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Addressing structural and observational uncertainty in resource management

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ABSTRACT

Most natural resource management and conservation problems are plagued with high levels of uncertainties, which make good decision making difficult. Although some kinds of uncertainties are easily incorporated into decision making, two types of uncertainty present more formidable difficulties. The first, structural uncertainty, represents our imperfect knowledge about how a managed system behaves. The second, observational uncertainty, arises because the state of the system must be inferred from imperfect monitoring systems. The former type of uncertainty has been addressed in ecology using Adaptive Management (AM) and the latter using the Partially Observable Markov Decision Processes (POMDP) framework. Here we present a unifying framework that extends standard POMDPs and encompasses both standard POMDPs and AM. The approach allows any system variable to be observed or not observed and uses any relevant observed variable to update beliefs about unknown variables and parameters. This extends standard AM, which only uses realizations of the state variable to update beliefs and extends standard POMDP by allowing more general stochastic dependence among the observable variables and the state variables. This framework enables both structural and observational uncertainty to be simultaneously modeled. We illustrate the features of the extended POMDP framework with an example.

1. Introduction

There is growing interest in the world of natural resource and conservation management in making dynamic decisions that are optimal with respect to the current state of knowledge and specified performance objectives (e.g., meet a target of level of biodiversity at the lowest cost possible). Although several approaches exist for obtaining optimal solutions for dynamic decision problems, perhaps the most common approach uses Markov Decision Process (MDP) framework (Puterman, 2005; Marescot et al., 2013). Recent examples in the ecological literature include confronting climate change (Conroy et al., 2011; Martin et al., 2011a), controlling invasive species (Regan et al., 2006, 2011), monitoring/managing rare or threatened species (Chadès et al., 2008, 2011; McDonald-Madden et al., 2010), managing disease outbreaks (Chadès et al., 2011), determining optimal harvest rates (Johnson et al., 1997; Moore et al., 2008; Williams, 1996; Williams et al., 1996), efficiently allocating conservation resources (McCarthy et al., 2010; McDonald-Madden et al., 2011), and balancing human-wildlife conflicts (Martin et al., 2011b).

An important feature of the MDP framework is the ability to account for several sources of uncertainty that directly influence system dynamics. Williams (2011a) suggests a classification for uncertainties that commonly arise in natural resource conservation and management. These include (1) environmental variation, due to the natural randomness of environmental conditions, (2) partial controllability, which arises due to the inability of managers to perfectly predict the results of their actions, (3) structural uncertainty, due to imperfect knowledge of how a system works and (4) observational uncertainty, which arises because the state of a system must be inferred from imperfect monitoring systems. The first two types of uncertainty (environmental and partial controllability) can be handled in the standard MDP framework whereas the latter two types of uncertainty (structural and observational) require modifying the standard approach by replacing unobserved variables or parameters with probability distributions.

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Structural uncertainty arises when the system describing either state variables dynamics or performance variables (variables directly affecting utility) is not well understood. This uncertainty can be described in terms of a discrete set of uncertain parameters (often referred to as model uncertainty) or in terms of one or more uncertain continuous parameters (often referred to as parametric uncertainty). In ecological applications, addressing structural uncertainty is known as adaptive management (Holling, 1978; Walters, 1986; Williams, 2011a), wherein management decisions are made at the same time that system information is accruing, a kind of "learning while doing." In this framework newly collected information helps to resolve structural uncertainty, resulting in new estimates of unknown parameters. Management decisions may be taken that reflect an anticipation of this learning. It is therefore possible that some actions that lead to faster learning may be optimal even though these actions would be sub-optimal if the system structure were known with certainty.[1]

Structural uncertainty can be addressed by augmenting a model with a set of additional state variables that define a probability distribution over the unknown features of that structure. As new information becomes available these belief distributions are updated using Bayes Rule. When the uncertainty is characterized by a discrete set of possible values (i.e. model uncertainty) this distribution can be represented by a discrete set of probability weights. When uncertain parameters are continuous, a density function can be defined for each uncertain parameter. In some cases these distributions and the system model form conjugate pairs (so the updated belief distribution has the same functional form as the prior). An example in the ecological literature is the Beta/Binomial model used in Hauser and Possingham (2008). More generally, projection methods can be used wherein the updated (posterior) distribution is projected onto a parametric family of belief distributions. The projection approach is described in detail in Zhou et al. (2010) and is applied to a resource management problem by Springborn and Sanchirico (2013). In the current paper we concentrate on the discrete parameter case, which is sufficient to illustrate the principles involved.

