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Context-based behaviour modelling and classification of marine vessels in an abalone poaching situation

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A B S T R A C T

A decision-support system for combating abalone poaching is proposed. A dynamic Bayesian network (DBN) is used to model context-based behaviour of vessels in a maritime abalone poaching situation. The context and behaviour is informed by Expert knowledge. The model is utilised for both data generation and behaviour classification. Data generation is performed by sampling in the DBN. The result is that a set of vessels are simulated in an abalone poaching situation. Several vessel classes including poaching, patrol, fishing, tourist, and recreational vessels are modelled. The generated data is intended to model surveillance data that may have been produced by sensors such as optical, infrared or radar sensors. Classification is performed using the filtering and smoothing inference methods on the DBN. A vessel class is inferred given tracked vessel data and contextual information. The purpose is to identify vessels that exhibit poaching behaviour. The novelty of this work includes a derivation of the generalised pseudo Bayes smoothing algorithm for the classification model. This smoothing algorithm is demonstrated to provide more accurate classification results than the previously proposed filtering method.

1. Introduction

There is an increased need for behaviour modelling in problems such as human surveillance, homeland security, illegal immigration, and poaching. Behaviour is a temporal entity that is influenced by various contextual factors. Modelling behaviour requires complex models that are able to perform information fusion while modelling sequential data. The generative model by Dabrowski and de Villiers (2015a) and classification model by Dabrowski and de Villiers (2015b) were developed for the purpose of modelling such problems. The models provide a theoretical framework for modelling context-based behaviour using the dynamic Bayesian network (DBN). Behavioural activities are modelled using a regime based motion model. Contextual data from various sources are fused into the model through the entering of evidence into the DBN. In this study these models are applied to the abalone poaching problem using expert knowledge.

The abalone poaching problem has led to the depletion of abalone populations. Involvement of international drug related syndicates in poaching results in public safety concerns. Furthermore, local fishing industries are affected by seasonal quotas and region restrictions enforced to reduce over harvesting. Patrols have been deployed with limited success due to the vastness of the regions monitored. Electronic sensors may assist law enforcement agencies in monitoring the regions. The large amounts of data generated by these sensors may however require models and algorithms to assist in detecting poachers. In this study, the behavioural models are applied to identify abalone poachers in an abalone poaching situation.

The purpose of this study is to apply and test the generative and classification models to an abalone poaching situation. The application of the generative and classification models is informed by expert knowledge from literature on abalone poachers. The generative model has the purpose of generating data that could emulate electronic sensor data of surveyed regions. This generated data consists of sequential tracks of modelled vessels as well as contextual information that influence behaviour. The classification model uses such data in the behavioural

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model to infer the vessel class. Inferring the class of a poacher vessel provides the means to identify abalone poachers. Classification is performed using filtering and smoothing inference methods.

The contribution of this study includes the extension the work presented by Dabrowski and de Villiers (2015b) with a smoothing algorithm. This smoothing algorithm is demonstrated to improve the results of the previously proposed filtering algorithm. Furthermore, this is the first application of poacher behaviour modelling and detection found in the scarce abalone poaching literature. The results of this work could be useful to law enforcement and government agencies in understanding and combating abalone poaching. Finally, this study demonstrates how expert knowledge of a new problem can be applied to the generative (Dabrowski and de Villiers, 2015a) and classification (Dabrowski and de Villiers, 2015b) models. These are generic models that may be applied to wide variety of related problems.

This paper begins by introducing the generative and classification models used in this study in Section 2. Section 3 provides a review of the literature. The review describes related models and anti-poaching methods. In Section 4 a survey on abalone poacher behaviour is presented. The expert knowledge from this survey is used to inform how the generative and classification models are applied to the abalone poaching problem. The application of the generative and classification models to the abalone poaching problem are presented in Section 5 and Section 6, respectively. The generative model is used to produce a dataset consisting of simulations of various vessel classes. Results of the generative model are provided in Section 7. The classification model is applied to the dataset that is produced by the generative model. The classification results are provided in Section 8. The methodology of application of the models in a decision support system is presented in Section 9. A summary and conclusion is presented in Section 10

2. Generative and classification models

The models used in this study provide the means to model the behaviour of various agents in a particular situation. The models are in the form of a DBN. The DBN is an extension of a Bayesian network (BN) through time. The BN is directed acyclic graphical model (Koller and Friedman, 2009). A directed graphical model comprises nodes that represent random variables and directed links or edges that represent conditional dependencies between the random variables.

