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Sensor selection for tracking multiple groups of targets

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ABSTRACT

Group target tracking is a challenge for sensor networks. It occurs where large numbers of closely spaced targets move together in different groups. In these applications, the sensor selection scheme plays a vital role in extending network lifetime while providing high tracking accuracy. Existing schemes cause an extreme imbalance between energy usages and tracking accuracy. They are capable of tracking only individual groups and without using prior knowledge about the groups. These problems make them impractical for group target tracking. With the aim of balancing the trade-off between lifetime and accuracy, we present a novel Multi-Sensor Group Tracking (MSGT) scheme. MSGT comprises the following steps to accomplish concurrent tracking of multiple groups: (1) Clustering to capture changes in the behavioural properties of groups, such as formation, merging, and splitting; (2) Sensor selection to activate the contributory sensors for the estimated group regions; and (3) Group tracking using the activated sensors. We develop a probabilistic decision-making strategy that triggers the clustering step adaptively with any detected change in group behavioural patterns. The sensor selection step coordinates periodic selection of leader and tracking sensor nodes in a distributed manner. We introduce cost metrics that include sensor's energy parameters in the selection of active sensors that fully cover the group regions. The tracking step is a Bayesian modelling of the target groups which uses particle filtering algorithm to estimate the group locations. Simulation results show that our scheme achieves substantial improvements over existing approaches in terms of network lifetime and tracking accuracy.

1. Introduction

Wireless Sensor Networks (WSNs) are an increasingly important prerequisite for many applications, such as navigation, environmental monitoring, wildlife tracking, and surveillance. The primary factors driving such pervasive applications are the flexibility, fault tolerance, high sensing fidelity, low cost, and rapid deployment characteristics of WSNs (Akyildiz and Vuran 2010). Energy efficiency is a critical feature of WSNs because sensor nodes run mainly on batteries. Batteries are generally difficult to recharge after deployment (Akyildiz and Vuran 2010; Dargie and Poellabauer 2010a). The principal way of increasing the network lifetime is to minimise the number of active sensors in the region of interest.

This study tackles one of the crucial applications in WSNs, namely group target tracking. In such applications, high densities of moving targets travel together in various groups. For example, groups of animals migrating towards one or more destinations. In group target tracking applications, sensors are used to estimate the locations of the groups. An important measurement for quality of tracking is the accuracy of a location estimation which indicates the distance between the estimation and the ground truth (Dargie and Poellabauer 2010b). In most sensing models, the accuracy of estimations improves with increasing number of active sensors (Smith and Singh 2006). However, this approach to increasing accuracy can result in higher energy consumption and a shorter network lifetime due to the excessive use of energy by many active sensors (Rowaihy et al., 2007). Therefore, a reliable and effective sensor selection scheme is necessary to rotate the tracking task among the sets of active sensors, to balance the trade-off between estimation accuracy and network lifetime.

Existing research studies on sensor selection for tracking targets mainly focus on tracking the trajectories of each individual target (Wei et al., 2009; Tharmarasa et al., 2011; Tharmarasa et al., 2009; Ling et al., 2011; Vercauteren and Wang 2010; Kaplan 2006; Armaghani et al., 2012; Armaghani et al., 2012). However, it is very expensive to perform the sensor selection for every individual target in congested groups. Therefore, the main goal in group

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target tracking is to select sensors for the groups leading to conservation of total energy consumption by tracking the groups.

With the aim of balancing the accuracy-lifetime trade-off, a sensor selection scheme for group target tracking applications should have the following features:

1. Intelligent: In group target tracking applications, the areas of multiple groups may overlap with each other. Therefore, the requirement for a better accuracy-lifetime trade-off highlights the need for a network to make intelligent decisions about the active sensors for concurrent tracking of multiple groups.
2. Adaptive: Efficient and practical sensor selection schemes should be adaptive to changes in behavioural properties of the groups, such as the birth and death of group members, splitting, and merging. Thus, an efficient clustering algorithm should be incorporated to estimate and form the groups for their constituent members.
3. Distributed: A distributed sensor selection scheme is necessary due to limited power of the sensors. In such an approach, parallel calculations and decision-making occur locally at the sensor level. Distributed approaches are more scalable, more survivable to dynamic changes in the network, and more energy-efficient in terms of computation and communication (Durrant-Whyte et al., 2001).

