to space limit, they do not present the details of the movement prediction technique. However, only nodes located within the estimated monitoring region are added to the tree. The proposed system defines an important problem and lays out a theoretical foundation.

DCTC stands for Dynamic Convoy Tree-Based Collaboration for Target Tracking in Sensor Networks says that an optimal solution which achieves 100% coverage and minimizes the energy consumption under certain ideal situations. Concrete algorithm, Classification algorithms, Centralized algorithm. The advantage of using prediction outweighs its negative effects. Due to space limit, it does not present the details of the movement prediction technique. When the same tree expansion and pruning design is used, the contained reconfiguration performs better when the node concentration is high, and the movement is reversed when the node density is low. The proposed system defines an important problem and lays out a theoretical foundation.

Achieving Real-Time Target Tracking Using Wireless Sensor Networks says that the real-time design and analysis of VigilNet, a large-scale sensor network system which tracks, detects and classifies targets in a timely and energy efficient manner. Detection algorithm, Sensing algorithms, Classification algorithms. First, to guarantee the same sub-deadline, a higher node density is desired in the slow-target case, however a slower duty cycle can be tolerated without jeopardizing the detection. Second, it is beneficial to increase the wake-up delay, when possible, in exchange for the energy saving. Third, fast detection algorithms are essential. Fourth, a low network density increases the group aggregation delay, which indirectly reduces the detection confidence. Fifth, theoretically, honeycomb is the optimal base placement strategy to meet the communication sub-deadline. Due to the dynamic and unpredictable nature of the sensor networks, it is a long-term research goal for us to achieve precise worst-case real-time analysis across the whole system.

Intensity-based Event Localization in Wireless Sensor Networks proposed a fully distributed localization scheme that consists of two algorithms Distributed election-winner notification algorithm. Intensity based localization algorithm (ILA). To minimize this complexity, but nevertheless benefit from its advantages it redesigned the DFD metric. A main advantage of the DDB protocol architecture is the absence of any states. The main disadvantage of these approaches is the increased data traffic.The DENA algorithm causes every node in the two-hop neighborhood of the winner node to respond. The possibility to query only a subset of these nodes will be considered. The ILA algorithm needs the information of all neighboring nodes.

Posterior Cramér–Rao Lower Bounds for Target Tracking in Sensor Networks With Quantized Range-Only Measurements The problem of target tracking in a wireless sensor network (WSN) that consists of randomly distributed range-only sensors. Traditional nonlinear filtering algorithms. Tracking algorithms. It is a challenging task since each sensor node typically has very limited power budget and communication bandwidth. The analysis of posterior CRLB for tracking a target with noisy circular trajectories. Sensor scheduling is usually adopted to further reduce the energy consumption and enhance the lifetime of whole network. To calculate the posterior CRLB for given scenario, the most important and difficult task is to obtain as stated earlier, each sensor node has limited power budget and communication bandwidth.

Target Tracking in Wireless Sensor Networks Based on the Combination of KF and MLE Using Distance Measurements Propose an improved noise model which incorporates both additive noises and multiplicative noises in distance sensing. EKF algorithms Multistep adaptive sensor scheduling algorithm (MASS). To use the maximum likelihood estimator initially and switch to the proposed estimator later when the target turns, which can be detected using the methods for target maneuver detection. The advantages of the proposed approach are demonstrated via experimental and simulation results. The proposed approach is very simple and yet effective. Simulation and experimental results have shown that the proposed approach improve the tracking accuracy compared to the commonly used extended Kalman filtering approach.

Scalable Information-Driven Sensor Querying and Routing for ad hoc Heterogeneous Sensor Networks. The key idea is to introduce an information utility measure to select which sensors to query and to dynamically guide data routing. Collaborative signal processing (CSP) algorithms. The type of networks can be stealthy and is advantageous for security reasons. It is key to the scalability of large-scale sensor networks through selective sensor tasking. It can drastically reduce latency in detection and tracking by application-aware optimal routing. The results show that the information-driven sensor queries proposed are more energy efficient. Have lower latency, and provide distributed anytime algorithms to mitigate the risk of link/node failures.