In contrast to structural uncertainty, observational uncertainty arises when state variables cannot be directly observed and decisions must be made on the basis of observed variables that do not fully describe the system dynamics. This situation arises quite commonly in resource management. For example many rare, threatened or cryptic species are very difficult to observe and even populations of commercially harvested species, especially marine species, are only known imperfectly. Additionally, much of our information on system states comes through empirical data and inferential models subject to many sources of bias (Williams et al., 2002). To address imperfect observation data in the context of decision making, conservation scientists have relied on Partially Observable Markov Decision Processes (POMDP) (Monahan, 1982). As with adaptive management, the POMDP approach replaces the unobserved state variable with a probability distribution and actions are taken based on the current value of that distribution.

[1] Discussions of adaptive management often distinguish between "passive" and "active" adaptive management (Williams, 2011b). With passive adaptive management structural uncertainty in making current decisions is ignored but probability models are updated as new information becomes available before future decisions are taken. This approach does not require any modifications to standard dynamic programming algorithms. Here we focus on active adaptive management where actions may be taken in order to learn about the system if that learning is expected to improve future management decisions.

Lane (1989) was the first to apply the POMDP approach to a resource management problem in an application to salmon fishing decisions when the stock of salmon is not directly observed. Most of the studies using the POMDP approach in the resource management area have examined issues relating to monitoring, including applications to the monitoring of conservation contracts (Crowe and White, 2007; White, 2005), monitoring and control of invasive species (Haight and Polasky, 2010; Regan et al., 2006, 2011), monitoring habitat quality (Tomberlin and Ish, 2007) and monitoring for the presence of endangered species (Chadès et al., 2008; Tomberlin, 2010).

Recently a few studies have explored linkages between POMDPs and structural uncertainty. Williams (2011a) describes the conceptual issues and argues that the computational techniques for solving POMDPs might be fruitfully applied to problems involving structural uncertainty. McDonald-Madden et al. (2010) solves an adaptive management problem in which the goal was to identify the unknown correct model out of three possible models. The true model is viewed as an unobservable state which is replaced by a set of belief weights. Although the explicit link to POMDPs is not made in McDonald-Madden et al. (2010), this model can be solved using a standard POMDP approach. The linkages between structural uncertainty and POMDPs have also been a topic that several authors have addressed outside of the ecological or environmental literature. Ko et al. (2010) discuss adaptive learning, which they refer to as parameter elicitation, where in addition to the traditional partial observability (handled via POMDP), there is an active effort to gather information about parameter values that describe the physical system (i.e., to resolve structural uncertainty). Chadès et al. (2012) has taken the furthest step in this direction by describing a framework using Mixed Observability MDPs (MOMDPs), in which some state variables are directly observed and some are not, and showing how it can be used to solve standard AM problems. Chadès et al. (2012) also suggest that this framework (via MOMDPs) could be used to address partial observability (referred to as detection probability) and structural uncertainty simultaneously, but do not explicitly do so.

Addressing structural and observational uncertainty has been hampered by a lack of flexibility in existing approaches. In standard AM applications beliefs are updated using only the new observations of the state variables. In POMDP applications the observational variables are taken to be pure monitoring variables that have no influence on the system; such pure monitoring variables would not need to be considered if observational uncertainty was not present. Furthermore, until the development of the MOMDP framework, POMDP approaches assumed that all state variables are unobserved. In this paper we aim to build a synthesis by suggesting a more general framework that extends POMDPs and encompasses both standard POMDP and adaptive management. By allowing for mixed observability, in which some state variables are observed and some are not, those aspects of a model in which uncertainty plays the largest role can be targeted. By allowing for non-state system variables to be observed, learning is not limited simply to monitoring signals about the state variable, thereby leading to possible increases in the speed and value of learning. In addition the approach allows for both structural uncertainty and partial observability to be handled in a common framework in which both could play a role simultaneously. The software for solving models using the extended POMDP approach will be incorporated into the next release of the MDPSolve program (Fackler, 2011), a MATLAB based program available at https://sites.google.com/site/mdpsolve/.

In the remainder of the paper we provide an overview of MDPs, AM, and POMDPs, then describe our extension of POMDPs, and provide a simple example which incorporates both structural and