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A unified model for context-based behavioural modelling and classification

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ABSTRACT

A unified Bayesian model that simultaneously performs behavioural modelling, information fusion and classification is presented. The model is expressed in the form of a dynamic Bayesian network (DBN). Behavioural modelling is performed by tracking the continuous dynamics of a entity and incorporating various contextual elements that influence behaviour. The entity is classified according to its behaviour. Classification is expressed as a conditional probability of the entity class given its tracked trajectory and the contextual elements. Inference in the DBN is performed using a derived Gaussian sum filter. The model is applied to classify vessels, according to their behaviour, in a maritime piracy situation. The novel aspects of this work include the unified approach to behaviour modelling and classification, the way in which contextual information is fused, the unique approach to classification according to behaviour and the associated derived Gaussian sum filter inference algorithm.

1. Introduction

Several dynamical models have been proposed in expert system literature for behaviour modelling, information fusion and classification of time series data. Methods include machine learning algorithms, fuzzy time series models, Box–Jenkins models, state space models, Bayesian networks and dynamic Bayesian networks. The models are often formulated with layers of different methods to achieve the desired goal. The layers or steps involve operations such as data preprocessing, feature extraction, information fusion and training. Preprocessing methods often involve partitioning and clustering of time series data resulting in loss of information. The complexity and variation increase with the number of methods and layers included in such models. Furthermore, behaviour is often a complex temporal entity. Many methods are not able to naturally consider causal relationships of variables over time. Methods that are able to consider temporal relationships are however often limited to application or task.

In this study a novel model that performs behaviour modelling, information fusion and classification simultaneously is proposed. Behaviour modelling is performed by modelling the continuous dynamics of a target. Information fusion involves the integration of contextual elements that influence behaviour. Classification is performed based on behaviour. The model is initialised by defining probabilistic relationships between variables. Once initialised, no preprocessing or feature extraction is required during its on-line operation. Only sequential tracked locations of a target and the contextual element data are required. The Markovian component of the model allows for the modelling of temporal relationships in a causal manner.

In the context of this study, behaviour may be described according to the activities a system engages and how the system transitions between these activities. The behaviour is modelled by defining a set of behavioural activities and ascribing Markovian transition probabilities between the activities. Each activity is modelled according to predefined dynamics. The transitions between activities are influenced by contextual information. By tracking the behaviour of the system, a class may be inferred.

The proposed model is in the form of a dynamic Bayesian network (DBN). It consists of several functional components that include a linear dynamic system (LDS), a switching state variable, a set of contextual element variables and a class variable. The LDS is included to model the continuous dynamics of behavioural activities. The Markov based switching state variable is included to model the transitions between various behavioural activities. The LDS and switching state variable together form a switching

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linear dynamical system (SLDS). The set of contextual element variables are included for the fusion of contextual information that influences behaviour. The class variable is included for classification. The Gaussian sum filtering (GSF) algorithm is applied to perform inference on the DBN for the purpose of classification.

The model is applied to the problem of classifying vessels in a maritime piracy situation. The problem of identifying maritime pirate vessels is scarcely addressed in literature. A dataset of simulated vessels operating within a maritime piracy situation is utilised. The simulated data consists of tracked location data, ocean conditions, weather conditions, time of day, season of year, regional location data and vessel class ground truth. Each vessel in an environment is classified as either a pirate, transport or fishing vessel. The results presented demonstrate a classification accuracy of between 71.6% and 99.5% depending on the differences in kinematics of the vessel classes.

2. Related work

The method presented in this study is unique. To affirm this, a literature study that covers a wide range of applications and methods is thus conducted. The survey has a focus on expert systems and recent publications. Studies that consider behaviour modelling of maritime vessels, humans and animals considered. Time series analysis and forecasting methods are explored. Forecasting methods are relevant as they require a dynamic model of a system to perform forecasting. Related context-based and information fusion applications are discussed. Finally, maritime piracy related methods are covered. It is noted that there are few studies in the literature that attempt to identify maritime pirate vessels.

