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RESEARCH ARTICLE

Decision-aware data suppression in wireless sensor networks for target tracking applications

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Abstract Target tracking applications of wireless sensor networks (WSNs) may provide a high performance only when a reliable collection of target positions from sensor nodes is ensured. The performance of target tracking in WSNs is affected by transmission delay, failure probability, and nodes energy depletion. These negative factors can be effectively mitigated by decreasing the amount of transmitted data. Thus, the minimization of data transfers from sensor nodes is an important research issue for the development of WSN-based target tracking applications. In this paper, a data suppression approach is proposed for target chasing in WSNs. The aim of the considered target chasing task is to catch a moving target by a mobile sink in the shortest time. According to the introduced approach, a sensor node sends actual target position to the mobile sink only if this information is expected to be useful for minimizing the time in which target will be caught by the sink. The presented method allows sensor nodes to evaluate the usefulness of sensor readings and select those readings that have to be reported to the sink. Experiments were performed in a simulation environment to compare effectiveness of the proposed approach against state-of-the-art methods. Results of the experiments show that the presented suppression method enables a substantial reduction in the amount of transmitted data with no significant negative effect on target chasing time.

Keywords data collection, data suppression, target tracking, wireless sensor networks

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1 Introduction

Wireless sensor networks (WSNs) have demonstrated a great potential for a wide range of control applications, including building automation, industrial control systems, electric-utility automation, military systems, road traffic control, inventory management, and target tracking [1–6]. In this kind of applications, data registered by sensor nodes are transferred wirelessly to a sink node. The sensor readings collected at sink node are then utilized for decision making. Such applications can provide a high performance only if the WSN ensures a reliable and timely data delivery. Transmission failures, delays and energy depletion of sensor nodes may result in non-optimal decisions. The probability of transmission failure and transmission delay as well as the energy consumption can be reduced by decreasing the amount of transmitted data [7]. Thus, minimization of data transfers from sensor nodes is an important research issue for the development of WSN applications.

Data suppression is an approach to collect necessary information at a sink node, while reducing the data transfers from sensor nodes as much as possible [8,9]. When using suppression schemes, each sensor node collects data with a high sampling rate but sends only those data readings that represent a deviation from an expected behavior. Thus, the WSN is able to quickly recognize relevant events in the monitored environment. This cannot be ensured in case of adaptive sampling methods that reduce the data communication by adjusting the sampling rates of sensor nodes according to previously collected readings [10,11]. When using the adaptive sampling methods, the sampling rate is reduced if the previous measurements show that changes in a monitored process are slow. In such case, the information about unexpected abrupt changes of the monitored parameters may be missed or delivered with excessive delay. In such situation, the collected information would be insufficient for the target tracking applications. For instance, when the target remains in the same location for a long time and then moves rapidly to a new location, the new location may be reported belatedly and in result the tracking performance would be decreased.

In this paper, a decision-aware data suppression approach is proposed for target chasing in WSNs. The aim of the considered target chasing task is to catch a moving target by a mobile sink in the shortest time. The mobile sink has to make decisions, i.e., select its movement direction, based on information about target position delivered from sensor nodes.

The data suppression methods available in the literature were designed for monitoring applications that require the WSN to collect information on a given set of parameters with a defined precision or to report a predetermined set of events. These methods exploit temporal and spatial correlations among sensor readings to eliminate redundant data reports [12–14]. Such approaches can be effective in case when values of some parameter (e.g., temperature) have to be determined within fixed error bounds (e.g., ±1°C). However, there is a lack of suppression methods designed specifically for the target chasing applications in WSNs, where the required precision of the information about target position can vary significantly in time. It means that the admissible error bounds of the estimated target position cannot be specified in advance for the considered application. These error bounds depend on current distance between the target and the mobile sink as well as on location of the sink in the monitored area [15]. For example, if the distance between target and sink is large then it is not necessary to know the precise current target position because the sink will need a considerable time to reach this location and during that time the target can change its position significantly. Thus, the new target position will have to be reported in the future (when the distance from sink to target will be lower), and the current position can be roughly estimated based on a previously reported position. Another example is a situation when the mobile sink is close to borders of the monitored area. In such situation a lower precision of the information about target position is required, because the borders restrict possible moves of the sink.

The proposed suppression approach eliminates transfers of sensor readings (target positions) that are not useful for the decisions of mobile sink. The introduction of this approach was motivated by an observation that for the target tracking tasks large amounts of sensor readings often do not have to be transferred to the sink node as the decisions made with and without these data are the same. Moreover, a tracking objective can be usually achieved by implementing different decisions, including those that are based on incomplete information.

According to the proposed decision-aware approach, a sensor node sends actual target coordinates to the sink only if this information is expected to be useful for reducing the time which is necessary to catch the target. The introduced method allows the sensor nodes to evaluate usefulness of registered target position by taking into account the objective of target chasing task. A probabilistic approach is introduced to be used by sensor nodes for evaluation of the data usefulness.

The paper is organized as follows. Section 2 reviews related research works and outlines the contribution of this paper. In Section 3, the decision-aware data suppression method is described in details. Section 4 presents results of simulation experiments. Finally, in Section 5, conclusions are drawn and some future research directions are suggested.

2 Related work and contribution

Several methods have been proposed in the related literature for data collection tasks that aim at reducing communication in WSNs. These methods can be categorized either as centralized or decentralized. In case of centralized methods, the data collection is managed by a sink node, which sends queries to sensor nodes in order to retrieve the needful data. When using the decentralized methods, sensor nodes analyze data readings and autonomously decide if they should be reported to the sink. This category includes temporal, spatiotemporal and cascaded data suppression methods [9,12–14,16].

