Automatica 47 (2011) 2749–2756

Contents lists available at SciVerse ScienceDirect

Automatica

journal homepage: www.elsevier.com/locate/automatica

Brief paper

Decentralized adaptive awareness coverage control for multi-agent networks☆

Cheng Song[a,b,c,1], Gang Feng[a,c,d], Yuan Fan[e], Yong Wang[b,c]

[a] Department of Manufacturing Engineering and Engineering Management, City University of Hong Kong, Kowloon, Hong Kong
[b] Department of Automation, University of Science and Technology of China, Hefei 230026, China
[c] USTC-CityU Suzhou Joint Advanced Research Centre, Suzhou 215123, China
[d] School of Automation, Nanjing University of Science and Technology, Nanjing 210094, China
[e] School of Electrical Engineering and Automation, Anhui University, Hefei 230601, China

ARTICLE INFO

Article history:
Received 8 November 2010
Received in revised form
27 April 2011
Accepted 30 May 2011
Available online 4 October 2011

Keywords:
Awareness coverage
Adaptive control
Multi-agent networks

ABSTRACT

In this paper a novel problem of adaptive awareness coverage is formulated. We model the mission domain using a density function which characterizes the importance of each point and is unknown beforehand. The desired awareness coverage level over the mission domain is defined as a non-decreasing differentiable function of the density distribution. A decentralized adaptive control strategy is developed to accomplish the awareness coverage task and learning task simultaneously. The proposed control law is memoryless and can guarantee the achievement of satisfactory awareness coverage of the mission domain in finite time with the approximation error of the density function converging to zero.

1. Introduction

Recently, there has been an increasing interest in the development of coordination algorithms that allow the use of multiple sensor-equipped agents in practical applications (Cortes, Martinez, Karatus, & Bullo, 2004; Dimarogonas & Kyriakopoulos, 2009; Leonard et al., 2007; Ogren, Fiorelli, & Leonard, 2004; Zavlanos, Tanner, Jadbabaie, & Papps, 2009). These applications include search and rescue, environment surveillance and weather monitoring. One of the challenging problems in the coordination of sensing agents, in addition to tracking and swarm, is coverage.

In literature, coverage control is generally classified into two categories, that is, static coverage and dynamic coverage. In static coverage, the goal is to optimize the locations of agents to improve the quality of service provided by the multi-agent network. In Cortes et al. (2004), given a density function characterizing the importance of each point, a coverage control strategy based on centroidal Voronoi partitions is developed to drive each sensor to move towards the centroid of its corresponding Voronoi partition. In Cortes (2010), this approach is extended to the case with area-constraints. Distributed coverage algorithms for mobile sensor networks with limited power are developed in Kwok and Martinez (2010a). Instead of making use of a constrained optimization technique, this approach takes into account power constraints by assigning non-homogeneously time varying regions to each robot. The coverage control scheme based on Voronoi partitions is addressed in Kwok and Martinez (2010b) for a group of nonholonomic vehicles. In Li and Cassandras (2005), the authors consider a probabilistic network model and develop a distributed gradient-based algorithm to maximize the joint detection probabilities of random events.

Static coverage combined with other tasks has also been studied. The problem of simultaneously covering an environment and tracking intruders is addressed in Pimenta et al. (2010) by translating it to the task of covering environments with time-varying density functions under the locational optimization framework. In Schwager, Rus, and Slotine (2009), an adaptive, decentralized controller is presented to accomplish the static coverage task and learning task simultaneously. A consensus component is also introduced to improve the quality and speed of the learning procedure. In Wagenpfeil, Trachte, Hatanaka, Fujita, and Sawodny (2009), the authors propose an algorithm for switching from exploration task to coverage task to maximize the detected events taking place randomly in the mission space.

☆ This work was partially supported by a grant from the Research Grants Council of the Hong Kong Special Administrative Region of China under Project CityU-113209. This paper was not presented at any IFAC meeting. This paper was recommended for publication in revised form by Associate Editor Andrey V. Savkin under the direction of Editor Ian R. Petersen.

E-mail addresses: songchen@mail.ustc.edu.cn (C. Song), megfeng@cityu.edu.hk (G. Feng), yuanf@mail.ustc.edu.cn (Y. Fan), yongwang@ustc.edu.cn (Y. Wang).

[1] Tel.: +86 512 87161281; fax: +86 512 87161381.

0005-1098/$ – see front matter © 2011 Elsevier Ltd. All rights reserved.
doi:10.1016/j.automatica.2011.09.006

In the dynamic coverage scenario, sensors move in order to sample the area until every point in the given region has been covered with a prescribed coverage level. In Hussein and Stipanovic (2007a), coverage control laws for fully connected and partially connected networks are developed to achieve a satisfactory coverage of the mission domain. The coverage control law proposed in Hussein and Stipanovic (2007a) is modified in Hussein and Stipanovic (2007b) to guarantee collision-free coverage with a flocking behavior, which results in improved communication quality. Dynamic coverage control with heterogeneous vehicles is considered in Hussein, Stipanovic, and Wang (2007). Two classes of vehicles, coordination vehicles and coverage vehicles, are distinguished. The coordination vehicles simply coordinate the motions of the coverage vehicles by relaying coverage information in the connected network. The persistent coverage control problem is also addressed (Hokayem, Stipanovic, & Spong, 2007), where every point in the given region is revisited periodically. In Wang and Hussein (2010), the authors propose a novel dynamic awareness coverage model which describes how "aware" a group of vehicles is of events occurring over the task domain. A decentralized control law is developed to guarantee full awareness over a large-scale domain when awareness loss is not taken into account. Intermittent communication is also considered in reducing the amount of redundant coverage.

