

# User-Centric Retrieval of Visual Surveillance Content

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**Abstract**—An interactive retrieval method adapted to surveillance video is presented. The approach is formulated as an iterative SVM classification and builds upon the two major specificities of the surveillance context, namely the multiple instance nature of the data and the reduced number of training examples the user can provide at each round. The later issue is solved thanks to a new adaptive active learning strategy as well as an intuitive graphical user interface. The system has been validated on both synthetic and real datasets. It will be demonstrated during the conference.

**Index Terms**—Surveillance video retrieval, multiple-instance, relevance feedback, active learning.

## I. INTRODUCTION

THIS paper addresses the problem of retrieving arbitrary scenes of interest within surveillance video sequences stored in a database. A scene is described by one or several video frames with a common configuration of (some of) their foreground objects. The goal of our system is to learn which particular configuration of objects the user is looking for, while minimizing his/her work load.

Nowadays, such solutions for content-based retrieval of surveillance data are ever more required as the number of video surveillance systems and the amount of stored data drastically increase. Since there is no a priori knowledge about the target, the system must adapt his learning to identify the new target class of scenes, by interpreting the new increasing training set. In other words, compared to existing surveillance video retrieval systems, we adopt a versatile content-based approach, guided by the interactions with the user, rather than relying on the indexation of pre-defined scenarios.

Our retrieval method is modelled as an interactive supervised classification problem. A session is composed of a few steps repeated until the retrieval performances satisfy the user. This is depicted on Figure 1.

First, the user labels a few frames. This operation is kept very simple: the user only tells the system whether the presented frames are matching his/her target scene or not. The number of frames labeled at each round is expected to be small, i.e. typically 5 to 10.

Based on extracted features, either at low/mid visual level or at higher semantic level, the labeled frames are used to train a soft-margin SVM (Support Vector Machine) classifier. This classifier is then exploited to predict a label for the unknown frames as well as their similarity to the guessed target class.

Finally, the system carefully selects the next frames that should be presented to the user for labelling.

The specific constraints of the surveillance context led us to face two major problems:

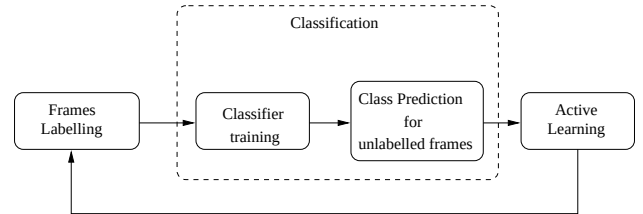


Fig. 1. Flow chart of a retrieval session

- 1) The nature of the surveillance data imposes a specific classification approach. Here, we present a multiple-instance framework which allows classification of the data.
- 2) The load on the user must be minimized. So, the system must learn as fast as possible what the target class is, while the number of training examples is small and slowly growing. This is achieved by carefully selecting the frames to be presented to the user. In this paper, we propose an online adaptation of the progressing training set. Moreover, a graphical user interface is designed so as to provide intuitive navigation through the retrieval results. It allows the user to easily label groups of frames and consequently boost the classification performances.

The presented system will be demonstrated during the SAMT07 conference.

## II. MULTIPLE-INSTANCE FRAMEWORK

Surveillance video data have a very specific nature compared to classical images. Basically, through background learning, foreground objects can be extracted and described by features such as position, texture, dimensions, direction etc. However, the number of objects per frame can be very large in noisy conditions and varies a lot from frame to frame. Moreover, not all objects trully correspond to real-life objects, vehicles or individuals.

The classification of surveillance video frames then is formalized as a multiple-instance problem, where the frames are the *Bags* -, while the foreground objects are the *- instances*[3], [2]. Since the number of instances per bag is highly variable, there exist an ambiguity on their relevance to the received label. While a few instances may justify a positive label, other instances from the same bag may indeed be totally irrelevant. In [1], we presented a framework to represent the data and enable a SVM classification.

It consists of two steps. First, we define a similarity measure  $s(B_i, x^k)$  between a bag  $B_i$  and an instance  $x^k$ , which is used

to map the bags into a new space, where the multiple-instance problem can be solved. Second, in this space, a soft-margin SVM (Support Vector Machine) is trained to predict the label of the unlabelled bags:

$$y = \text{sign} \left( \sum_k w_k s(x^k, B_i) + b \right), \quad (1)$$

where  $k$  is the number of instances among the training bags.  $w_k$  and  $b$  are the decision plane parameters provided by the SVM training.

### III. ADAPTIVE ACTIVE LEARNING

Successfully achieving a fast learning when only a few training examples are provided at a time is only possible by carefully selecting the frames to be presented to the user. The goal is to maximize the information gain these new examples will offer, if the user labels them. Such a selection process is called active learning and is a well known challenge in information retrieval[4], [5].

The traditional approach consists in selecting, after each class prediction, the most uncertain examples. It has been shown that the proximity to the decision plane is a good approximation of such uncertainty. Receiving labels for these examples indeed allows refining the classification hyperplane.

In our case, given the weight vector  $\mathbf{w}$  obtained from the last classification step (Equ.(1)), the most ambiguous bags  $B^m$  have instances with minimal distance to the separation plane:

$$B^m = \arg \min_i |\mathbf{w}^T \mathbf{m}_i + b| \quad (2)$$

Such refinement is powerful only if the learner already has knowledge of the data distribution in the feature space. In other words, the features space must first be roughly explored to discover all “clusters” of instances, before trying to refine the decision plane. A compromise must then be found between exploring the feature space and refining the decision plane, resulting in a combination of different active learning strategies, as discussed in [6], [7].

Nonetheless, the exploration starts being useful only when a minimum of positive examples are known so that a first rough decision plane can be estimated. In our specific case, given the possible disproportion between the classes and the small number of training examples provided at each round, it is not obvious that random exploration will be performant at the beginning of the retrieval session.

Here, our proposed approach dynamically combines these three active learning methods. This will be detailed in the camera ready paper.

### IV. GRAPHICAL USER INTERFACE

The retrieval performances, as every classification task, is very dependent on the training set. Even though active learning allows dealing with small training sets, we developed an intuitive graphical user interface (GUI) that helps the user to quickly and easily label video frames. The GUI includes several tools and functionalities such as navigation through and multiple resolution display of the retrieval results. A separate window invites the user to check the frames selected by the active learning engine (see Figure 2)

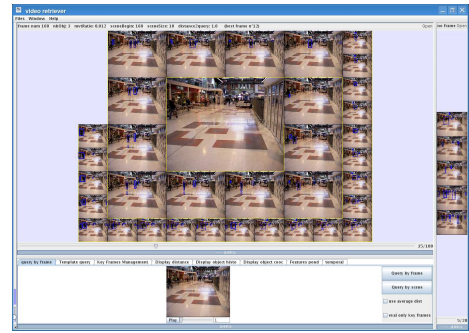


Fig. 2. Snapshot of the retrieval interface

### V. CONCLUSION AND FUTURE WORK

A new approach for interactive retrieval of CCTV content is presented and will be demonstrated during the conference. It has been validated and compared to state-of-the-art methods on both synthetic multiple-instance data and realistic reference data from the IEEE PETS workshop[10]. The experiments will be detailed in the camera ready paper. Future work include the use of new modalities like voice or gesture recognition to help the user interacting with the results. This is in line with our original philosophy stating that the user’s task must be intuitive and simple.

### ACKNOWLEDGMENT

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