Examples of the centralized methods are model-based querying [17] and uncertainty-based information extraction [18]. According to these methods, a predictive model is used at the sink node to infer current values of the monitored parameters. If uncertainty associated with the inferred values is too high then the sink node sends a query to obtain actual data readings from the sensor nodes. In case of the centralized data collection, abrupt changes of a monitored parameter will remain undetected for a long time if the model fails in predicting actual value of the parameter and the sink postpones acquisition of sensor readings. When using the decentralized methods, each relevant sensor reading can be reported to the sink node.

Data aggregation methods reduce communication in WSN by processing sensor readings at intermediate nodes before transmitting them further. When an intermediate node receives data from multiple sensor nodes, instead of forwarding all of them, it checks the contents of the incoming data and then combines them by eliminating redundant information under some accuracy constraints. For instance, readings from different sensor nodes that are related to the same event can be fused together and jointly reported to the sink [19]. The aggregation approach can exploit spatial correlation of sensed data [20]. Main disadvantage of the in-network data aggregation is a delay in transmission, which is a consequence of the time-consuming data processing by the intermediate nodes.

Existing suppression methods [8,9,12–14] exploit the fact that a large subset of sensor readings does not need to be transmitted to the sink as these readings can be inferred from the other reported data. In order to infer suppressed data, the sink uses a predictive model of the monitored process. The same model is used by sensor nodes to decide if particular data readings have to be transmitted. A sensor node suppresses transmission of a data reading only when it can be inferred within a given error bound.

Temporal suppression is based on correlations between actual and previous data readings of a sensor node. The basic approach uses a naive model, which assumes that actual sensor reading is the same as the last reported one [21]. According to this method, a sensor node reports its actual reading to sink only if deviation between the actual reading and the previously reported reading is above a given threshold.

Processes monitored by WSNs often exhibit correlations in both time and space [22]. Thus, spatiotemporal suppression methods were introduced that combine the temporal suppression with recognition of spatially correlated sensor readings from neighboring nodes [13,14,23]. When using the spatiotemporal suppression, sensor nodes are clustered by taking into account the spatial correlations. Sensor readings within each cluster are reported to a cluster head node, which then uses a spatiotemporal model to decide if the readings have to be transmitted to sink.

In case of cascaded approach [12], a data suppression method is used in transmitting sensor reading between a source node to another node, and then the suppression is applied again in reporting the reading together with other readings to a third node. The procedure is repeated until the sink is reached. Temporal suppression is used at the first level of the cascade, i.e., at the source sensor node. Spatiotemporal suppression is utilized for higher cascade levels at the cluster head nodes.

In this paper, a decision-aware data suppression method is introduced for the target tracking applications of WSNs. Unlike the existing approaches, the proposed method does not assume any required precision level of the collected information. It is based on an observation that a large part of sensor readings does not need to be reported to the sink as these readings are not necessary for effective target tracking. The introduced method allows sensor nodes to evaluate the usefulness of sensor readings. The data usefulness is evaluated by taking into account an expected effect of a sensor reading on the target tracking performance. Thus, only those sensor readings are reported to the sink that are useful for making an optimal decision, i.e., for selection of a movement direction which will minimize distance between sink and target.

In the proposed approach, a probabilistic model is used to estimate possible effects of the sink decisions. Since different possibilities are taken into account, the sensor nodes can evaluate a probability with which the condition of data suppression is satisfied. A threshold of this probability is used to decide if sensor readings should be suppressed. This threshold parameter allows a trade-off between the amount of transmitted data and the target tracking performance to be effectively managed.

3 Proposed method

In the considered target chasing application of WSN, sensor nodes detect a target and determine its actual position. The position of target $\mathbf{p_T} = [x_\mathrm{T}, y_\mathrm{T}]$ is transmitted to a mobile sink. This information is then utilized for selecting movement direction. The aim is to reach the moving target in the shortest possible time, thus the mobile sink selects a movement direction that minimizes its distance to the target. Movement direction of the target is random. Both the target and the sink can move in one of the four directions: north, west, south or east.

3.1 Target chasing by mobile sink

The selection of sink movement direction is performed periodically with a constant decision time interval τ. During the decision time interval, the sink will move to position $\mathbf{p_S^+} = [x_\mathrm{S}^+, y_\mathrm{S}^+]$, which is determined by solving the following optimization problem:

$$\begin{aligned} &\text{minimize } d(\mathbf{p_S^+}, \bar{\mathbf{p}}_\mathbf{T}) \\ &\text{subject to } \mathbf{p_S^+} \in MR, \end{aligned} \tag{1}$$

where d denotes the Euclidean distance, $\bar{\mathbf{p}}_\mathbf{T}$ is the target position which has been recently reported to the sink node. MR is the sink movement range, i.e., a set of positions that can be reached by the sink during time interval τ. Since the sink can move in one of the four directions, its movement range is determined as follows:

$$MR = \left\{p = [x, y] : |x - x_{\mathrm{S}}| + |y - y_{\mathrm{S}}| \leqslant v_{\mathrm{S}}^{\max} \cdot \tau\right\}, \quad (2)$$

where $\mathbf{p_S} = [x_{\mathrm{S}}, y_{\mathrm{S}}]$ is current sink position, and $v_{\mathrm{S}}^{\max}$ denotes maximum sink speed.

