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Hierarchical and incremental event learning approach based on concept formation models

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ABSTRACT

We propose an event learning approach for video, based on concept formation models. This approach incrementally learns on-line a hierarchy of states and event by aggregating the attribute values of tracked objects in the scene. The model can aggregate both numerical and symbolic values.

The utilisation of symbolic attributes gives high flexibility to the approach. The approach also proposes the integration of attributes as a doublet value-reliability, for considering the effect in the event learning process of the uncertainty inherited from previous phases of the video analysis process.

Simultaneously, the approach recognises the states and events of the tracked objects, giving a multi-level description of the object situation.

The approach has been evaluated for an elderly care application and a rat behaviour analysis application. The results show that the approach is capable of learning and recognising meaningful events occurring in the scene, and to build a rich model of the objects behaviour. The results also show that the approach can give a description of the activities of a person (e.g. approaching to a table, crouching), and to detect abnormal events based on the frequency of occurrence.

1. Introduction

Video event learning presents relevant applications related to abnormal behaviour detection, as elderly health care [1,2], and traffic monitoring [3]. In this sense, the utilisation of incremental models for event learning should be the natural step further real-time applications for handling unexpected events. Apart from being well-suited for real-time applications because of the inexpensive learning process, this incremental characteristic learning allows the systems to easily adapt their response to different situations. Also, the dependence on enormous data-sets for each particular application is reduced.

The focus of this work is in applications for incremental event learning, where several objects of diverse type can interact in the scene (e.g. persons, vehicles). The events of interest are also diverse (e.g. events related to trajectories, human posture) as the focus of interest is learning events in general. The objects simultaneously evolving in the scene can be many, but the interest is centred in objects which can be individually tracked in order to be able of recognising the events each object is participating.

We propose a new event learning approach, which aggregates on-line the attributes and reliability information of tracked objects (e.g. people) to learn a hierarchy of concepts corresponding to states and events. Reliability measures are used to focus the learning process on the most valuable information. Simultaneously, the approach recognises new occurrences of states and events previously learnt. The only hypothesis of the approach is the availability of tracked object attributes, which are the needed input for the approach. This approach is able to learn states and events in general, so no limitation is imposed on the nature or number of attributes to be utilised in the learning process.

As previously described, the hierarchical model of the proposed approach can be incrementally updated. This feature is based on incremental concept formation models [4]. These concept formation models evaluate the goodness of the concepts represented by the formed clusters in a hierarchical model, with the added constraint that learning must be incremental. The main contributions of the proposed learning approach, with respect to incremental concept formation models, are:

- The capability of the hierarchical model to learn events, as an explicit transition between two states (described in Sections 3.1 and 4.4).

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- The utilisation of reliability measures for weighting the contribution of data according to their quality, as a way to focus learning on meaningful information (for details, see Section 4.3).
- The extended utilisation of the concept of acuity to represent different normalisation scales and units associated to different attributes, and also represent the interest of users for different applications (see Section 3.2, for details).
- The incorporation of the acuity to the numerical category utility, in order to balance the contribution of numerical and symbolic attributes to the category utility (see Section 4.2).

In a step further to bridge the gap between image-level data and high-level semantic information, this work extends previous work presented in [5,6] by integrating symbolic attribute information to the hierarchical model in a way that both numerical and symbolic attribute values can be in a common state model. The utilisation of symbolic attributes gives high flexibility to the approach, allowing the user to add significantly semantic attributes for assisting on scene interpretation.

Also, the approach can simultaneously learn different hierarchies representing different learning contexts (i.e. different states and events of interest). We propose a general representation for the context of each learning process and extend the analysis of each involved process for an easier implementation. The source code of the algorithm is publicly available.[1]

The approach has been extensively verified over both simulated and real data-sets. The real data-sets have been utilised for specific events for home-care (e.g. approaching to a table, crouching) and rat behaviour learning (position and velocity events).

This paper is organised as follows. In Section 2 the state-of-the-art on incremental event learning approaches is presented. Section 3 describes the proposed event learning approach in general, and Section 4 focuses on describing the learning process in detail. Finally, Section 5 presents the experiments performed on simulated and real data-sets.