Although much research has been devoted to the dynamic coverage problem, little attention has been paid to the design of coverage control laws to adapt to changes in the environment. In many applications, agents often have no prior knowledge of the distribution of the density function in the mission domain, but they can reconstruct the distribution from their measurements by using the field estimation which has been studied intensively (Choi, Oh, & Horowitz, 2009; Graham & Cortes, 2009; Hussein, 2007; Martinez, 2010). In Martinez (2010), the author introduces a procedure to adapt local interpolations to provide a non-parametric estimation of spatial fields for a multi-vehicle sensor system. A control strategy based on Kalman filters is developed in Hussein (2007) to estimate a spatially-decoupled scalar field for mobile sensor networks. In Choi et al. (2009), a novel class of self-organizing sensing agents is presented, which can form a swarm and learn through noisy measurements to estimate an unknown field of interest.

In many existing works on the dynamic coverage problem, the desired coverage level is assumed to be identical for all points over the mission domain. However, in many applications the region of significant importance should be covered with a higher level with respect to other regions. For example, when a group of robots are deployed to monitor human activity over a town, the region with high intensity of the frequency range corresponding to the human voice should be sampled more frequently. This situation is modeled in this paper by introducing a concept of density functions which characterize the importance of each point in the mission domain. The main contributions of the present paper are threefold. Firstly, we formulate a novel problem named adaptive awareness coverage in which the coverage problem and learning problem are coupled. The desired coverage level is defined as a non-decreasing differentiable function of the unknown density distribution. Secondly, a decentralized motion control law and corresponding adaptation law are developed to accomplish the adaptive awareness coverage task when awareness loss is not taken into account. The proposed control strategy is memoryless in the sense that it is entirely based on the current information of the agents, independently of the historical information of the multi-agent network. It is therefore easily implementable. An update of awareness coverage is also considered to enhance cooperation of the networked agents. This procedure makes the adaptive control strategy discontinuous at the update time instants. Finally, the satisfactory awareness coverage of the mission domain can be achieved in finite time via the proposed control strategy due to the development of a finite-time perturbation motion control law in this paper.

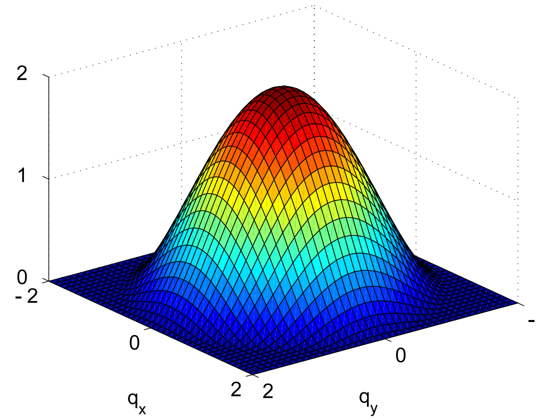

Fig. 1. Sensor function M_i with $q_i = (0, 0)$, $G_i = 2$, and $r_i = 2$.

The rest of the paper is organized as follows. In Section 2, the problem formulation of adaptive awareness coverage is presented. In Section 3, we derive a decentralized adaptive control scheme and prove its convergence. Simulation results are provided to illustrate the performance of the proposed control strategy in Section 4. Section 5 concludes the paper and describes directions for future work.

2. Problem formulation

Consider a system of N agents operating in the workspace $Q = \mathbb{R}^2$. The mission domain D is a compact subset of $\mathbb{R}^2$ which represents the region that should be covered by the agents. An arbitrary point in D is denoted by q. Each agent denoted by A_i, $i \in S = \{1, 2, \ldots, N\}$ has integrator dynamics

$$\dot{q}_i = u_i, \tag{1}$$

where $q_i(t)$ is the position of agent A_i and $u_i(t)$ is the control input.

2.1. Awareness coverage model

In this paper, we use the sensor model proposed in Hussein and Stipanovic (2007a) which is a polynomial function of $s_i = \|q_i - q\|^2$ within the sensory domain and zero otherwise

$$M_i(s_i) = \begin{cases} \dfrac{G_i}{{r_i}^4}(s_i - r_i^2)^2 & \text{if } s_i \le {r_i}^2, \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

An important feature of this model is a limited sensory domain $W_i = \{q \in D : \|q_i - q\| < r_i\}$ with sensory range r_i. Each agent has a peak sensory capability at the agent's position q_i and decreasing sensory capability along with the sensory range. Fig. 1 shows an example of the sensor model.

Given the sensor model, we can introduce the concept of awareness coverage. Each agent's awareness coverage of the mission domain is a distribution $\tilde{x}_i(q, t)$ which describes how "aware" the agent is of events occurring at a specific location q at time t. Without any loss of generality, we assume that $\tilde{x}_i(q, t) \in [0, 1]$. When the agent has no awareness of the point q, $\tilde{x}_i(q, t) = 0$. And $\tilde{x}_i(q, t) = 1$ indicates the point has attained full awareness coverage. Fixing a point $q \in D$, the awareness coverage of agent A_i at time t evolves according to the following differential equation

$$\begin{aligned} \dot{\tilde{x}}_i(q, t) &= -(M_i(\|q - q_i\|) - \alpha)(\tilde{x}_i(q, t) - 1), \\ \tilde{x}_i(q, 0) &= 0, \quad i \in S, \end{aligned} \tag{3}$$