Details of the operations performed by the mobile sink are described in Algorithm 1. A special attention is paid to transmission failures that can significantly affect the performance of target tracking. The sink node assumes that a missing sensor message was intentionally suppressed and moves towards previously reported target position. However, if the message was not received due to transmission failure, the selected movement direction will be not optimal. According to the proposed algorithm, automatic repeat request method (ARQ) is applied to deal with transmission failures. It means that successfully received target coordinates ($\mathbf{p_T}$) have to be acknowledged by the mobile sink.

Algorithm 1 Mobile sink operations

while target not caught **do**
begin
    if $\mathbf{p_T}$ received **then**
    begin
        $\bar{\mathbf{p}}_\mathbf{T} := \mathbf{p_T}$
        send acknowledgement to sensor node
    end
    if decision time interval passed **then**
        if target in acting range **then** catch target
        else begin
            find $\mathbf{p}_\mathbf{S}^+ \in MR : d(\mathbf{p}_\mathbf{S}^+, \bar{\mathbf{p}}_\mathbf{T}) = \min_{\mathbf{p} \in MR} d(\mathbf{p}, \bar{\mathbf{p}}_\mathbf{T})$
            move towards $\mathbf{p}_\mathbf{S}^+$
        end
end

3.2 Data sensing and communication

Algorithm 2 presents the operations that are performed by each sensor node. Position of the target is acquired with a constant rate, which is determined by the sensing time interval. A packet with actual target coordinates ($\mathbf{p_T}$) is transmitted from a sensor node to the mobile sink only if a suppression condition is dissatisfied. The data report to sink can be accomplished by using the geographical routing [24].

After transmitting target coordinates, the sensor node waits for acknowledgement from the mobile sink. If the acknowledgement is not received, then the coordinates are retransmitted. The source sensor node executes retransmissions until the acknowledgement is delivered or a limit of retransmissions is reached.

Algorithm 2 Sensor node operations

if sensing time interval passed **then**
begin
    detect target in sensing range
    if target detected **then**
    begin
        determine $\mathbf{p_T}$
        verify *suppression condition*
        if *suppression condition* is false **then**
        repeat
            send $\mathbf{p_T}$ to sink
            wait until timeout or ack. received
        until acknowledgement received or max number of retransmissions reached
        broadcast $\bar{\mathbf{p}}_\mathbf{T}$ and $\mathbf{p_S}$
    end
end

Each acknowledgement sent by the mobile sink includes sink coordinates ($\mathbf{p_S}$). Thus, the acknowledgements allow the sensor node to update its information about current position of the mobile sink and to predict its future movements. The knowledge of sink position is utilized for routing as well as for suppressing unnecessary data transfers, as discussed later in this section.

The known maximum velocity and the possible movement directions of the target are used to minimize the number of active sensor nodes. A sensor node, which has detected the target, (so-called target node) broadcasts packets to activate the sensor nodes in locations that can be reached by the target during the sensing time interval. The broadcasted packets include information about location of the mobile sink and the target position that was recently reported to the sink. One activated sensor node, which detects the target, takes over the role of the target node. The remaining sensor nodes deactivate.

3.3 Decision-aware data suppression

The proposed decision-aware data suppression method takes into account usefulness of sensor readings for sink decisions. As it was already mentioned, the sink has to catch a moving target in the shortest possible time. To this end, the sink should move towards a nearest position where the target can be caught. Such position cannot be unambiguously determined as the future target trajectory is not known. Thus, the sink selects a movement direction which minimizes distance to the recently reported target position, as defined in Eq. (1).

According to the introduced data suppression method, actual target position $\mathbf{p_T}$ do not have to be transmitted to the sink if the expected effect of the sink decision made on the basis of the recently reported target position $\bar{\mathbf{p}}_\mathbf{T}$ is not worse than the effect that would be obtained based on the actual position. The worse effect of sink decision corresponds to a greater distance between the position into which the sink will move during next decision interval and the nearest position where target can be caught. Formally, the actual target position does not have to be reported to the sink node if the following condition is satisfied:

$$dist(\bar{\mathbf{p}}^*, \mathbf{p_C}) \leqslant dist(\mathbf{p}^*, \mathbf{p_C}), \tag{3}$$

where $\bar{p}^*$ and p^* are the alternative positions that will be reached by the mobile sink during next decision time interval if the sink selects movement direction based on the last reported target position or the actual target position, respectively; $\mathbf{p_C}$ is the nearest position where the target can be catch.

As it was mentioned above, position $\mathbf{p_C}$ cannot be uniquely determined. However, it is possible to determine a region that includes nearest positions in which the sink will be able to catch the target for all possible target trajectories. This region is defined as follows:

$$R_\mathrm{C} = \{\mathbf{p}_\mathrm{C} : t_\mathrm{T}(\mathbf{p}_\mathrm{C}) \leqslant t_\mathrm{S}(\mathbf{p}_\mathrm{C})\}, \tag{4}$$

where:

$$t_\mathrm{T}(\mathbf{p}_\mathrm{C}) = (|x_\mathrm{C} - x_\mathrm{T}| + |y_\mathrm{C} - y_\mathrm{T}|)/v_\mathrm{T}^{\max}, \tag{5}$$

$$t_\mathrm{S}(\mathbf{p}_\mathrm{C}) = (|x_\mathrm{C} - x_\mathrm{S}| + |y_\mathrm{C} - y_\mathrm{S}|)/v_\mathrm{S}^{\max}, \tag{6}$$

are the minimum times required for the target (Eq. (5)) and the sink (Eq. (6)) to reach position $p_\mathrm{C} = [x_\mathrm{C}, y_\mathrm{C}]$, $v_\mathrm{S}^{\max}$ denotes maximum speed of sink, and the remaining symbols were previously defined.