Path Vector Face Routing: Geographic Routing with Local Face Information says that improve routing performance by storing a small amount of local face information at each node. Geographic routing algorithms, Planarization algorithms. It demonstrates that by storing a small amount of local face information at each node, it can achieve better routing performance in terms of reduced path and hop stretch. The extra storage helps because the local face information can be exploited by a greedy-face forwarding mode. Using the available face information where regular greedy-neighbor forwarding fails to avoid switching to the costly perimeter forwarding mode. That while it is possible to guarantee packet delivery with an oblivious algorithm in a network where nodes have full face information, it is impossible to do so when nodes are limited to knowing about nodes up to a fixed number of hops away on each face. It developed Greedy Path Vector Face Routing (GPVFR), a non-oblivious algorithm that guarantees delivery even when nodes do not have complete face information.

GPSR is built upon graph planarization algorithms that are amenable to distributed implementation. Geographic routing algorithms, planarization algorithms. A link in the planar subgraph is removed when it should not be partitioned planar sub- graph. The nodes at the two ends of a link disagree on whether or not the link belongs in the planar graph unidirectional links. These pathologies, in turn, can result in persistent routing failures in the network, where geographic routing fails. Kinds of wireless devices as well, since the failure of the unit disk assumption as a result of obstacles or multi pathing are fairly fundamental. As an aside, they note that while many of the pathologies it describe above are caused by radio range irregularities, localization errors can also cause the same pathologies. It leaves measurement of the effects of localization errors in test bed deployments to future work.

III .PROPOSED SYSTEM

To explore efficient use of mobile sensors to address the limitations of static WSNs in target detection, in proposed, propose a data fusion model that enables static and mobile sensors to effectively collaborate in target detection. An optimal sensor movement scheduling algorithm is developed to minimize the total moving distance of sensors while achieving a set of spatiotemporal performance requirements including high detection probability, low system false alarm rate and bounded detection delay. The effectiveness of approach is validated by extensive simulations based on real data traces collected by 23 sensor nodes. The fidelity of final detection decision is then improved by a second-phase detection that fuses the measurements of both static and mobile sensors. Optimal sensor movement scheduling algorithm that enables mobile sensors to gather the maximum amount of target energy under a given moving distance bound.

IV.IMPLEMENTATIONS

a. knob consumption

The mobile nodes are designed and configured dynamically, designed to employ across the network, the nodes are set according to the X, Y, Z dimension, which the nodes have the direct transmission range to all other nodes. All the mobile nodes tend to have a unique id for its identification process, since the mobile nodes communicates with other nodes through its own network id. If any mobile node opted out of the network then the particular node should surrender its network id to the head node. There are 23 sensor nodes of type both dynamic and static.

b. Generation of clusters

Nodes should be organized into clusters to track a mobile target. Initially sensor nodes randomly clustered and assumed to have some faulty/damaged nodes. It is randomly set after initialization. If a target is detected by a node after a time window, a target is detected by another node. It is assumed to be the same target. This assumption is made because the target does not carry any form of classification, nor can any different target be distinguished. Once the clusters are generated then for each cluster a cluster head will be created. It is done by using optimal node selection algorithm.

c. Multi sensor fusion

This proposed technique, a decision fusion based detection model in which each mobile sensor makes its own detection decision and locally controls its movement. This adopts a value fusion based detection model that significantly simplifies the task of mobile sensors. Specifically, each mobile sensor in a detection process is only required to move a certain distance and send its measurements to its cluster head. Such a model is more suitable for mobile sensors with limited capability of signal processing and motion control. Initially, all sensors periodically send the measurements to the cluster head that compares the average energy against a threshold.