2.1. Maritime vessel behaviour modelling

Various methods in the literature have been proposed for modelling behaviour of maritime vessels. DBN and kinematic based models are of particular interest. A DBN is applied for abnormal maritime vessel behaviour detection in Castaldo, Palmieri, Bastani, Marcenaro, and Regazzoni (2014). An event-based DBN is applied to describe causal relationships of normal ship movements. Normal ship movements are related to specific zones defined by a topographical map. A low level observation layer is defined to analyse trajectories. A high level event layer is defined where zone changes are used to detect abnormal behaviour. The method performs on-line learning of behaviours. Mazzarella, Vespe, Damalas, and Osio (2014) propose a method for discovering maritime vessel activities using automatic identification system (AIS) data. The AIS data is used to discover fishing areas. A 'stops' and 'moves' trajectory partitioning method is used to detect fishing behaviour events. This method essentially utilises the motion dynamics of the vessel to detect activities. For example, fishing is characterised by significant variations in course over ground. Fishing regions are discovered through the clustering of detected fishing events. These studies demonstrate that tracked data and trajectory may be effectively used for behaviour modelling.

2.2. Human behaviour modelling

Human behaviour modelling and detection is an application that has been widely studied in the field of computer vision and surveillance. The approach to behaviour modelling proposed in this study may be considered to stem from approaches presented in this field. Furthermore, the model proposed in this study may easily be applied to the human behaviour detection problem. Surveys on human behaviour recognition are presented in Gowsikhaa, Abirami, and Baskaran (2014), Turaga, Chellappa, Subrahmanian, and Udrea (2008) and Hu, Tan, Wang, and Maybank (2004). Methods for human behaviour analysis include graphical models (including the DBN), the HMM, rule-based approaches, support vector machines, syntactic approaches, dynamic time warping, finite state machines and neural networks. Of particular relevance to this study is the DBN, the HMM and other state space methods such as the linear dynamical system (LDS).

State space models are the most commonly used methods for modelling temporal dynamics in human behaviour recognition applications (Turaga et al., 2008). The Kalman and particle filters are popular filtering methods for tracking. Hernàndez, Cabido, Montemayor, and Pantrigo (2014) propose a method for human activity recognition based on kinematic features. Of particular interest, the humans are tracked using a state space model and a local search particle filter. Walia and Kapoor (2014) propose an evolutionary particle filter for object tracking that is based on the improved cuckoo search. Luo et al. (2014) use the parameters of a robust linear dynamical system as motion features. Human actions are classified using the maximum margin distance learning method by combining the motion features and local appearance features. A recent expert system application using the HMM is presented in Kodagoda and Sehestedt (2014). A sampled HMM is used to model pedestrian motion patterns and simultaneously track people with a particle filter. The model provides the means to track pedestrians under long term occlusions. These studies demonstrate the ability for state space methods to track and model complex objects.

The DBN is a parametric method that is well suited to model complex actions (Gowsikhaa et al., 2014; Turaga et al., 2008). Various forms of DBNs have been proposed in literature for human behaviour modelling (Gowsikhaa et al., 2014; Turaga et al., 2008). A recent example of such a system is presented in Wang and Ji (2014). The model provides the means to simultaneously incorporate contexts into a unified model. Various layers of the model are compiled. These layers include object detection, tracking and feature selection. The DBN is trained according to the features. The DBN is described as a coupled HMM that captures dynamic interaction between target appearance and motion.

The human behaviour modelling applications described generally use the DBN to model dynamics of the systems. The DBN is not necessarily used for information fusion as well as classification. The method proposed in Wang and Ji (2014) does allow for context to be included. However, the DBN is modelled on high level features that have been extracted from the data.

2.3. Animal behaviour modelling

Expert systems for animal behaviour classification is particularly relevant in livestock applications. Classification of behaviour provides a means to manage and monitor livestock. In general, the livestock are monitored using collars containing sensors such as global positioning systems and inertial measurement units (accelerometers). A method that represents different cattle motions using mixture models has been proposed in Gonzalez, Bishop-Hurley, Handcock, and Crossman (2015). A decision tree is used to classify behaviour according to thresholds defined by the mixture models. In another application, a two stage classifier is proposed for cattle behaviour classification (Dutta et al., 2015). In the first stage, clustering is performed using probabilistic principle component analysis, Fuzzy C-means and self organising maps. In the second phase the clustering results are classified using an ensemble classifier using ensemble methods such as bagging and AdaBoost along with classification methods such as binary tree, linear discriminative analysis and naive Bayes classifiers. Similar