Verification of condition (Eq. (3)) based on region R_C gives an uncertain result, i.e., the conclusion that the suppression condition is satisfied (or not satisfied) is uncertain. In order to handle this uncertainty, the proposed method evaluates a probability P with which the suppression condition is satisfied. A report of target position can be suppressed if this probability is greater or equal to a predetermined threshold:

$$P[dist(\bar{\mathbf{p}}^*, \mathbf{p_C}) \leqslant dist(\mathbf{p}^*, \mathbf{p_C})] \geqslant \theta, \tag{7}$$

The probability in Eq. (7) is estimated as follows:

$$P[dist(\bar{\mathbf{p}}^*, \mathbf{p_C}) \leqslant dist(\mathbf{p}^*, \mathbf{p_C})] = |\bar{R}_\mathrm{C}|/|R_\mathrm{C}|, \tag{8}$$

where $|R_\mathrm{C}|$ denotes area of region R_C and $|\bar{R}_\mathrm{C}|$ is area of region $\bar{R}_\mathrm{C}$ which includes positions that belong to R_C and satisfy the distance condition defined in Eq. (3):

$$\bar{R}_\mathrm{C} = \{\mathbf{p}_\mathrm{C} : \mathbf{p}_\mathrm{C} \in R_\mathrm{C} \wedge dist(\bar{\mathbf{p}}^*, \mathbf{p_C}) \leqslant dist(\mathbf{p}^*, \mathbf{p_C})\}. \tag{9}$$

Thus, the final form of the suppression condition used in the proposed method is given by the formula:

$$|\bar{R}_\mathrm{C}|/|R_\mathrm{C}| \geqslant \theta. \tag{10}$$

Detailed implementation of the decision-aware data suppression procedure is presented in Algorithm 3.

Algorithm 3 Verification of suppression condition

suppression condition := true
if $d(\bar{\mathbf{p}}_\mathbf{T}, \mathbf{p_T}) > \varepsilon$ **then**
begin
  determine $\mathbf{p_S}$ and MR
  find $\mathbf{p}^* \in MR : d(\mathbf{p}^*, \mathbf{p_T}) = \min_{\mathbf{p} \in MR} d(\mathbf{p}, \mathbf{p_T})$
  find $\bar{\mathbf{p}}^* \in MR : d(\bar{\mathbf{p}}^*, \bar{\mathbf{p}}_\mathbf{T}) = \min_{\mathbf{p} \in MR} d(\mathbf{p}, \bar{\mathbf{p}}_\mathbf{T})$
  if $d(\bar{\mathbf{p}}^*, \mathbf{p}^*) > \varepsilon$ **then**
  begin
    estimate $P[dist(\bar{\mathbf{p}}^*, \mathbf{p_C}) \leqslant dist(\mathbf{p}^*, \mathbf{p_C})]$
    if $P[dist(\bar{\mathbf{p}}^*, \mathbf{p_C}) \leqslant dist(\mathbf{p}^*, \mathbf{p_C})] < \theta$ **then**
      suppression condition := false
  end
end

Figure 1 shows a verification example of the suppression condition. In this example the actual target position is $x = 6$, $y = 3$. The target position that has been last reported to mobile sink is $x = 6$, $y = 7$. The sink is located at position $x = 0$, $y = 0$. Maximum speed of target equals 1, and maximum speed of sink is 2 (distance units per decision time interval). If the sink receives the information about current target

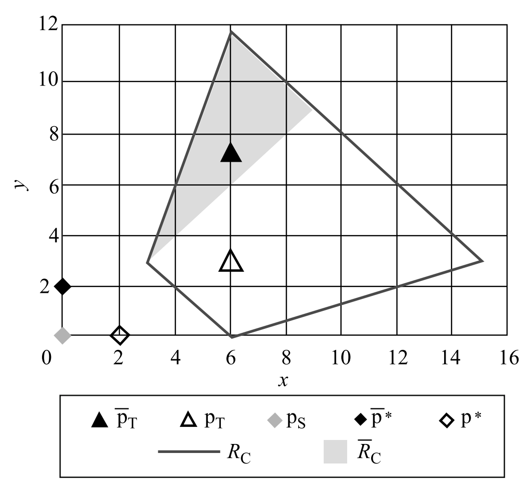

Fig. 1 Verification example of suppression condition

position, it will move to $x = 2$, $y = 0$ during the next decision time interval. In opposite situation, the sink will move to position $x = 0$, $y = 2$. The region of trapezoidal shape (R_C) includes the nearest positions at which the target can be caught for each of its possible movement trajectories. The shaded triangular area corresponds to region $\bar{R}_C$. Area of region R_C is 72 and area of $\bar{R}_C$ amounts to 18 (square distance units). Thus, the estimated probability (Eq. (8)) equals 0.25. Assuming that $\theta = 0.5$, the suppression condition (Eq. (10)) is not satisfied and the actual target position will be reported to the sink.

Table 1 Parameters of simulation

Parameter	Value
Monitored area	600m×600m
Transmission range of sensor node	50m
Sensing area of sensor node	30m×30m
Transmission range of sink	50m
Acting range of sink	2m
Maximum speed of sink	6m/s
Maximum speed of target	3m/s
Bandwidth	250kbit/s
Packet size	56bytes
Sensing time interval	1s
Decision time interval	1s

4 Experiments

Simulation experiments were performed in order to determine data transmission cost and target tracking performance for the proposed decision-aware data suppression method. Data transmission cost is evaluated using two criteria: total hop count and average packet rate. Target tracking performance is evaluated by measuring time which is necessary for the mobile sink to reach the moving target (time to catch).