d. Movement schedule

Once a positive detection decision is made, the cluster head initiates the second phase of detection by sending mobile sensors a movement schedule that specifies which sensors should move, the time instances to start moving and the distances to move. Mobile sensors then move toward the surveillance location according to the schedule.

e. ***Two-phase detection***

The performance of detection is characterized by the probability of false alarm (PF) (or false alarm rate) and probability of detection (PD). PF is the probability that a target is regarded to be present when the target is actually absent. PD is the probability that a target is correctly detected. After a certain delay, all sensors send the cluster head the sum of their energy measurements and the final detection decision is then made by comparing against another threshold. A key advantage of the above two-phase detection model is the reduced total distance of moving as the mobile sensors move in a reactive manner. Moreover, this model facilitates the collaboration between static and mobile sensors. As the decision of the first phase is made based on the measurements of all sensors in a cluster, the static sensors help filter out false alarms that would trigger unnecessary movement of mobile sensors. In addition, the accuracy of the final detection decision is improved in the second phase because the signal to noise ratios (SNR) are increased as the mobile sensors move closer to the surveillance location.

f. Multi-sensor Fusion Model

Assume that the network is organized into clusters. Sensors send their energy measurements to the cluster head, which in turn compares the average of all measurements to a threshold η. If the average is greater than η (referred to as the detection threshold), the cluster head decides that a target is present. Otherwise, it decides there is no target. The performance of detection is characterized by the probability of false alarm (PF) (or false alarm rate) and probability of detection (PD). PF is the probability that a target is regarded to be present when the target is actually absent. PD is the probability that a target is correctly detected. Suppose there exist n sensors and each sensor measures signal energy for duration T .

The Mobility-assisted Spatiotemporal Detection Problem Overview of the Approach

The MSD problem is characterized by a 4-tuple (A, α, β,D). For a given set of static and mobile sensors and any target that appears at one of the locations in set A, objective is to minimize the total expected moving distance of the mobile sensors subject to: 1) PD is no lower than β; 2) PF is no higher than α; and 3) the expected detection delay is no greater than D seconds. Assume that the surveillance locations are chosen before the deployment or identified by the network autonomously after the deployment. The network is organized into clusters around surveillance locations by running a clustering protocol such as the one proposed.

Proposed system employs the following data-fusion model. Initially, all sensors periodically send the measurements to the cluster head that compares the average energy against a threshold $\lambda 1$. Once a positive detection decision is made, the cluster head initiates the second phase of detection by sending mobile sensors a movement schedule S that specifies which sensors should move, the time instances to start moving and the distances to move.

Mobile sensors then move toward the surveillance location according to the schedule. After a certain delay, all sensors send the cluster head the sum of their energy measurements and the final detection decision is then made by comparing against another threshold λ2. The detection thresholds, λ1, λ2 and the movement schedule S are determined under the constraints that the aggregate delay, PD and PF of the two phases must satisfy the requirements specified by D, β and α, respectively. A key advantage of the above two-phase detection model is the reduced total distance of moving as the mobile sensors move in a reactive manner. Moreover, this model facilitates the collaboration between static and mobile sensors. As the decision of the first phase is made based on the measurements of all sensors in a cluster, the static sensors help filter out false alarms that would trigger unnecessary movement of mobile sensors. In addition, the accuracy of the final detection decision is improved in the second phase because the signal to noise ratios (SNR) are increased as the mobile sensors move closer to the surveillance location.

Assumptions

First, all sensors have synchronized clocks. Second, assume that each mobile node knows its own location and can orient its movement in a given direction. In the first phase of detection, all sensors operate in a synchronous schedule in which the sample energy at a period of S seconds. Assume the probability that a target may appear at any time instance is uniform. Therefore, the expected detection delay is S/2. Suppose S = 2Γd where D is the required detection delay bound. Thus the expected delay of the first-phase detection is S/2 = Γd where γ ∈ (0, 1) is a constant chosen according to the desirable trade-off between detection delay and power consumption. For the convenience of discussion, assume γ = ½ in the rest of discussion. Each sensor samples energy for T seconds and sends to the cluster head. For instance, the acoustic data is recorded at a frequency of 4960 Hz in every 0.75s in the experiments, i.e., T is 0.75s.

