Semantic Feature Extraction using Mpeg Macro-block Classification

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Abstract

In this paper, we present some first results in the extraction of semantic features from video sequences. Our approach is based on the classification of Mpeg DCT macro-blocks. Although it is clear that using macro-blocks imposes severe restrictions on the precise analysis of the image, it has the advantage of avoiding the complete decoding of the Mpeg stream. Our objective is to evaluate the quality of the Semantic Feature Extraction that can be obtained with this direct approach, to serve as a comparative baseline with more elaborate approaches.

Keywords: *Semantic classification, Discrete Cosine Transform, Gaussian Mixture Models, Compressed Domain.*

1 Introduction

The large amount of visual information, carried by video documents as well as still images, requires efficient and effective indexing and search tools [2, 5]. The U.S. Institute of Standards and Technology sponsors the serie of TREC [1] 2002 conferences to promote progress in content-based retrieval from digital video. Our work takes place in this context where we focus on the feature extraction task; video shots should be classified into the high level semantic concepts *indoor, outdoor, cityscape, landscape, text overlay, face* and *people*.

To extract relevant features, the content should in principle be decoded first. Since this operation is time consuming, especially when a whole database should be processed, feature extraction directly from the compressed domain would be particularly interesting by providing fast and reliable information analysis and selection tools. Lots of work have been conducted to achieve image or video segmentation, however only few researchers have given solutions to the challenging task of image segmentation into objects or regions with limited decoding of the mpeg stream [8, 3].

In this paper, we propose to extract semantic features from 16 by 16 pixels DCT macro-block classification. We have distinguished two types of feature in the TREC set, the **region-level** features like *face* and *text overlay* and the **frame-level** features like *indoor, outdoor, cityscape, landscape* and *people* that require elementary concepts like *building, greenery, sky* and *water* to be detected.

The next section details the supervised classification process via Gaussian Mixture Models [7, 6] of macro-blocks. Then we explain how the final decision is taken by introducing new elementary concepts to describe frame-level semantics. Finally, we will outline future improvements.

[1]TREC is a series of conferences which high-level goal is the investigation of content-based retrieval from digital video.
See http://www-nlpir.nist.gov/projects/t2002v/t2002v.html

2 Macro-block Classification

In the context of supervised classification, three steps are involved: feature extraction and representation, class modelisation and parameter estimation, finally classification with respect to decision rules.

In our approach, features are directly provided by the video stream after parsing since we work only on I-frames, which are encoded somehow like jpeg pictures. These frames are composed of macro-blocks that contain 6 DCT blocks, 4 for Y color component, 1 for U and 1 for V i.e. 4:2:0 video format. We can represent a DCT macro-block by a vector of size 64 corresponding to the zigzag scan of the DCT block coefficients and then make the concatenation of the 6 vectors to obtain the feature vector of the whole region. Since the first DCT coefficients are the most important i.e: to eye sensitivity and noise, the feature space dimension is simply reduced to 60 by truncation. Moreover coefficients are scaled with respect to their importance in order to increase the sensitivity of the classifier to important components and at the same time to slightly improve the initialisation of the training algorithm, which is usually obtained via k-means algorithm as explained in the next subsection.

We assume a mixture model to describe the distribution of macro-blocks for each class, and specifically a multi-dimensional Gaussian distribution. Gaussian models can capture the characteristics of a macro-block, while modeling the variation due to motion or lighting conditions. Moreover in [4], E.Y. Lam and J.W. Goodman have proven that the distribution of macro-block DCT coefficients can be well approximated by a Gaussian *when the variance is constant*; in the classification situation, the latter hypothesis is more or less true and mixtures should compensate it. So the probability density function can be written as follows:

$$\text{For } X \in C_i, P(X \mid \Phi_i) = \sum_j \alpha_j p_j(X)$$

where $\alpha_i \in \Re, \Phi_i = (\mu_j, \sigma_j)$ and $p_j(X) \sim \mathcal{N}(\mu_j, \sigma_j)$

The GMM parameters α_j, μ_j and σ_j are estimated using the traditional Expectation-Maximization algorithm [1] which is initialized with a classical k-means algorithm. In our current experiments, we also make the hypothesis that feature vector components are independent, thus σ_i is a diagonal matrix. Finally the choice of the number of mixtures is simply achieved by looking at the test set loglikelihood evolution of the EM algorithm for various mixture numbers. It should not increase to much in order to avoid data overfitting.

Given an unlabeled macro-block X, the maximum a posteriori rule:

$$\hat{C} = arg \max_i P(\Phi_i \mid X)$$

gives an estimation of the class it belongs to. The posterior probabilities can be expanded by Baye's rule:

$$P(\Phi_i \mid X) = \frac{P(X \mid \Phi_i) P(\Phi_i)}{P(X)}$$

finally,

$$P(\Phi_i \mid X) \propto P(X \mid \Phi_i)$$

since we assume the *equiprobability* of classes and vectors.
However, it is possible that a macro-block does not belong to any predefined class. Thus we introduce for each model i a minimum bound $-mb_i$ for the loglikelihood which is selected to eliminate 10% of the training data set. Of course there is a trade-off to find between precision and recall. Finally the decision rule can be written:

$$\hat{C} = arg \max_i \{P(X \mid \Phi_i) \mid -\log(P(X \mid \Phi_i)) \leq mb_i\}$$

3 Feature detection

The presented classification method allows to detect **region-level** features only. Thus a heuristic two-step hierarchy, depicted in figure 1, was introduced to detect **frame-level** concepts via additional elementary semantics. The hierarchy contains two kinds of elements:

- elementary concepts that are the leaves,
- Trec features that are enclosed in boxes.

The detection of features present in one shot is finally achieved with respect to the following procedure:

1. Classify all macro-blocks of the shot into elementary concepts,
2. Compute the detection score for each feature.

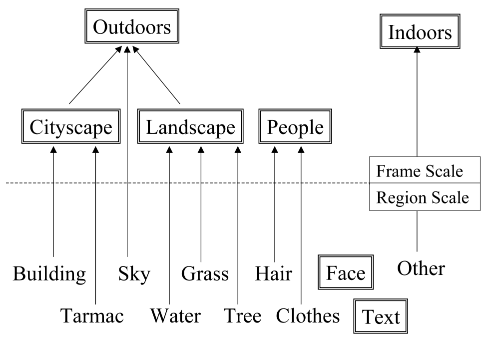

Figure 1: Concepts hierarchy.

The detection score of the feature i whose elementary childrens are J is:

$$Ds_i = \sum_j P(j) \text{ where } j \in J$$

$$P(j) = \frac{\text{Number of macro-blocks with label j}}{\text{Total number of macro-blocks in the shot}}$$

It represents the posterior probability of a feature to be in the given shot. Finally, for each feature, shots are ordered by decreasing detection score.

4 Conclusion

We have presented a method based on DCT information of macro-blocks to extract Trec features from video shots. Since macro-blocks carry only local information, a heuristic hierarchy was introduced to build the final decision rule at the **frame-level** and **region-level**. In future works we plan to investigate methods to automatically elaborate the hierarchy. This will also set up a complete probabilistic framework to detect features from low level observations.

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