To address the central aim described earlier, we present a novel *Multi-Sensor Group Tracking* (MSGT) scheme that is intelligent and adaptive, and the sensor selection is distributed. In this regard, MSGT makes the following contributions:

1. MSGT is able to track multiple groups concurrently by estimating the group regions. Each region represents a convex hull covering all the predicted grouped targets. The estimated group regions are used to determine the subset of sensors whose sensing ranges cover the entire regions. We introduce cost metrics that utilise the energy parameters of sensors and the region coverage requirements for selection of contributory sensors. The use of the proposed cost metric increases the network lifetime while ensuring an accurate tracking of the groups.
2. MSGT incorporates the adaptive-Predictive Clustering of Moving Targets (adaptive-PCMT) framework in order to capture the behavioural properties of groups. Adaptive-PCMT utilises a decision-making strategy that makes a probabilistic decision on whether clustering is required to estimate the groups for their constituent members. The outcome of decision-making strategy triggers the clustering only when grouped targets evolve out of the estimated group regions. Otherwise, tracking continues mapping the convex-hull regions through the time. The adaptive-PCMT greatly reduces communication and processing overhead that can result from the periodic clustering of groups. Moreover, it enhances the accurate tracking of overlapping groups.
3. We introduce a Bayesian modelling of the target groups which incorporates the Rao-Blackwellized Particle Filtering (RBPF) algorithm (Särkkä et al., 2007) as the localisation algorithm and to evaluate the origin of selected sensor measurements for the groups instead of individual targets. Enormous energy is conserved by tracking of the groups. Additionally, the Bayesian modelling of the groups shows a better performance in modelling the tracking uncertainty.

The rest of this paper is organised as following: we begin by reviewing related works on sensor selection schemes for group target tracking (Section 2). We explain the models and assumptions that form the underlying foundations of this study in Section 3. We propose and discuss different steps of MSGT scheme in Section 4. The simulation settings and performance of the proposed MSGT is illustrated in Section 5, and Section 6 concludes the paper.

2. Related work

There are many existing works to address the problem of single target and multiple-target tracking in the context of Bayesian estimation (Wei et al., 2009; Tharmarasa et al., 2011; Tharmarasa et al., 2009; Ling et al., 2011; Vercauteren and Wang 2010; Kaplan 2006; Armaghani et al., 2012; Armaghani et al., 2012; Lundgren et al., 2013; Pulford 2005; Mahler 2013). However, sensor selection for group target tracking under Bayesian framework has so far not been addressed adequately in the literature. Most of the studies in group target tracking aimed at modelling the behaviour of groups and their evolutions, e.g., splitting and merging, and developed a joint group localisation strategy accordingly. The main observations of these studies could be summarised as follows: since a large number of targets move together with locations normally close to each other, e.g. a convoy of targets, it is not easy to associate the data and separately localise the targets. However, the joint tracking of dependant targets is computationally more efficient and will lead to greater estimation ability (Sze Kim et al., 2008; Mihaylova et al., 2014). Moreover, sensor energy could be greatly conserved by processing less computation and communication.

The joint tracking of a single group was presented in (Feldmann et al., 2011; Koch 2008; Gilholm and Salmond 2005; Mahler 2003). Obviously, these methods suffer from low performance in dealing with multiple groups. Since it is important for a group target tracking algorithm to be intelligent and adaptive, recent research studies incorporated the behavioural properties of groups in concurrent tracking of multiple groups (Sze Kim et al., 2011; Lian et al., 2010; Septier et al., 2009; Carmi et al., 2009).

Concurrent tracking of multiple groups based on evolving graphs has been recently addressed in a few studies (Gning et al., 2011; Clark and Godsill 2007). The idea of evolving graphs is to model the behavioural properties of groups by creating a graph of connected components. Each node of the graph corresponds to a target's location. Edges between the targets exist when the positions and velocities fall within some distance criterion. The modelling of the graph facilitates the incorporation of new nodes, removal of nonexistent nodes, and update of the edges.

The common approach in most of previously discussed studies is to use Particle Filtering as the localisation algorithm. Particle Filtering is regarded as one of the most practical and efficient class of methods for the solution of optimal estimation of probability distributions (Vermaak et al., 2005; Doucet and Johansen 2009).

The previously discussed works on tracking multiple groups suffer from the following limitations: (1) No strategy is considered for the number of active sensors in dealing with the accuracy-lifetime trade-off. Thus, sensor resources are wasted by collecting measurements from all sensors in the estimation procedure. (2) The employed clustering techniques to capture the behavioural changes of the groups are not fully suitable for group target tracking applications. An efficient and suitable clustering algorithm should provide acceptable performance measures such as low computation time, high clustering accuracy, and low memory utilisation. In this paper, we primarily focus on the problem of sensor selection for group target tracking. One can refer to our previous publication (Armaghani et al., 2012) for more details on the clustering problem for group target tracking.

There are very limited studies in sensor selection for group target tracking in the literature. Cao et al. (2010) presented a