2. State-of-the-art

Most of video event learning approaches for abnormal behaviour recognition are supervised, requesting annotated videos representative of the events to be learnt in a training phase [7–9]. As well described in [10], these approaches normally use general techniques as hidden Markov models (HMM) [11]. Some authors use hierarchical models, as they facilitate learning and generalisation. HMMs are robust, but require hierarchical (HHMM) and time-duration modelling for representing events with varying temporal and spatial scales, increasing the complexity of these approaches.

Generalisation is one of the keys to simplify the process of semantic interpretation. In [12], the authors propose an approach for abnormal behaviour detection, using unsupervised learning for two hierarchical representations, one for description of the observation and the other for temporal description. In [13], the authors proposed a fall detection algorithm that uses HHMM, hand designed and operating on an observation sequence of rectified angles.

Few approaches can learn events in an unsupervised way using clustering techniques. For instance, [14] use the clusters of attributes obtained with a Gaussian mixture model to represent the states of an HMM, [15] learn events using spatial relationships between objects in an unsupervised way, but performed off-line, and [16] apply unsupervised learning of composite events using the APRIORI clustering algorithm. However, these unsupervised clustering techniques request to (re)process off-line (not real-time) the whole cluster distribution.

Some other techniques can learn on-line the event model by taking advantage of specific event distributions. For example, [17] propose a method for incremental trajectory clustering by mapping the trajectories into the ground plane decomposed in a zone partition. Their approach performs learning only on spatial information, it cannot take into account time information, and do not handle noisy data.

In conclusion, few work has been found on hierarchical and incremental approaches for abnormal behaviour detection. A critical aspect not considered in the current approaches is the uncertainty of mobile object attributes present in real applications and how this uncertainty can affect the model construction.

Following these directions, the current work is based on *incremental concept formation models* [4]. The knowledge is represented by a hierarchy of concepts partially ordered by generality. A *category utility* function is used to evaluate the quality of the obtained concept hierarchies [18].

The proposed approach takes profit of this hierarchical structure, extending it to represent events, incorporate the effect of uncertainty in data, and to manage symbolic attributes which facilitate semantic interpretation.

3. Incremental state and event learning approach

As previously stated, the proposed approach is an extension of incremental concept formation models [4,19] for learning video events. The approach uses as input a set of attributes from the tracked objects in the scene. Hence, the only hypothesis of the approach is the availability of tracked object attributes (e.g. position, posture, class, speed).

The proposed approach has been called *MILES*, acronym standing for Method for Incremental Learning of Events and States. The approach has received its name since its first version, presented in [5]. MILES state hierarchy construction is mostly based on COBWEB [20] algorithm, but also considering ideas from other existing incremental concept formation approaches, as CLASSIT [4] algorithm.

3.1. The hierarchy of states and events

MILES builds a hierarchy of state and event concepts **H**, based on the state and event instances extracted on-line from the tracked object attributes. It is desirable (but not necessary) that the input data contains an estimate of the reliability on information. This hierarchy is formed by two building blocks:

State concept: It is the modelling of a state, as previously defined. A state concept $S^{(c)}$, in a hierarchy **H**, is modelled as:

- its number of occurrences $N(S^{(c)})$ and its probability of occurrence $\mathcal{P}(S^{(c)}) = N(S^{(c)})/N(S^{(p)})$. ($S^{(p)}$ is the root state concept of **H**),
- the number of event occurrences $N_E(S^{(c)})$, corresponding to the number of times that the state $S^{(c)}$ passed to another state, generating an event.
- a set of numerical attribute models $\{n_i\}$, with $i \in \{1,..,T\}$, where n_i is modelled as a random variable N_i which follows a Gaussian distribution $N_i \sim \mathcal{N}(\mu_{n_i}; \sigma_{n_i})$,
- a set of symbolic attribute models $\{s_j\}$, with $j \in \{1,..,S\}$, where s_j is represented by every possible value for the attribute, and conditional probabilities $P(V_{s_j}^{(k)} | S^{(c)})$ representing the frequency of occurrence of a the k-th value $V_{s_j}^{(k)}$ for s_j, given $S^{(c)}$.

[1] The algorithm has been developed with C++, using QT libraries, and is available at http://profesores.elo.utfsm.cl/~mzuniga/MILES.zip.