The scope of the experiments includes a comparison of the proposed method against existing data collection algorithms that have been introduced in the literature for target chasing applications. The comparative evaluation takes into account also the effect of transmission failures on effectiveness of the compared algorithms.

4.1 Simulation setup

According to the experimental setup, the monitored area is a square of 600×600 meters. During simulation, a single target moves in random directions within the monitored area. The simulated WSN includes 400 sensor nodes that are arranged in a square grid topology (20×20). Each sensor node detects and localizes the target in a sensing area of 30×30 meters. Transmission range of each sensor node covers the eight nearest neighboring nodes. The geographical routing is used for multi-hop transmissions [24]. Detailed information on main parameters of the simulation is included in Table 1. The simulation environment was based on OMNET++ [25].

4.2 Compared algorithms

Performance and data transmission cost of the proposed decision-aware data suppression algorithm for target tracking (DADS) was compared against the results obtained for three algorithms (SUP, DOT, and UIE) that apply state-of-the-art approaches to reduce the data transmission in WSN.

The SUP and DOT algorithms are based on decentralized methods that allow the sensor node to decide if current target position has to be reported to the sink.

Spatiotemporal data suppression method [14] is applied in the SUP algorithm. According to this algorithm, current position of the target is reported by a sensor node to the sink only if Euclidean distance between current and previously reported target position ($d(\bar{\mathbf{p}}_\mathbf{T}, \mathbf{p}_\mathbf{T})$) is above a predetermined threshold ε.

DOT algorithm is based on the dynamical object tracking approach, which was proposed in Ref. [26]. When using this algorithm, the sensor node communicates current target position to the sink only if the sink has reached previously reported target position, i.e., the distance between sink position and last reported target position ($d(\bar{\mathbf{p}}_\mathbf{T}, \mathbf{p}_\mathbf{S})$) is shorter than the sink acting range.

In the UIE algorithm, a centralized method is used by the sink to decide when sensor nodes should be queried to retrieve the actual target position. This algorithm is based on the uncertainty-based information extraction approach [18]. According to UIE algorithm, the sink decides when data transfers from sensor nodes are necessary. At each decision time interval, the information about current location of the target is delivered from sensor node to so-called beacon node, which is located at previously reported target position. Sink determines possible locations of the target and predicts time needed to catch the target for each movement direction. If at a given time such prediction is insufficient to provide acceptable level of the decision uncertainty or the sink is close to the possible target locations, then the sink sends request to the beacon node and gets the actual target location. More detailed information about this method can be found in Ref. [18], where the above mentioned algorithm was introduced as Algorithm 5.

4.3 Experimental results

4.3.1 Tracking performance and communication cost

Simulation experiments were carried out in order to determine time to catch, hop count, and packet count for the compared algorithms. Time to catch is defined as the time in which the sink reaches the moving target. Packet rate was calculated as quotient of packet count and time to catch.

The results presented in this section are averaged for 50 random tracks of the target. Each test starts with the same location of both the sink ($x = 15$, $y = 15$) and the target ($x = 300$, $y = 300$). The simulation stops when target is caught by the sink.

The following parameter settings were used for particular algorithms: $\varepsilon = 6$m for SUP, $\alpha = 0.15$ and $\beta = 2$ for UIE, $\theta = 0.55$ and $\varepsilon = 0.5$m for DADS. Values of the UIE parameters were suggested in Ref. [18]. The selection of the remaining parameters is based on results that are presented later in Section 4.3.2.

Charts in Fig. 2 compare the results of the examined algorithms. It was experimentally verified that the minimum average time to catch, which can be obtained when the mobile sink receives the information about current target position at each time step, is equal to 106.2 seconds. This minimum time to catch was achieved by using three algorithms: DADS, UIE, and SUP. DOT algorithm did not allow the mobile sink to catch the target in the shortest possible time. For DOT the time to catch was longer by 53%. These results show that DOT does not fulfill the requirements of the considered target chasing application. Among the three remaining algorithms, the lowest communication costs (hop count and packet rate) were obtained for DADS. When comparing with DADS, UIE algorithm increases the hop count by 10% and the packet rate by 21%. It means that UIE generates relatively high data traffic in WSN during entire period of target tracking. For SUP the hop count is higher by 46% as compared to DADS. The increased hop count results in faster depletion of the energy resources in sensor nodes. The above results show that DADS enables target catching in the minimum time with reduced communication costs. DADS achieves better results than the compared algorithms as it takes into account the uncertainty associated with expected effects of sink decisions, by using the proposed approach.

4.3.2 Impact of algorithm parameters

Impact of the algorithm parameters on hop count and time to catch for SUP and DADS is presented in Figs. 3 and 4. A general observation is that for both algorithms hop count can be reduced by increasing the value of algorithm parameter. Minimum time to catch is achieved for SUP if $\varepsilon \leqslant 6$m and for DADS if $\theta \leqslant 0.55$. These findings motivate the selection of parameter settings for the compared algorithms.