In the second phase of detection, all sensors in the cluster sample energy at a period of T . After a delay of D/2, sensors report the sum of their energy measurements to the cluster head. This is necessary to bound the total expected detection delay within D as the expected delay of the first phase detection is D/2. The mobile sensors belong to multiple clusters and must return to their original locations after the second phase of detection as they may be requested to detect targets at other locations. In proposed system assumes that the average movement speed of a mobile sensor is v. To simplify the motion control of mobile sensors, assume the moving distance of a sensor in the second phase is always multiple of Vt. Furthermore, to simplify problem formulation, assume that the distance between a sensor and a surveillance location is also multiple of Vt . Note that this assumption has little impact on the system detection performance as both v and T are small in practice. For instance, T is 0.75s in the experiments and v is 0.5 ~ 2m/s for typical mobile sensor systems. Under such settings, Vt is at most 1.5 meters. Therefore, the assumption that the real sensor locations are multiple of Vt does not introduce significant errors.

Optimal Sensor Movement Scheduling

In this section, present an optimal movement scheduling algorithm that enables sensors to gather the maximum amount of energy for a given number of moves. Suppose the optimal movement schedule has H moves and there is only one sensor i. obviously, the measured energy always decreases with i's distance to the target and increases with the sensing duration.

Input: D, $\{E(n,j) \mid 0 \leq j \leq H\}$, P_u, $(x_1^0, x_2^0, \cdots, x_n^0)$, $[\eta_{1(0)}, \eta_{1(k)}]$, $[\eta_{2(0)}, \eta_{2(k)}]$
/*output movement schedule and two detection thresholds*/
Output: $\mathcal{S}, \eta_1, \eta_2$

$cost = \infty$;
for $l = [0 : H]$
    for $n_1 = [\eta_{1(0)} : \eta_{1(k)}]$
        Compute P_{D_1} and P_{F_1} using (14) and (12);
        Find the minimum $n_2 \in \{\eta_{2(0)} .. \eta_{2(k)}\}$ using (7);
        Compute P_{D_2} using $E(n,l)$ according to (15);
        if ((8) holds)
            Compute current cost C using (6);
            if $(C = 0)$ **exit; fi**;
            if $(C < cost)$
                $cost = C; \mathcal{S} = \mathcal{S}(n,l); \eta_1 = n_1; \eta_2 = n_2$
            fi
        fi
    end
end

Fig 2 The procedure of solving the MSD problem

Therefore, the optimal schedule for I is to move H steps consecutively from time zero, which allows it to sense at the closest location possible at any time instance. Interestingly, this conclusion still holds when there are more than one sensors. This is because sensors can move in parallel and hence optimizing the movement of each sensor individually maximizes the total amount of energy sensed by all sensors.

V. CONCLUSION

This explores the use of mobile sensors to address the limitation of static WSNs for target detection. In proposed approach, mobile sensors initially stationary are triggered to move toward possible target locations by a detection consensus arrived at by all sensors. The fidelity of final detection decision is then improved by a second-phase detection that fuses the measurements of both static and mobile sensors. Develop an optimal sensor movement scheduling algorithm that enables mobile sensors to gather the maximum amount of target energy under a given moving distance bound. The effectiveness of proposed approach is validated by extensive simulations based on real data traces. However, several challenges must be addressed in order to take advantage of the mobility of WSNs in target detection. First, due to the higher design complexity and manufacturing cost, the number of mobile nodes available in a network is often limited. Therefore, mobile sensors must effectively collaborate with static sensors to achieve the maximum utility. Second, mobile sensors are only capable of low-speed and short-distance movement in practice due to the high power consumption of locomotion.

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