In this study, the Markov assumption is used to extend the BN through time to form the DBN. The first order Markov assumption assumes that the current state is conditionally dependent only on the previous state. This assumption results in a Markov chain (Barber, 2012). In many applications, the random variables in a Markov chain are not observable. The Markov chain can be extended to include variables that are observable and are conditionally dependent on the unobservable variables. The graphical representation of this model is presented in Fig. 1. This graphical model describes both the hidden Markov model (HMM) and the linear dynamic system (LDS) (Barber, 2012). The markov chain is formed by the hidden (unobservable) random variables $\dots, h_{t-1}, h_t, h_{t+1}, \dots$. Each visible (observable) variable v_t is conditionally dependent on its corresponding hidden variable h_t. The joint probability distribution of this DBN over a time period of $t = 1 : T$ is given by

$$p(h_{1:T}, v_{1:T}) = p(h_1)p(v_1|h_1)\prod_{t=2}^{T} p(h_t|h_{t-1})p(v_t|h_t).$$

In this study we extend the LDS to include additional variables to provide the means for behaviour modelling and information fusion.

The graphical model structure of the general model, which represents both the generative and classification models is presented in Fig. 2 (Dabrowski and de Villiers, 2015a,b).

The model consists of an agent class c, a set of contextual elements $\bar{a}_t$, a switching state s_t, a state vector h_t, a control vector u_t, and a measurement vector v_t. Variables v_t, h_t, and optionally u_t form a LDS.

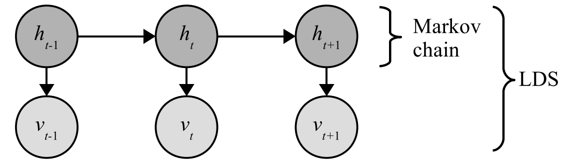

Fig. 1. The graphical model representing a Markov chain of unobservable variables with corresponding observable variables. This graphical model describes both the HMM and the LDS.

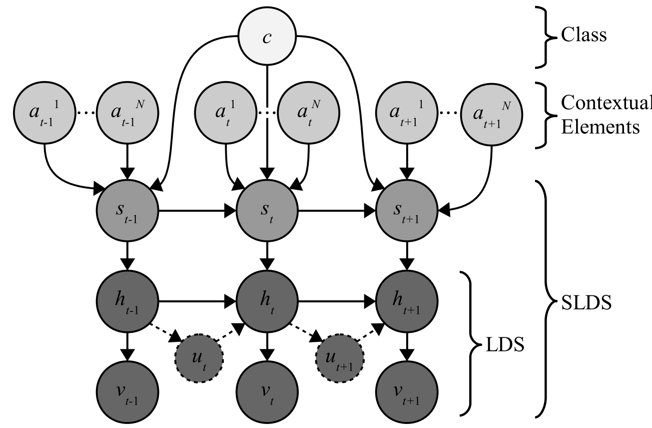

Fig. 2. General model for context-based behavioural modelling (Dabrowski and de Villiers, 2015a,b). The model is based on the switching linear dynamic system (SLDS) and the linear dynamic system (LDS). The control vector u_t is only necessary in the generative model and is thus represented with dashed lines. Note that for the sake of readability, links from the c to h_t and from a_t^n to h_t are not illustrated.

Variables s_t, v_t, u_t, and h_t form a switching linear dynamic system (SLDS).

The framework for behaviour modelling is provided by the SLDS. The SLDS is a regime based model that models systems that switch between various linear dynamic models (Barber, 2012; Murphy, 2012). This provides the means to model an agent that switches between various kinematic behavioural activities. A class variable c is added to the SLDS for the purpose of modelling various classes of agents that are involved in a considered situation. Contextual elements $\bar{a}_t$ are added to the SLDS for the purpose of fusing context-based information that influences behaviour into the model.

2.1. Generative model

The purpose of the generative model is to simulate agent behaviour and produce data. The measurement vector v_t could represent data from a sensor. The generation of data is performed by sampling from the class and contextual elements down to the measurement vector. This may be performed using the ancestral sampling method. By sampling at each time-step, a sequence of tracked measurements of the modelled agent is generated.

The control vector u_t and a journey parameter are required by the generative model. The control vector u_t is used to drive the LDS model of a particular agent. To direct the agent a journey parameter is required. This parameter is provided as a contextual element. The journey parameter defines start, destination, and routes that the agent should follow. The journey parameter is a unique contextual element in the sense that it is dependent on the agent class c and not necessarily dependent on time (Dabrowski and de Villiers, 2015a).

2.2. Classification model

The purpose of the classification model is to classify an agent according to its behaviour. Classification of agents is performed by