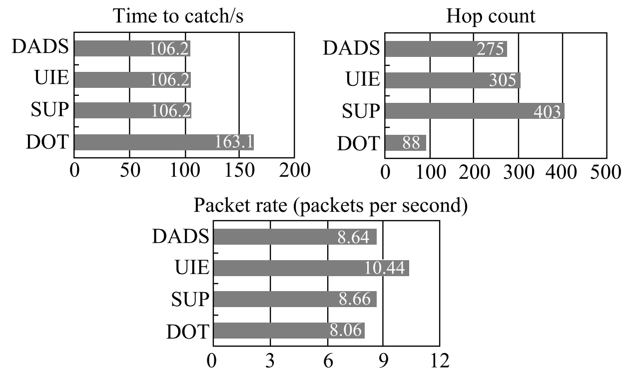

Fig. 2 Comparison of target tracking performance and communication cost for all examined algorithms

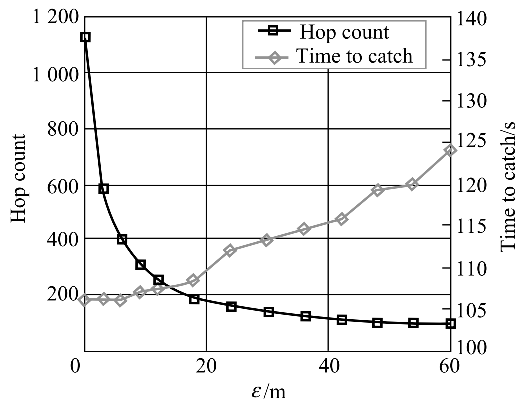

Fig. 3 Impact of parameter settings on hop count and time to catch for SUP algorithm

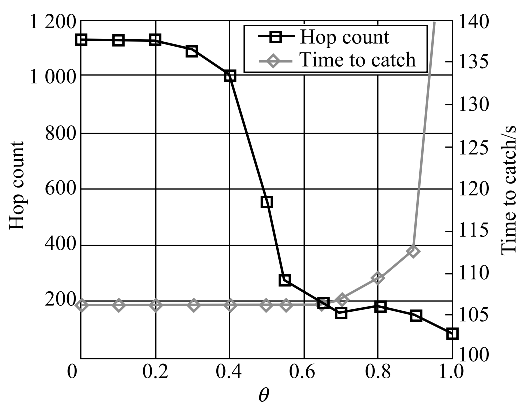

Fig. 4 Impact of parameter settings on hop count and time to catch for DADS algorithm

Figure 5 shows detailed comparison of the results achieved by SUP, UIE, and DADS. The dependencies between time to catch and hop count are illustrated for different parameter settings. An interesting remark is that DADS with $0.55 < \theta \leqslant 0.70$ enables considerable reduction of the hop count at the expense of a small increase in time to catch. The trade-off between target tracking performance and communication cost observed for SUP is clearly less advantageous.

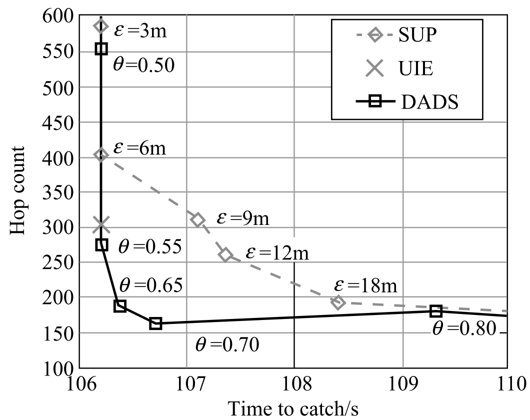

Fig. 5 Dependencies between time to catch and hop count for the examined algorithms

4.3.3 Target tracking example

One of the target tracks used during experiments is illustrated in Figs. 6 and 7. The charts in Figs. 6 and 7 show the target trajectory as well as sink trajectories that were achieved by using the five examined algorithms. The x- and y-coordinates are expressed in meters. The arrows indicate movement direction of both the sink and the target. When DOT algorithm is used, the sink reaches target after 186 seconds in position $x = 432$, $y = 510$. For the remaining algorithms the target is caught after 163 seconds in position $x = 501$, $y = 510$.

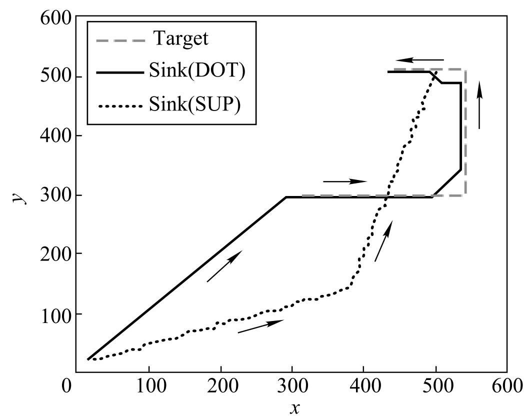

Fig. 6 Target and sink trajectories for DOT and SUP

Figures 8 and 9 show the course of changes in hop count as well as in number of packets sent to sink that was observed during target tracking for the example from Figs. 6 and 7. These results confirm advantages of the proposed DADS algorithm, which, in comparison with the state-of-the-art algorithms, effectively reduces the communication cost. A significantly slower increase in hop count and number of packets sent was achieved by DADS at the beginning of the experiment (seconds 0–100), when the sink is far from the target. The lowest communication cost was obtained by using DOT, however time to catch for this algorithm is considerably longer (increased by 12%).

