TRAJECTORY CLASSIFICATION

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ABSTRACT

This paper presents Hidden Markov Models as a method for statistical modeling and classification of motion. Additionally, an application of Hidden Markov Models on trajectories extracted from video sequences obtained from surveillance cameras is presented. Finally, comparison of efficiency on different data sets, is discussed.

1 INTRODUCTION

Nowadays, large amount of data is produced by an increased number of surveillance cameras. This data is a potential source of useful information; however, information is in general difficult to obtain as suitable processing methods are often not available. In the face of present day terrorism threats, it could be very useful to apply machine learning methods on surveillance data.

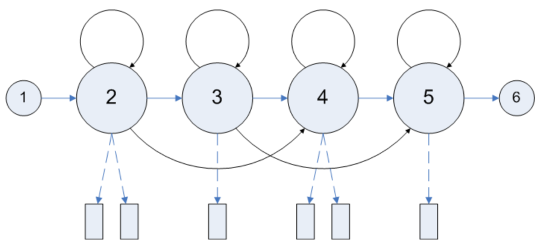


Figure 1: Hidden Markov Model

The recordings from surveillance cameras are usually processed as separated frames. In this way, an information about complex object behaviour cannot be extracted. The presented task, on the contrary, assumes that it is possible to identify security threats from behaviour of one object and to deduce information about complex behaviour from its trajectory.

The common sense suggests that the majority of trajectories from surveillance cameras belong to normal "boring" situations and the rest to potentially interesting situations. The presented approach is based on supervised training and classification using Hidden Markov Models.

2 BACKGROUND

Hidden Markov Models (HMM) approach belongs to supervised learning and statistical modelling methods for sequential data [1]. Example of a model shown Figure in 1.

The Baum-Welch algorithm [2] is used for training of the models. This algorithm modifies weights of transitions and statistics of the models. The Viterbi algorithm is used to evaluate the model by calculating probability of correspondence with the classes.

3 SYSTEM OVERVIEW

The process of classification is illustrated in Figure 2. Because tracking is very difficult task and the output of a simple tracker is usually very noisy, it is good to make some pre-processing to improve accuracy of results. The exploitation of HMM classifier could be divided into two phases – training and classification.

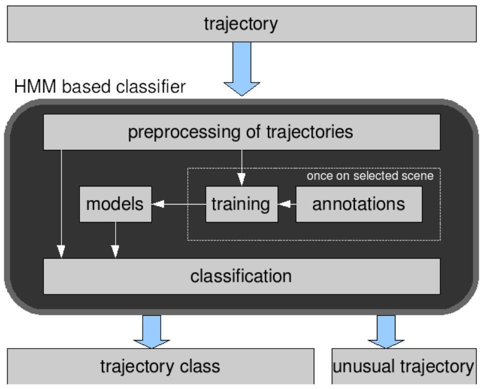


Figure 2: Schema of trajectory processing.

In Figure 2, the trajectory is a quadruple $[x, y, d_x, d_y]_t$, in which first two components are position and second two velocity parameters of an object at time t. Set of annotated trajectories represents the training set. The training phase is in the schematic diagram (Figure 2) highlighted using a dashed box and it is done once for each camera. First, the normal trajectories in the scene are defined. Secondly, initial models are defined for each trajectory class. Next, the trajectory classes in video sequence are marked (annotations) and models are adapted according to them (training process). The inputs are initial model and annotated trajectories, the output is a new classification model.

The classification step produces an evaluation for each trajectory. This part compares a trajectory with all models and decides which model best fits the trajectory. Inputs of the classification step are trajectories and classification models. The results are coefficients, which express the degree of correspondence of the trajectory with each class. According to the degree of correspondence, the class which best fits the trajectory is determined. In case the likelihood of trajectory is low for all models, the trajectory is assumed to be abnormal. The threshold for abnormal trajectories must be set by hand.

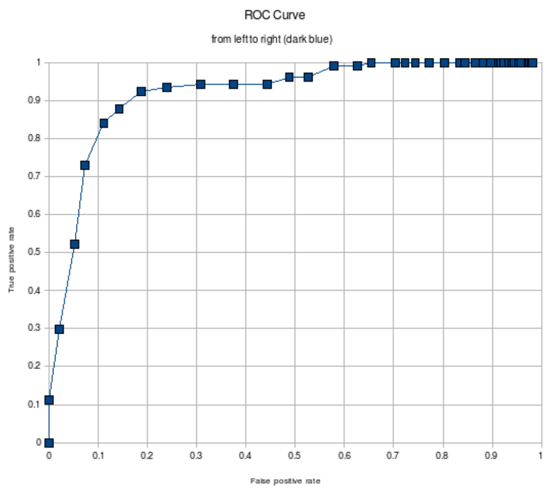
Initial model was chosen after a few experiments with training data. The topology of initial model is shown in Figure 1.

4 EVALUATION

For a successful classification of trajectories and a search for abnormal trajectories, it is important to have a well defined scene with well defined scenarios. The anomalous trajectories correspond to scenarios, that are not defined. It is very difficult to define all the possible normal scenarios in all scenes; therefore, scenes with simpler scenarios had to be selected.

Two experiments were performed with recordings from an underground station in Roma. The first one was with filtered trajectories, so the scene contained only well defined trajectories. Classification was performed with about 400 trajectories in the training set and about 400 trajectories in the evaluation set with hit rate 91.92 %.

Second experiment was performed with trajectories, that were not preprocessed. The hit rate was 37.63 % with the training set corresponding to first experiment and the evaluation set with about 10 000 trajectories.



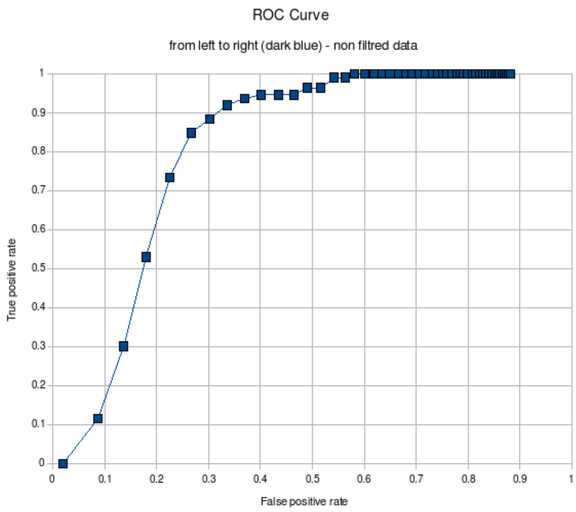


Figure 3: Comparison of ROC Curves for selected trajectory (model)
(a) left: filtered data (b) right: non filtered data.

5 CONCLUSIONS

A novel method for trajectory classification has been presented. With this method, it is possible to process the trajectories obtained from surveillance cameras recordings. The method can provide information about a degree of correspondence of trajectory to each model. It enables detection of objects with unusual behaviour. The necessary prerequisites for correct classification of normal and abnormal behaviour are well defined trajectories (e.g. defined in a simple scene or subscene) accurate object tracking, and well annotated abnormalities in trajectories.

REFERENCES

[1] Christopher M. Bishop. *Pattern Recognition and Machine Learning (Information Science and Statistics)*. Springer-Verlag New York, Inc., Secaucus, NJ, USA, 2006.

[2] Steve Young and *et. al.* *The HTK Book*. Cambridge University Engineering Department, 2006.