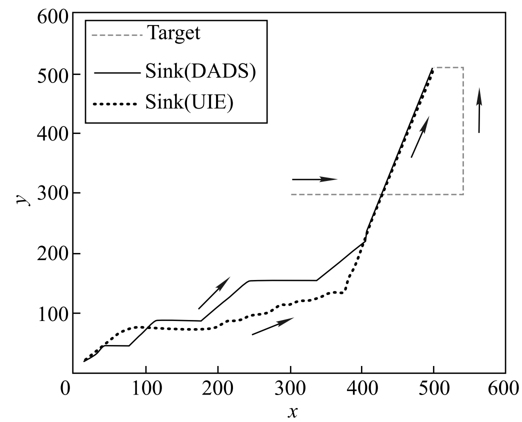

Fig. 7 Target and sink trajectories for DADS and UIE

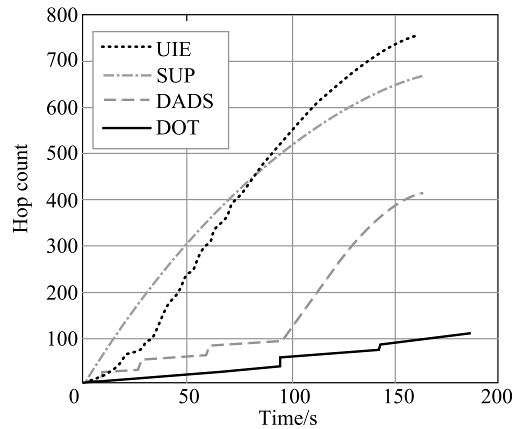

Fig. 8 Changes in hop count during target tracking

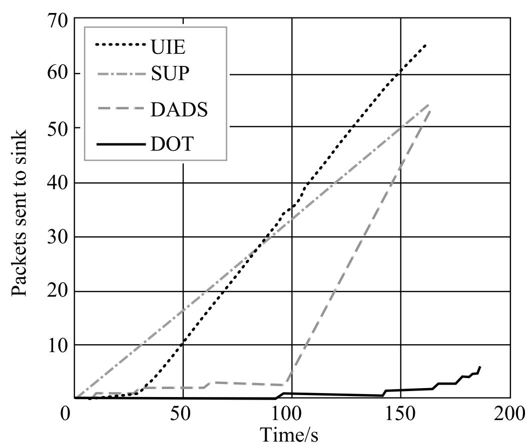

Fig. 9 Changes in number of packets sent to sink during target tracking

The high effectiveness of DADS in this example is related to the fact that target position is reported to sink only when the suppression would result in making inefficient decision (selection of non-optimal movement direction). This approach utilizes the fact that for the target tracking problem different sink decisions, made at particular time steps, can lead to the same optimal solution.

4.3.4 Impact of sink velocity

Additional experiments were performed in order to examine the influence of sink velocity on the target tracking performance and the data transmission in WSN. To this end, the sink velocity was changed from 6 to 15 m/s with steps of 3 m/s. The velocity of target was equal to 3 m/s for all simulations. Results of these experiments are presented in Figs. 10 and 11. If the mobile sink moves faster, the target tracking task is accomplished in a shorter time. As a consequence, the number of time steps at which the target position data are acquired, and can be suppressed, is lower. Therefore, the differences between the hop count and time to catch values for the compared algorithms decrease with increasing sink velocity.

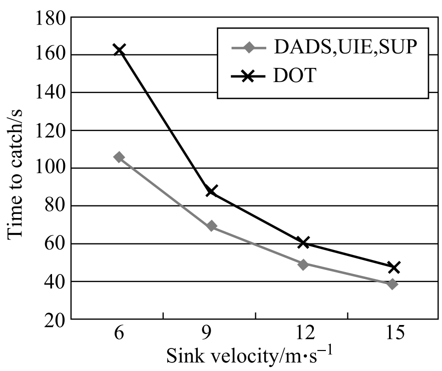

Fig. 10 Impact of sink velocity on time to catch

Figure 10 shows the dependency between sink velocity and time to catch. For all considered velocities of sink, the minimum time to catch was obtained by using DADS, UIE and SUP algorithms. In case of DOT, the minimum time to catch was not achieved. When taking into account the three algorithms that allows the sink to reach target in the minimum time, the lowest hop count was required by DOT for all velocities (Fig. 11). These results confirm the advantages of the proposed approach.

4.3.5 Impact of transmission failures

Impact of transmission failures on time to catch and hop count for algorithms SUP, UIE, and DADS was investigated in two scenarios. The first scenario implies that only one transmission attempt can be made during decision time interval. If the transmission fails (sensor node do not receive acknowledgement), it is repeated at the next decision time interval. In the second scenario it was assumed that four retransmissions can be carried out by a sensor node during one decision time interval. Figures 12 and 13 show the results for the first scenario, and Figs. 14 and 15 for the second scenario. In case of scenario 1 (Figs. 12 and 13), the minimum time to catch can be achieved by the state-of-the-art algorithms,

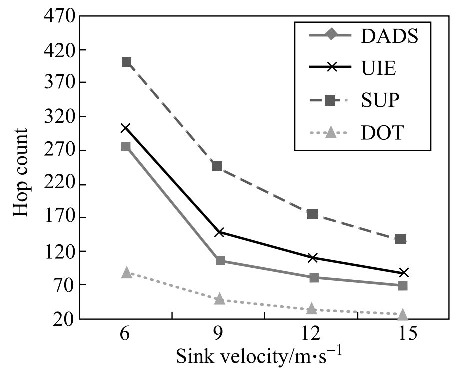

Fig. 11 Impact of sink velocity on hop count

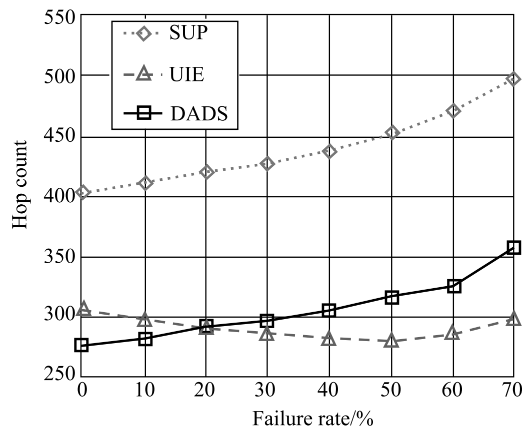

Fig. 12 Impact of transmission failures on time to catch for scenario 1

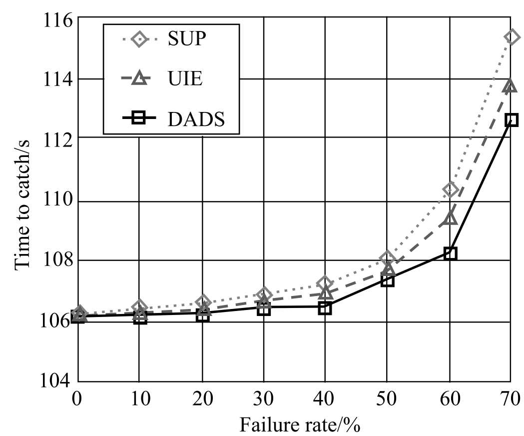

Fig. 13 Impact of transmission failures on hop count for scenario 1

provided that the failure rate equals 0%. For DADS the hop count does not increase if the failure rate is below or equal to 10%.

In scenario 2 (Figs. 14 and 15), transmission failures do not influence the time to catch if the failure rate is below 30% for state-of-the-art algorithms or below 60% for DADS. These results confirm the higher robustness of the proposed approach to transmission failures.

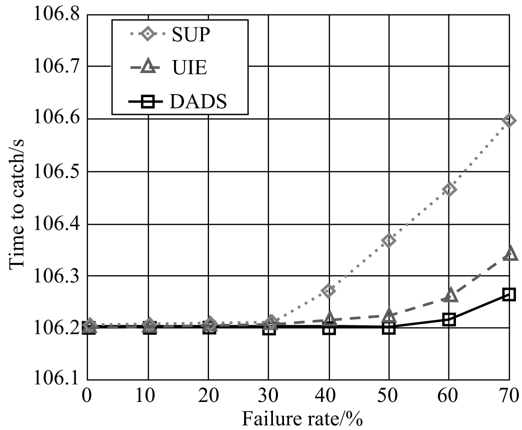

Fig. 14 Impact of transmission failures on time to catch for scenario 2

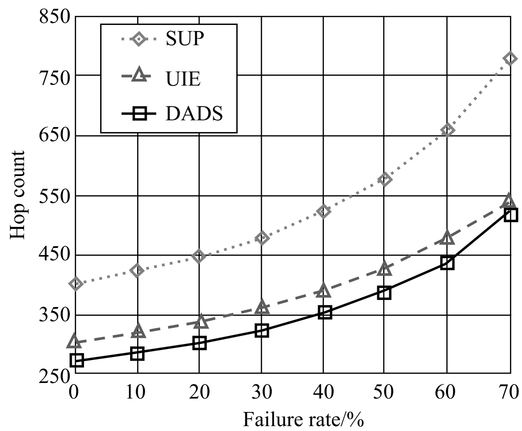

Fig. 15 Impact of transmission failures on hop count for scenario 2

When comparing the results for the two analyzed scenarios, it can be observed that the possibility of multiple retransmissions allows the data collection algorithm to significantly mitigate the negative effect of communication failures on the target tracking performance. This improvement is obtained at the cost of an increased hop count and higher packet rate.

5 Conclusions and future work

State-of-the-art data suppression methods aim at obtaining a predetermined accuracy level of the collected information for an entire period, when a monitoring task is executed. In target tracking applications, the required accuracy of collected target position information varies significantly in time. A reduced accuracy is often sufficient for making optimal sink decisions. The proposed suppression approach exploits the above insight to decrease the amount of data transmitted in WSN. Instead of suppressing transmissions of sensor readings that are not necessary to accurately estimate target position, the introduced method suppresses those sensor readings that are not useful for selecting optimal movement direction by the mobile sink.

According to the proposed approach, at each time step of the tracking procedure the mobile sink has to minimize its distance to a location in which the target can be caught. The data describing actual target position are useless and should be suppressed, if there is a high probability that the above mentioned distance will be minimized when the sink will move towards a recently reported target position instead of the actual target position.

Results of the simulation experiments clearly show advantages of the proposed approach. When comparing with state-of-the-art algorithms, the decision-aware suppression allows the data communication costs (packet rate and hop count) to be significantly reduced without decreasing performance of target tracking. Furthermore, the decision-aware suppression enables a beneficial trade-off between the tracking performance (time to catch) and the data communication cost. The negative effect of communication failures on the tracking performance can be effectively mitigated for this approach by using the ARQ method.

An extra cost introduced by the data suppression in WSN is related to the computations that are necessary to verify the suppression condition. In the proposed approach, the algorithm used for verification of the suppression condition (Algorithm 3) has low computational complexity. This algorithm is executed only by the sensor node, which detects the target. It should be noted that in sensor nodes the energy consumption of computations is significantly lower than this of data transmission. Moreover, data are usually transmitted through many nodes before reaching the mobile sink and additional computations are also necessary to find an appropriate transmission route. Thus, the extra cost of the suppression-related computations is negligible when compared to the benefits of reduced data transmission in WSN.

The decision-aware data suppression was introduced in this paper for target tracking applications of WSNs where a single sink collects data and chases the target. An interesting topic for further research is related to possible extensions of this approach to wireless sensor and actor networks with multiple actors that are capable of making decisions and performing appropriate actions based on the delivered senor readings. Another area for further research covers hybrid data collection approaches, which can be designed by combining the decision-aware suppression with other schemes, such as the centralized data collection methods and the in-network data aggregation.

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